THREE ESSAYS ON HOUSEHOLD CONSUMPTION EXPENDITURES

by

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I dedicate this thesis to my parents and siblings who have been a great source of support and inspiration in my life.

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This dissertation is based in part on the previously published article listed below. I have permission from my co-authors to use the work listed below in my dissertation. [Wahdat, A., Gunderson, M., & Lusk, J. (2021). Farm Producers' Household Consumption and Individual Risk Behavior after Natural Disasters. Agricultural and Resource Economics Review, 50(1), 127-149. doi:10.1017/age.2021.2].

Regarding the first essay (Chapter 2), which is co-authored with Prof. Michael Delgado, I acknowledge that it is our own analysis, calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are authors' own and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

Regarding the third essay (Chapter 4), I acknowledge that the essay uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. HILDA

Survey is conducted by the Australian Government Department of Social Services (DSS) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in the third essay, however, are my own and should not be attributed to the Australian Government, DSS, or any of DSS' contractors or partners. DOI: http://dx.doi.org/10.26193/IYBXHM

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ABBREVIATIONS

FAH	Food-at-Home
FAFH	Food Away from Home
WBAH	Water and Non-Alcoholic Beverages at Home
GPQI	Grocery Purchase Quality Index
GDD	Generalized Differences-in-Differenesc
ATET	Average Treatment Effect on Treated

ABSTRACT

In my dissertation, I investigate the relationship between household consumption expenditures and transitory income shocks. In the first two essays, I pay particular attention to household expenditures in the aftermath of natural disasters, which are becoming more frequent and costly in the U.S. since 1980. Additionally, I study specialty farm producers' risk attitudes after an income shock due to natural disasters. Although the permanent income hypothesis predicts that households smooth consumption over their lifetimes, credit-constrained households may find consumption smoothing impractical. This dissertation brings forth evidence regarding heterogeneity in the effect of income shocks on household expenditures. First, I find that floods and hurricanes affect food-at-home (FAH) spending in different ways. The average 15-day decrease in FAH spending is about \$2 in the 90 days after a flood and about \$7 in the 30 days after a hurricane. In other words, floods have a prolonged effect and hurricanes have an immediate effect. I find that floods and hurricanes remain a threat to the FAH expenditures of vulnerable households, for instance, low-income households and households in coastal states. Second, Indiana specialty farm households reduce their monthly expenses of food and miscellaneous categories by about \$119 and \$280, respectively, after an income loss of 20%-32%. I also find that Indiana specialty producers are less willing to take financial risk after an income loss experience, i.e., they have a decreasing absolute risk aversion. Finally, in the third essay, I show that Australian households exhibit loss aversion in consumption expenditures which also means that they behave asymmetrically in their consumption response to income shocks. However, it is only working-age younger households that show asymmetric consumption behavior as opposed to the symmetric behavior of retirement-age households. The main message of these various findings is clear: after an income shock, the magnitude of change in consumption expenditures and the saliency of certain expenditure categories for adjustment are context- and population-dependent. Hence, income support policies and post-disaster relief programs may benefit from a better understanding of the consumption behavior of beneficiary population, to achieve maximum impact through better targeting.

1. INTRODUCTION

In my dissertation, which is an amalgamation of three research essays, I study households' consumption expenditures in the aftermath of transitory income shocks. I also investigate households' risk attitudes and consumption loss aversion after natural disasters and income shocks. This line of research is important because shocks due to natural disasters, human conflict, or economic downturns are both rampant and carry substantial costs. These costs come in the form of income and asset losses, human losses, and psychological distress. After an exogenous shock, households may lose income and decrease consumption expenditures which can affect livelihoods and well-being. The experience of a negative shock can also distort individual attitudes and perceptions. For instance, a change in risk attitudes and perceptions can affect risk-taking capacity, which can further affect crucial financial decisions at the household- and firm-level. Given households' vulnerability to exogenous shocks and events, governments and international organizations often engage in economic support programs to boost household consumption and stabilize livelihoods.

The success of any economic recovery program mainly depends on its efficiency and efficacy, therefore, it is crucial to identify the type of support that is most effective in pulling livelihoods out of depression. If the support takes the form of transfer payments, then what is the right amount of transfer and which social strata should be targeted. If the support is in-kind, then what goods and services are most needed for recovery. This challenge motivates me to ask questions in the context of economic models as (i) which expenditure categories do households adjust after a natural disaster or income shock, and what is the magnitude of the expenditure adjustment, (ii) do households exhibit decreasing absolute risk aversion after the experience of an income shock due to natural disaster, and (iii) do households exhibit loss aversion in consumption expenditures, and whether consumption response to income shock is asymmetric after an income shock.

In the first essay, my co-author and I 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. We use two datasets: (i) the Storm Events Database to identify U.S.

counties that experience severe economic losses as a result of droughts, floods, hurricanes, and tornadoes, and (ii) the Nielsen Consumer Panel Data for grocery data. We find that only floods and hurricanes affect FAH spending. 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 quality effect of the four natural disasters is either inconsequential or nonexistent. We find the evidence that the FAH spending effect of natural disasters partially works through the price channel. We also find that hurricanes have an anticipation effect on total grocery spending which starts 15 days before the disaster date. Our results are robust to an alternative specification that controls for county-specific linear trends. The first essay adds to the growing body of literature on the effects of natural disasters on household finances and financial decisions (Gallagher and Hartley, 2017; Deryugina et al., 2018). Findings from the first essay could be of particular interest to post-disaster relief organizations and their programs.

In the second essay, which is a published work (Wahdat et al., 2021), we investigate how farm household consumption responds to adverse income shocks. Understanding farm households' consumption response and risk attitude after an income shock can provide insight into household well-being and appropriate agricultural policy. Using a split-sample survey of Indiana specialty producers, where we randomly assign respondents to treatments that vary the size of a hypothetical income shock, we estimate the relationship between income loss and household consumption. Given that post-disaster producers' risk preferences are important for business decisions, we also elicit producers' risk preferences. We find that food and miscellaneous expenditures are the most sensitive to income losses. We also find evidence for decreasing absolute risk aversion among producers after the income loss shock. The second essay adds to two strands of literature. First, it contributes to the literature on agricultural vulnerability to climate change and weather shocks (Walthall et al., 2013; Kistner et al., 2018; Grabrucker and Grimm, 2020). Second, it contributes to the literature on decreasing absolute risk aversion (Pratt, 1964; Arrow, 1971) and the nonstability of risk preferences over time (Malmendier and Nagel, 2011; Guiso et al., 2018).

In the third essay, I investigate household consumption response to realized income shocks when households have reference-dependent preferences for consumption expenditures. I consider households' reference level of consumption expenditures in the current period to be equal to last period's expenditures. With reference-dependent preferences, the concept of loss aversion comes in play, i.e., people tend to prefer avoiding losses compared to receiving equal value gains (Kahneman et al., 1991; Kőszegi and Rabin, 2006). Using longitudinal data on Australian households and exploiting variation in income shocks at the household level, I estimate loss aversion in consumption expenditures. I find that losses in consumption expenditures loom about 1.4 times larger than equal value gains. The magnitude and statistical significance of the loss aversion estimate is robust to an alternative reference point, which is the average expenditures of last two periods. I also show that retirement-age households (working-age households) have a symmetric (asymmetric) consumption response to realized income shocks. This essay contributes to two strands of literature. First, it adds to literature on estimating loss aversion (Tversky and Kahneman, 1992) and consumption behavior under loss aversion (Kőszegi and Rabin, 2009; Pagel, 2017). This study also contributes to the literature on consumption response to income shocks (Christelis et al., 2019). The findings from this study are relevant for Australian household consumption, which has become more vulnerable to economic shocks since 2009-10. In recent years, Australian households could be more loss averse in consumption when compared to the loss aversion finding of 1.4 in this study which is based on 2007-10 financial years. Finally, Australian working-age households could benefit relatively more from income support programs than retirement-age households because younger households are more consumption responsive to negative income shocks.

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2. A DECADE OF U.S. NATURAL DISASTERS AND HOUSEHOLD FOOD-AT-HOME EXPENDITURES AND QUALITY: A QUASI-EXPERIMENTAL STUDY

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

[1] ↑CPI adjusted as of 2018.

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

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 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% (or \$0.118) and decrease fresh fruit spending by about 3.5% (or \$0.141) 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 facilitate the use of the GDD regression method by introducing a spatial-temporal algorithm to identify disaster-affected counties and their controls over time and space (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.

2.1 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 Gross Domestic Product (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

[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).

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 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

[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.

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

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).

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 versus 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).

2.2 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

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

2.3 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

[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/

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 events. The socio-demographic variables are 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. 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 B 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.

[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.

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$^{\text{th}}$ 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 group (see Table 2.A1). 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.A2 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 2.A3).

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 2.A4 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 2.A5 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 2.A5 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.

2.4 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 versus 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,

$$Y_{i,c,t} = \beta D_{c,t} + \boldsymbol{\gamma}_t + \boldsymbol{\lambda}_c + \mathbf{X}_{i,c,t}\boldsymbol{\delta} + \varepsilon_{i,c,t}, \tag{2.1}$$

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 county level.

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.

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

[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.

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.

2.4.1 Choosing Generalized DiD (GDD) over Classic DiD (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 2.A5 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.

2.5 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. In the Tables and Appendix Tables sections, we present tables with the ATET estimates from equation (1), and the ATET estimates from the robust specification that includes county-specific linear trends (see sections 2.8 and 2.A). In this section, we only discuss those estimates that are statistically 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.

2.5.1 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 2.1). 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 2.2). 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 2.1 and 2.2). Floods do have a negative impact on FAH spending, albeit not within the first 30 days after the flooding (Column 3 in Table 2.1). After flooding, average 15-day FAH spending decreases by \$1.314 in 90 days, and \$1.403 in 180 days (Column 3 in Table 2.1). Although floods affect FAH spending in 90-180 days, they have no impact on GPQI in any post-flooding window (Column 3 in Table 2.2).

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 2.1). 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 2.1). Finally, tornadoes have no effect on FAH spending in any post-tornado window (Column 5 in Table 2.1). 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 2.2).

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 2.3). 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 2.3). 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 2.3). 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 2.4), 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 2.5), and the negative effect on average 15-day GPQI is rather very small (-0.212 or $\sim 0.3\%$ of max GPQI score) in the 90 days after the events (Column 2 in Table 2.5).

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.A2), 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 appears late after the floods.

2.5.2 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 2.A6). 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 2.A6). 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 2.A7). 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 2.A7). In case of hurricanes, we do not find an immediate impact on total grocery spending in the 30 days (Column 4 in Table 2.A7). 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 2.A8). After flooding, the average 15-day alcohol spending decreases by \$0.234 in 180 days (Column 3 in Table 2.A8). 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 2.A8). 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.[15]

2.5.3 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

[15] ↑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.

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 2.A9). 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 2.A10). We do not find an anticipation effect of flooding or hurricane on FAH spending or WBAH spending (Columns 1-4 in Table 2.A9). Meanwhile, flooding does not have an anticipation effect on total grocery spending (Column 5 in Table 2.A9).

2.5.4 Do Natural Disasters Affect FAH Spending through the Income Channel?

The short answer is: yes. Natural disasters can affect household FAH spending through the income channel and we indirectly test it, 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.[16] Our low-income household definition includes poor households.

We find that after the four natural disaster events altogether, the average 15-day FAH spending of low-income households decreases by $1.613 in 30 days, and that there is no

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

impact of natural disasters on the FAH spending of households that are not in the low-income class (Columns 1-2 in Table 2.A11). This provides evidence that the income channel is one potential channel through which natural disasters affect FAH spending.

2.5.5 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 increase food prices and lead to a decrease in FAH spending. To carry out this exercise, we look into fresh fruit price (per unit) and fresh fruit 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 during the active harvesting period for majority of fruits, i.e., June to December (U.S. Department of Agriculture, 2006).

We find that flooding and hurricanes do lead to an increase in fresh fruit price and a decrease 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 2.A12).[17] 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

[17] ↑Fresh fruit unit is either pound or count.

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).

2.6 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 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 hurricanes decrease average 15-day total grocery spending by 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.

2.7 Tables

Table 2.1. 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 2.2. 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 2.3. Floods' and Hurricanes' Impact on Food Spending by Damage Quartiles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	q1	q2	q3	q4	q1	q2	q3	q4
	Flood				Hurricane			
	(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. 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 2.4. Floods' and Hurricanes' Impact on GPQI by Damage Quartiles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	q1	q2	q3	q4	q1	q2	q3	q4
	Flood				Hurricane			
	(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). 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 2.5. Floods' and Hurricanes' Impact on Food-At-Home Spending and Grocery Purchase Quality Index in High-Exposure Coastal States

	(1) 30-Day	(2) 90-Day	(3) 180-Day
Panel A. Food-At-Home Spending			
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
Panel B. Grocery Purchase Quality Index			
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: In Panel A, dependent variable is food-at-home (FAH) spending in 2017 constant dollars. In Panel B, dependent variable is Grocery Purchase Quality Index. FAH 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

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2.A Appendix Tables

Table 2.A1. 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 section and Appendix B. This data is based on 2005-2016 period, using NOAA's Storm Event Database.

Table 2.A2. 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 2.A3. 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 2.A4. 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 2.A5. Household Demographics by Treatment and Control Households

	Treatment	Control	Balance Test	Balance Test
	Mean (SD)	Mean (SD)	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 (%)	Frequency (%)	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				
< $5,000	291 (0.9)	132 (1.1)	0.01	0.87
$5,000-$14,999	1,582 (5.0)	764 (6.1)	0.05	0.82
$15,000-$29,999	4,723 (14.9)	2,193 (17.6)	0.07	0.87
$30,000-$59,999	11,425 (36.0)	4,530 (36.4)	0.01	1.00
$60,000-$99,999	8,966 (28.2)	3,284 (26.4)	0.04	1.04
>= $100,000	4,753 (15.0)	1,554 (12.5)	0.07	1.17
Education				
High School (graduate or below)	8,575 (27.0)	3,642 (29.2)	0.05	0.95
College (graduate or below)	19,245 (60.6)	7,358 (59.1)	0.03	0.99
Post-College Graduate	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 18 Years				
No Child < 18 Years	25,585 (80.6)	9,951 (79.9)	0.02	0.97
Child < 18 Years	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. SD stands for standard deviation.

Table 2.A6. 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 2.A7. 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 2.A8. 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

Table 2.A9. 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 2.A10. 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

Table 2.A11. Disasters' Impact on Food Spending by Household Income Class (Post-Disaster=30 Days)

	(1) Above Low-Income Households	(2) Low-Income Households
Treated $\times$ 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

Table 2.A12. 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

Table 2.A13. 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 2.A14. 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 2.A15. 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 cluster-robust at the county level. * p<0.1, ** p<0.05, *** p<0.01

Table 2.A16. 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 2.A17. Floods' and Hurricanes' Impact on Food Spending and Grocery Purchase Quality Index in High-Exposure Coastal States with County Trends

	(1) 30-Day	(2) 90-Day	(3) 180-Day
Panel A. Food-At-Home Spending			
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
Panel B. Grocery Purchase Quality Index			
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: In Panel A, dependent variable is food-at-home (FAH) spending in 2017 constant dollars. In Panel B, dependent variable is Grocery Purchase Quality Index. FAH 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 2.A18. 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 2.A19. 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 2.A20. 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 2.A21. 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 2.A22. 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 2.A23. 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 2.A24. 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. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

2.B Appendix Data Steps

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.

2.B.1 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.[18] 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.[19]

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.

2.B.2 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$^{\text{th}}$ 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

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

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 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$^{\text{th}}$ 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.

2.B.3 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.

2.B.4 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.

3. FARM PRODUCERS' HOUSEHOLD CONSUMPTION AND INDIVIDUAL RISK BEHAVIOR AFTER NATURAL DISASTERS

A prediction of the permanent income hypothesis is that households use savings in the event of an income shock to smooth consumption over their lifetimes. However, when households are lacking assets, it is likely that they have insufficient savings and face credit constraints, which render consumption smoothing almost impractical (Jappelli and Pistaferri, 2010; Hallegatte et al., 2017). It becomes obvious that an income shock to a low-asset household would imply a decrease in consumption expenses. Whether a decrease in expenses is concentrated in one consumption category or multiple categories is an important and relevant question for household well-being after income shocks.

The objective of this study is twofold, first, to determine how farm households adjust consumption expenses after an unexpected income loss due to natural disasters, and second, to evaluate whether an income loss experience affects producers' risk-taking behavior. We further complement the analysis with a survey of producers' resilience capacity against natural disasters. We focus specifically on specialty crop farm households in the Midwestern state of Indiana. This is due to the fact that (i) specialty crops in the Midwestern region are vulnerable to natural disasters, (ii) specialty crops' acres are the least covered by federal crop insurance, and (iii) Indiana specialty crop enterprises are mainly small in size and rely on family labor. In our results we find that farm households reduce their monthly expenditures of food and miscellaneous categories by ∼\$119 and ∼\$280, respectively, after an income loss of 20%-32%.[1] We also find that producers are less willing to take financial risk after an income loss experience.

Our study contributes to the literature on agricultural vulnerability to climate change and weather shocks (Grabrucker and Grimm, 2020; Kistner et al., 2018; Walthall et al., 2013). We estimate the potential impact of income loss due to natural disasters on Indiana specialty producers' household consumption expenses. Furthermore, our study contributes to the literature on producers' risk preferences in two areas: (i) we measure producers' risk

[1] ↑Miscellaneous expenses include mortgage fees, charity, life insurance, and retirement expenses.

preferences immediately after they experience natural disasters because it is an important time in terms of farm investment and household consumption decisions, and (ii) we assess whether producers who receive a hypothetical negative income shock are more risk averse compared to a counterfactual group of producers. These contributions relate to the literature on decreasing absolute risk aversion (Pratt, 1964; Arrow, 1971) and non-stability of risk preferences over time (Guiso et al., 2018; Malmendier and Nagel, 2011).

Specialty crops' production in the Midwestern United States was worth $5.24 billion in market value in 2017 (National Agricultural Statistics Service, 2019c).[2] These crops' yields are subject to weather and climate threats, which are projected to be intensified by wetter springs and drier summers in the future (Kistner et al., 2018). It is already the case that U.S. agricultural losses are primarily driven by weather and climate disasters, i.e., floods, droughts, and severe freezes (Smith, 2018). How well do producer households recover from a disaster depends on the recovery tools and mechanisms in place. Despite federal crop insurance being an important risk management tool for the U.S. agricultural producers, specialty crops are among the least covered agricultural crops. Nationally, only 34% of eligible vegetable crops' acreage was enrolled in federal crop insurance programs in 2015 as compared to 89% of major crops, i.e., corn, wheat, and soybean (Shields, 2017). In case of fruits and nuts, 74% of the acreage was insured which is still much lower than that of major crops (Shields, 2017). Moreover, the average total loss deductible for vegetables (35%) and fruits and nuts (41%) is higher compared to major crops (26%) (Shields, 2017).[3] Meanwhile, 86% of Indiana vegetable farms are classified as small and medium (less than $10,000 and $250,000 gross annual sales, respectively); and these farms mainly rely on family labor (Torres and Marshall, 2016). Although farming is the primary occupation of around 41% of Indiana specialty producers (National Agricultural Statistics Service, 2019a), the agricultural and asset losses from natural disasters can still have deleterious effect on every farm-household's income.

[2]↑The Midwest comprises the states of Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, Ohio, and Wisconsin. The figure $5.24 billion is based on the following specialty crops: (i) vegetables, melons, potatoes, sweet potatoes, (ii) fruits, tree nuts, berries, and (iii) nursery, greenhouse, floriculture, sod.

[3]↑Among vegetables, processing tomatoes' acreage is insured at a high rate of 94% (probably due to the presence of processor contracts). Producers might be able to purchase insurance coverage for non-insurable vegetable crops through the non-insured crop disaster assistance program (NAP) (Shields, 2017).

The consumption of low-income households is relatively more vulnerable to the negative effects of natural disasters than that of high-income households because low-income households often lack the assets to protect them against natural disasters (Hallegatte et al., 2017). When a low-income household's consumption falls across food, health, and education categories, the household suffers a loss in well-being (Hallegatte et al., 2017). For instance, a consumption decline across food, health, and education categories can translate into poor health for household members or low employment prospects for the children in the future.

Given that farm producers' insurance, marketing, and commodity supply decisions partially depend on their risk-taking capacity (Zhao and Yue, 2020; Chavas and Holt, 1996; Eckman et al., 1996), we investigate producers' risk preferences after a natural disaster and income loss experience. Understanding producers' consumption and risk behavior after a disaster can help with policies related to household recovery and designing credit and insurance instruments that can lessen the negative effects of natural disasters.

The study of consumption response and risk behavior after transitory income shocks is an active research area, although mired with data limitations (Attanasio and Weber, 2010; Christelis et al., 2019). A natural disaster, or any income shock, happens at irregular intervals while survey collections mostly happen at regular intervals, so aligning them together becomes difficult, particularly if interest is in measuring consumption and risk before and after a shock. To the best of our knowledge, we are the first to study farm household consumption responses to exogenous income shocks, where identification is clearly obtained by using an experimental design, albeit through a hypothetical survey. Our methods can be easily extended to other contexts to study producers' household and farm decisions.

3.1 Literature Review

Agricultural production activity is mired with risk due to price and production volatility, policies, institutional arrangements, and weather (Hardaker et al., 2004, p. 1-4). In case of rare "catastrophic" risks posed by natural weather events, producers lose crop production which can directly affect their farm finances (Ogurtsov et al., 2008). Agricultural risk can affect farm output and finances, hence the reason that U.S. agricultural policy allocates considerable resources to farm risk management. In what follows, we discuss research related to agricultural losses due to natural disasters and their potential economic impacts. Next, we discuss the literature on farmers' and non-farmers' risk preferences, which are sometimes measured in the aftermath of natural disasters.

Too little or too much of precipitation, compounded with erratic temperatures, can bring about drought, floods, and severe freezes. Such natural disasters pose substantial and perpetual threats to agricultural production. In the U.S., droughts inflicted \$15 billion in crop losses in 1988-1989 (Reibsame et al., 1991), reduced corn and soybean yields by 0.1% to 1.2% per additional drought-week in 2001-13 (Kuwayama et al., 2019), and inflicted losses of \$2 billion (crops) and \$553 million (dairy and livestock) in California in 2014-16 (Howitt et al., 2014, 2015; Medellín-Azuara et al., 2016). The 1993 flooding in the Central United States caused \$5 billion in crop losses (Shannon and Motha, 2015). In 2019, the flooding in Nebraska led to \$440 million in crop losses (Di Liberto, 2019). Damaging freezes, which are common to the U.S. and Canada, have historically led to orange and citrus production losses in California and Florida; and crop and fruit damages in the Plains, the South, and the Midwest in 2007 (Shannon and Motha, 2015). In 2020, the COVID-19 pandemic (if considered a natural disaster) severely affected the U.S. agricultural sector; it is estimated that the net farm income will decrease by about \$20 billion (Westhoff et al., 2020). The derecho of August 10, 2020 wreaked havoc on crops in Iowa and the U.S. Midwest – the estimated losses are projected to be about \$4 billion, thus making the 2020 derecho one of the costliest weather events of the past decade (Voiland, 2020).

Although natural disasters are a threat to agricultural production, they have pushed U.S. farmers to adapt and consider new methods and strategies, for instance, the use of climate data in farm decision-making, participation in crop insurance programs, crop diversification, soil conservation, and livestock breed selection (Walthall et al., 2013). Adaptive strategies may protect farm production if there is climatic stability, however the 21st century is predicted to have more variable climatic conditions (Walthall et al., 2013). Erratic weather and climate are specifically harmful to specialty crops, which are more sensitive to climatic stressors than row crops (Kistner et al., 2018). From 1989 to 2015, specialty crops in the Midwest have been constantly affected by weather hazards (Kistner et al., 2018). In 2007, California lost about 20% of orange production due to severe freeze (Shannon and Motha, 2015).

Given that natural disasters affect specialty crops' production, the low insurance coverage of these crops pose a financial risk to specialty crop farms. Despite the availability of Non-Insurance Assistance Program (NAP) under the Federal Crop Insurance Reform Act of 1994, research shows that specialty producers were not compensated well enough compared to ad hoc disaster payments in 1988-93 (Lee et al., 1997). The Whole Farm Revenue Protection (WFRP) insurance serves as an attractive risk management option for specialty crop producers due to its higher premium subsidy rates than other insurance policies, however, participation rates for WFRP remain low (for instance, 0.1% of all insurance policies in Indiana are WFRP) (Olen and Wu, 2017). The gist of the above literature points toward increasing vulnerability of farms and farmer livelihoods to climate change, more so true for small family farms (Walthall et al., 2013).

The impact of natural disasters on farmers' income and consumption is well documented for developing countries, where farming is small-scale, and livelihoods depend on agricultural production. For instance, natural disasters' effects have been studied for consumption (Townsend, 1994; Morduch, 1995; Kazianga and Udry, 2006; Porter, 2012), farm and livestock management (Rosenzweig and Binswanger, 1993; Hoddinott, 2006), and nutrition and health (Kazianga and Udry, 2006; Hoddinott, 2006). Results from a recent study on the effects of rainfall shocks in rural Thailand suggest that (i) the impact of weather-based agricultural shocks is larger than what the current literature suggests, and (ii) agricultural shocks affect input availability and costs for farm and non-farm enterprises, and consumption expenditures for farm households (Grabrucker and Grimm, 2020). Our study contributes to the above strand of literature by estimating the potential impact of income loss due to natural disasters on Indiana specialty producers' consumption expenditures.

Given that farmers make decisions in risky environments, it is also important to understand their risk preferences, which affect business decisions regarding crop insurance, marketing, and commodity supply (Zhao and Yue, 2020; Chavas and Holt, 1996; Eckman et al., 1996). Following are the two key findings in the literature on farmers' risk preferences: (i) farmers' risk preferences are not the same across studies, on average, farmers are risk averse, and (ii) from a methodological perspective, farmers should be able to comprehend the risk elicitation task, which can be improved with contextualized presentation of the elicitation task (Iyer et al., 2019). In terms of methodological developments in measuring farmers' risk preferences, the multi-item 5-point scales and lottery-based choice tasks are the most widely used methods since 2010, especially in European studies (Iyer et al., 2019).

While there is a large economics literature on measuring risk preferences (see Starmer, 2000; DellaVigna, 2009; Barseghyan et al., 2018), there is comparatively less on exploring how risk preferences might respond to exogenous income shocks or catastrophic disasters. To that regard, Chuang and Schechter (2015) provide a literature review of risk preferences after natural disasters, where some studies find an increase in risk aversion after disasters (Cameron and Shah, 2015), others find a decrease in risk aversion (Eckel et al., 2009), and some find no change in risk aversion (Becchetti et al., 2012). The diverging results on risk preferences after natural disasters are probably due to subtleties intrinsic to natural disasters; or it is possible that the experimental method in each study is contributing to the different results across studies (Chuang and Schechter, 2015). By measuring producers' risk preferences immediately after they experience a hypothetical natural disaster, our study aims to contribute to the diverse findings on disasters' effect on risk preferences (Chuang and Schechter, 2015).

Conceptual Framework

The decision-making units in our study are farm households. We are interested to investigate the effect of an unexpected income loss due to natural disasters on farm household consumption categories.

Chetty and Szeidl (2007) provide the theoretical framework and initial evidence that when income shocks are "small" (income loss of up to 33%), households make downward adjustment in the consumption expenditures of "adjustable" goods like food rather than "commitment" goods such as durables, which have adjustment costs associated with them. The authors show that less than 33% of U.S. households cut the expenditures of durables like apparel and furniture, however, about 42% and 49% of U.S households cut the expenditures of adjustable goods like food and entertainment, respectively.

Regarding the impact of income loss due to natural disasters on farm household consumption expenditures, our first hypothesis is as following,

H1: After a farm household receives a small negative income shock due to natural disasters, it will reduce the consumption expenditures of adjustable goods such as food, education, transportation, clothing, utilities, and miscellaneous.

Under assumption four of Chetty and Szeidl (2007), the presence of commitments (like durables) in household consumption magnifies risk aversion with respect to wealth (income) in the (S,s) band (Chetty and Szeidl, 2007). The (S,s) band is a rule where a household finds it optimal to hold onto a durable good as long as the after-shock income level is within an upper (S) and lower (s) band, however, when the after-shock income falls outside the (S,s) band, it is optimal to adjust the consumption of the durable good. For instance, if a household head gets unemployed and the income level falls below (s), then it would be optimal to move to a lower-rent house rather than reducing food and health consumption by a large amount. Chetty and Szeidl (2007) classify an income loss of up to 33% as a small income shock, which allows income to stay within the (S,s) band, hence allowing a household to only reduce the consumption of adjustable categories (Chetty and Szeidl, 2007). This is true for the two following reasons: (i) the elasticity of adjustable goods with respect to income is higher in the presence of commitments than without commitments, and (ii) complementarity between adjustable and commitment goods magnify risk aversion (Chetty and Szeidl, 2007).

Our second objective is to estimate the impact of income loss on producers' risk behavior. Our second hypothesis is about the risk aversion of producers after receiving a negative income shock, i.e.,

H2: Producers that lose income after a natural disaster (treatment group) will be more risk averse compared to producers that do not lose income (control group).

The second hypothesis implies decreasing absolute risk aversion. Arrow (1971) and Pratt (1964) argue that absolute risk aversion is decreasing in wealth (income). And numerous studies provide the evidence for decreasing absolute risk aversion, for instance, Binswanger

(1980, 1981), Lins et al. (1981), Hamal and Anderson (1982), Chavas and Holt (1996), Bar-Shira et al. (1997), and Holt and Laury (2002).

3.2 Survey Design

In order to test the study hypotheses and to collect socio-economic and farm operation data on Indiana specialty producers, we administered a survey in the second half of 2019. The survey had three major sections. The first section pertains to assessing producers' resiliency in the face of natural disasters. The second section is about producers' income and consumption, i.e., their average monthly income and itemized consumption expenditures in the past 12 months, and how consumption expenditures would change in the next 12 months for a given income loss due to a natural disaster.[4] The third section pertains to eliciting producers' risk preferences.

In terms of sample selection, we first identified the population of Indiana specialty producers, which amounts to 2,301 producers based on the 2017 Census of Agriculture (National Agricultural Statistics Service, 2019b). We created our survey sample by combining unique producers from five sources, i.e., Farm Market ID, Indiana Horticultural Society (IHS), Indiana Vegetable Growers Association (IVGA), Indiana Grown - Indiana State Department of Agriculture (ISDA), and MarketMaker. We sent surveys to a total of 1,600 unique producers which is about 70% of the population sample. We conducted the survey in three different phases, where each phase included an invitation letter, the survey itself, and a follow-up notification. In the first phase in July 2019, we sent mail surveys to a 1,000 unique specialty crop producers. In the second and third phases in August 2019 and November 2019, we sent online surveys to 400 and 200 unique specialty crop producers, respectively. The overall response rate was 6% (98 surveys) with 14 incomplete surveys that were discarded. The usable sample size of 84 remaining surveys yields a sampling error of +/- 10.5% for a binary question, with 95% confidence. Despite this wide confidence interval, as we soon discuss, we are mainly interested in comparisons of individuals assigned to treatment and control groups, for which we have greater power to reject the null of no difference. It is also worth

[4]↑The survey questionnaire includes modified questions on household and farm financials from the ARMS survey.

noting that although we only have a small share of producers represented in our survey (84 out of 2,301), we have a much larger share of specialty crop acres represented (5,432 acres out of 24,930 irrigated acres in the state).

Respondents were randomly assigned to either a treatment or control group. The treatment variable is a hypothetical income loss shock. And the treatment group is made of five sub-groups. Each treatment sub-group differs from the others based on the size of hypothetical income shock assigned. Households in each treatment sub-group receive an income loss shock of 20%, 24%, 26%, 30%, or 32%.[5] The size of income shock to a household in the control group is only $120, which is about 0.2% of income. Households' pre-shock income is calculated as the total after-tax income from farm and non-farm sources in the past 12 months. The source of income loss for treatment group is crop and house damages due to a natural disaster. The source of income loss for control group is farm equipment damage due to a natural disaster.

Both the treatment and control groups go through the hypothetical income loss intervention by observing pictures of flooding and crop freeze. The pictures do not change between treatment and control groups.[6] Treatment producers are told to imagine that due to the natural disasters as shown in the pictures, they suffer crop yield losses and home damages. Treatment producers are then told that these two damages reduce average monthly income by 20-32% for the next 12 months. Control group producers are told to imagine that the natural disasters as shown in the pictures destroy parts of their town, and fortunately, it only affects some of their farm equipment that can be fixed with expenses of $120. Hence, control group households' average monthly income in the next 12 months is only lower by a mere $10. Itemized household-level expenditures are recorded before and after the income loss intervention.[7] Income and consumption expenses are actual (hypothetical) in the pre-shock (post-shock) period.

[5]↑We provide variation in hypothetical income shock as a solution for netting out hypothetical bias in consumption responses.

[6]↑This makes sure that if there are any expenditure changes merely due to the pictures, it is accounted for both groups.

[7]↑If prices are constant, as would likely be the case with a localized weather shock, any changes in consumption expenditures translate into changes in consumption quantity for various household consumption categories.

In order to let the household budget constraint bind in post-shock period, we control additional aspects in the household's economic environment like insurance coverage, borrowing limits, assets usage, and labor supply. Producers in the treatment group are told that their average monthly income drops by 20-32% in the next 12 months, including any partial amounts from their insurance coverage, loan application, and savings account. Finally, respondents are asked to assume that household labor in non-farm jobs is held constant for the post-shock 12 months, with no additional opportunities for extra hours of work.

In order to elicit risk preferences of producers, first, we employ an 11-point Likert scale question as in Dohmen et al. (2011). We place this question before the hypothetical income loss exercise. Producers are asked, "Are you generally a person who is willing to take risks in financial matters or do you try to avoid taking risks in financial matters?" By ordering the 0 - 10 point Likert scale into intervals, our first method provides a measure of relative risk aversion as in Guiso et al. (2018). Second, we present to the producers a series of hypothetical risky prospect choices as in Guiso et al. (2018) which is similar to the Holt and Laury (2002) task. We present a risky lottery ($10,000 versus $0) with equal chances, and then ask the producers whether they will choose the risky lottery or a certain amount, which keeps increasing, i.e., $100, $500, etc. The second method is presented after the hypothetical income shock and provides us with a quantitative measure of absolute risk aversion. The second method is adjusted in wording to make it relevant for a producer's agribusiness context: "Imagine you are offered a farm investment opportunity, called the 'first opportunity,' that will pay you an annual net return of either $10,000 or nothing ($0). The chances are half-and-half like a coin toss: $10,000 when heads turn up and $0 when tails turn up. Alternatively, you are offered a 'second opportunity' that has a fixed annual net return all the time. If the fixed annual net return is $100, would you choose it instead of the first opportunity?"

3.3 Descriptive Statistics

Before presenting our empirical results regarding consumption and risk behavior, we discuss the descriptive statistics of producers' socio-demographics, farm operation, and resiliency. We also present covariates' balance between control and treatment samples. For socio-demographics and farm operation statistics, we also provide corresponding statistics from the USDA 2017 Census of Agriculture to get a sense of the representative nature of our sample.[8]

As presented in appendix Table 3.A1, the overall sample is characterized by producers with a mean age in late fifties, a household size of three members, and farm assets that are five times as large as household assets (approximately, \$2.5 million versus \$0.5 million). Furthermore, about 80% of producers are male, 75% are married, and almost everyone classifies as White. More than half of producers and their wives have above high school education. Majority of producers work more than 50% of their time in farming while their spouses do not. In comparison to our sample, USDA Indiana census is characterized by a slightly larger family size (+ 1), lower level of farm assets (- \$0.5 million), and a higher percentage of females (+ 10%). These slight differences might emerge because the census statistics represent all agricultural producers.

Moving to producers' farm operation statistics (appendix Table 3.A2), the mean percentage of farm ownership is about 71% which means that specialty producers in Indiana hold a majority of share in their farm operations. In our sample, the mean irrigated acreage of each vegetables-melons (∼60), fruits-nuts-berries (∼8), and other crops (∼640) is bigger than the respective acreage of Indiana specialty producers in the USDA 2017 Census of Agriculture. This difference is most certainly due to a couple of producers in our sample with large scale operations. The most prevalent legal status of operation is family- or individual-run business (more than 50%), followed by corporation (30.6%) and partnership (21%). In terms of the financial instrument that is available to run a farm operation, more than half of our sample producers select insurance, bank loan, personal savings, and credit card. This is in sharp contrast with government loan and relatives' loan, which are selected by less than half of producers. Interestingly, about 8% of our sample producers consider none of the listed financial instruments as available to them.

[8]↑In appendix Table 3.A1 (appendix Table 3.A2), the USDA census statistics are for all producers (specialty producers only).

When evaluating covariates' balance between treatment and control groups, we use the normalized difference score, which is the difference in mean covariate value between treatment and control groups, divided by the square root of the average of sample variances Imbens and Rubin (2015). A normalized difference score of 0 to 0.25 indicates a good balance, such that any remaining differences can be accounted for linearly via the regression (Imbens and Rubin, 2015).

Using data from the regression sample, we present normalized difference scores for socio-demographic variables (Table 3.1). The regression sample includes only those respondents that fully answer the questions in consumption and risk attitude sections. The average normalized difference score for all socio-demographic variables is 0.25. Seven variables have normalized difference scores above 0.25 but not above 0.5. The variable Household Assets has the highest score of 0.56, however, we would be more concerned if the variable Farm Assets had a score above 0.5. The variable Farm Assets is directly relevant to farming and it is much larger in dollar value than Household Assets. The normalized difference score for Farm Assets is 0.04.

In Table 3.2, we present average monthly income and consumption expenses by treatment and control households during pre- and post-shock periods. We observe that treatment (control) households' average monthly income decreases by about 28% (0.2%) after the shock; expenses for the commitments category decrease by 8% (4%); and expenses for the adjustables category decrease by 25% (5%). We clearly see that a large decrease in treatment households' income is accompanied by a large decrease in their expenses for the adjustables category. We follow Table 1 of Chetty and Szeidl (2007) to identify if an expense belongs to the commitments category or to the adjustables category. Expenses for health, rent, and furnishings belong to the commitments category, and the rest of the expenses belong to the adjustables category. Since our definition of transportation includes gas and maintenance, and clothing includes personal care items, we assign these expenses to the adjustables category.

In appendix Table 3.A3, we evaluate the distributional balance of income and consumption variables from the pre-shock period. The average normalized difference score for all variables in appendix Table 3.A3 is 0.17, and four variables have a score above 0.25 but below 0.5. In appendix Table 3.A3, the last column presents each consumption category's mean share of income. Interestingly, adjustables' mean share of income is 64%, which is about four times larger than 18% of commitments. And total consumption's mean share of income is 80%.

3.4 Estimation Strategy

Using data from the randomized survey of specialty producers in Indiana, we aim to empirically identify whether farm households reduce the consumption expenses of adjustable goods after the hypothetical income shock. Using panel data from the randomized survey, the empirical specification for testing hypothesis one is a differences-in-differences (DiD) regression model with household fixed-effects, i.e.,

$$Y_{ijt} = \alpha + \rho_i + \gamma P_t + \delta(D_j \times P_t) + u_{ijt}, \tag{3.1}$$

where Y_{ijt} represents the level of monthly expenditures as reported by household i in treatment group j at time period t. Additionally, ρ_i is a household-specific intercept ("fixed effect"), capturing time-invariant household unobservable factors. P_t is an indicator variable for pre-shock ($P_t = 0$) and post-shock ($P_t = 1$) periods. D_j is an indicator variable for treatment ($D_j = 1$) and control ($D_j = 0$) groups. Our parameter of interest is δ, which measures the average difference in expenditures between treatment and control households in the post-shock period in comparison to the pre-shock period. Error terms are denoted by u_{ijt}. We use cluster-robust standard errors when estimating equation (1). We cluster the error terms at the household level and assume error independence across households.

Regarding empirical testing of hypothesis two, we follow the quantitative risk elicitation method of Guiso et al. (2018). Hypothesis two states that producers who lose income after a natural disaster (treatment group) are more risk averse than producers who do not lose income (control group). The quantitative risk elicitation method elicits producers' certainty equivalent in the face of a risky lottery ($10,000 versus $0) with equal chances. The certainty equivalent amount gradually increases as in the following sequence, so the producer may choose a given amount: $100, $500, $1,500, $3,000, $4,000, $5,000, $5,500, $7,000, $9,000, and more than \$9,000. We then calculate the risk premium of each producer which is the expected value of the risky lottery less the certainty equivalent, i.e., (\$5,000 - CE). The quantitative risk elicitation method provides us with a measure of absolute risk aversion. We use the interval regression method to model the risk premium (r_i) of producer i as,

$$r_i = \alpha + \delta D_j + \beta \boldsymbol{X_i} + u_i, \tag{3.2}$$

where δ is our coefficient of interest which captures the average difference in risk premium between treatment and control producers. We also control for producers' socio-demographics and farm operation variables, $\boldsymbol{X_i}$. We assume the error terms u_i to be normally distributed.

3.5 Results

In Table 3.3, we present the main results on farm households' consumption behavior after the income shock. From left to right, we present results by (i) total consumption expenses, (ii) expenses for the commitments category, which includes health, rent, and furnishings expenses, and (iii) expenses for the adjustables category, which includes expenses for food and every other expense up to miscellaneous.[9] In a differences-in-differences specification with household fixed-effects, we identify whether a change in the average level of consumption expenses between pre-shock period and post-shock period is statistically different between treatment and control households. We find a statistically significant decrease in the consumption expenses of treatment households for the following categories: (i) total consumption expenses ($\sim$ \$675), and (ii) expenses for the adjustables category ($\sim$ \$579) and its two sub-categories that are food ($\sim$ \$119) and miscellaneous ($\sim$ \$280). We find a statistically insignificant decrease in the consumption expenses of treatment households for the commitments category and its two sub-categories (i.e., health and furnishings). Finally, we observe that treatment households increase the consumption expenses of rent and education, however, the changes are small and insignificant.

[9] ↑Miscellaneous consumption expenses include mortgage fees, charity, life insurance, and retirement expenses.

The above results are in conformity with the theoretical predictions of Chetty and Szeidl (2007), i.e., after a small income shock, households reduce the consumption expenses of adjustable goods. We find evidence in support of our first hypothesis (**H1**) for the following expenses: all adjustable goods (decrease of ∼\$579), food (decrease of ∼\$119), and miscellaneous (decrease of ∼\$280). However, we do not find evidence in support of our first hypothesis (**H1**) for the following expenses: education, transportation, clothing, and utilities. Two key take-aways from the consumption analysis of farm households in our sample are as following: (i) a small income shock results in a downward adjustment of total consumption expenses; and the adjustment is primarily concentrated in the adjustables category, and (ii) within the adjustables category, a decrease in consumption expenses emanates from food and miscellaneous sub-categories. In the last two columns of Table 3.3, we also show the regression results for commitments' and adjustables' share of pre-shock income. Among treatment households, on average, adjustables' share of income decreases by a significant 18.7%, which is in sharp contrast to the insignificant decrease of commitments' share of income (3.45%).

3.5.1 Risk Behavior before and after Income Shock

Our risk elicitation method before the income loss intervention is based on an 11-point Likert scale method of Dohmen et al. (2011), while the risk elicitation method after the intervention is based on the risky lottery choice method of Guiso et al. (2018). The former and latter risk elicitation methods provide measures of 'relative risk aversion' and 'absolute risk aversion,' respectively (Guiso et al., 2018).[10]

Using an ordered logit specification for the relative risk aversion measure, we do not find any significant difference in risk taking behavior between treatment and control producers (see Table 3.4). However, in an interval regression specification for the absolute risk aversion measure, we find that, on average, the risk premium of treatment producers is about \$2,307 higher than that of control producers after the income loss intervention. Since an increase in risk premium translates into an increase in absolute risk aversion, we find the evidence

[10]↑The reason that we do not use the same risk elicitation method before and after the income loss intervention is to avoid the pre-intervention method potentially biasing the post-intervention risky choices.

in support of our second hypothesis (**H2**). We also confirm that absolute risk aversion is decreasing in wealth (income) as argued by Arrow (1971) and Pratt (1964).

3.5.2 Discussion of Results

During the summer of 2019, when we started implementing the survey, the emotional state of Indiana farmers was mired with frustration due to the concurrent rainfalls, which postponed the growing season. The flooding in some Midwestern states like Nebraska cost many farm producers their year-long farm yields. Such erratic weather outcomes are to be expected due to climate change (IPCC, 2018). In the agriculture sector, farm producers are the most vulnerable to the adverse effects of natural disasters. After a disaster's negative income shock, the impact on producers' household consumption and individual risk behavior cannot be discounted.

Due to a disaster's hypothetical income loss, the treatment producers in our study reduced their food and miscellaneous expenses by about \$119 and \$280, respectively. Each of these two downward adjustments is equal to ∼21% of the expenses for food and miscellaneous categories before the income loss, respectively. It is easy to adjust food and miscellaneous expenses during hard times, but they can have real consequences over producers' life. Meanwhile, a post-disaster increase in risk aversion can have implications for specialty producers' financial decisions. For instance, post-disaster farm investment can be critical for farm output and revenues, but an increase in producers' risk aversion would mean that they are not willing enough to take on farm investment.

In our study, we find that Indiana specialty producers have a moderate resiliency against natural disasters. When we compare the consumption and risk-taking findings in our study against the moderate resiliency of specialty producers in our study, it becomes clear that the producer households and their farm enterprises are vulnerable to natural disasters. On average, 42% of total planted acres in our survey sample are insured which is not quite high enough (appendix Table 3.A4). We also learn that about 80% of producers' farms have been affected by extreme events at some point, but only 53% of producers engage in farm financial planning for worst times such as farm losses due to a natural disaster (appendix Table 3.A4).

Potential solutions for improving the resilience capacity of Indiana specialty producers could include, (i) connecting producers with digital technologies to help them in predicting weather and climate risks, and (ii) educating producers about farm risk management tools that could help them to proactively manage their farms.

3.6 Conclusion

Specialty crops play a vital role in the U.S. farm sector due to their contribution to farm income and U.S. households' nutrition. However, specialty crops' production involves more risk than commodity crops' production due to adverse weather shocks, specialty crops' low insurance coverage and low participation rates, labor shortages, and perishability of fresh produce. And it is mainly the small- and medium-sized producers who are easily exposed to the aforementioned risks and challenges. The objective of this study is twofold, first, to determine how specialty producers' household consumption responds to adverse income shock due to natural disasters, and second, to evaluate whether an income loss experience affects specialty producers' risk-taking behavior.

In this study, we focus on specialty producers in the Midwestern state of Indiana. We administered a split-sample survey in the second half of 2019, where we randomly assigned producers to treatments that vary the size of a hypothetical income shock due to natural disasters. We collected information on (i) producers' resiliency in the face of natural disasters, (ii) households' monthly consumption expenditures before and after an income loss of 20%-32% due to natural disasters, and (iii) producers' risk preferences.

We find that farm households in our sample reduce their monthly expenses of food and miscellaneous categories by $\sim$\$119 and $\sim$\$280, respectively, after an income loss of 20%-32%. We also find that our sample producers are less willing to take financial risk after an income loss experience, i.e., they have decreasing absolute risk aversion. Finally, we find in our data that Indiana specialty producers have a moderate resilience capacity to withstand the adverse effects of natural disasters. Although specialty crops' production is risky and challenging, the good news is that specialty producers can become resilient and manage farm risk with sufficient knowledge and resources. We believe Indiana specialty producers would benefit from (i) farm financial planning for worst times, (ii) immediate access to federal aid and commercial loans after natural disasters, (iii) high participation rate in federal crop insurance, (iv) investment in agriculture-related digital technologies, and (v) more research on vulnerability and adaptive capacity of specialty producers.

3.7 Tables

Table 3.1. Treatment/Control Balance - Producer Demographics and Farm Operation Variables

	Regression Sample (N = 47)		
	Treatment Mean	Control Mean	Norm. Diff. Score
Respondent Age	57.37	63.17	0.41
Members Living in Household	2.52	2.74	0.15
Gender *(Male=1)*	0.89	0.79	0.28
Married *(Yes=1)*	0.78	0.58	0.43
Race *(White=1)*	0.96	0.94	0.08
Education *(Above High School=1)*	0.78	0.78	0.00
Occupation-Majority Time *(Farming=1)*	0.70	0.78	0.17
Farm Assets ($)	2,898,269.23	2,683,629.83	0.04
Household Assets ($)	562,288.46	291,080.35	0.56
Farm Ownership Percent	62.56	73.84	0.29
Acres of Vegetables & Melons	9.84	2.53	0.35
Acres of Fruits, Nuts & Berries	4.04	4.33	0.01
Acres of Other Crops	783.39	317.87	0.45
All Variables (Average)			0.25

Notes: Normalized difference scores are calculated based on Imbens and Rubin (2015) method (please see text for more discussion of this table and normalized scores). The mean of 'Acres of Vegetables & Melons' in treatment group is quite large compared to the control mean. This is due to a single producer in the treatment arm with a large number of vegetable and melons acres.

Table 3.2. Household Income & Consumption Expenses before/after the Income Shock

	Regression Sample (N = 47)			
	Pre-Shock		Post-Shock	
	Treatment Mean ($)	Control Mean ($)	Treatment Mean ($)	Control Mean ($)
Monthly:				
Income	5,827.18	5,422.37	4224.42	5,412.37
Health	698.61	561.58	671.11	556.37
Rent	53.57	41.32	62.50	38.68
Household Furnishings	68.79	70.79	22.32	55.37
Commitments Category	820.96	673.68	755.93	650.42
Food	569.68	533.84	415.18	498.53
Education	40.61	130.26	29.89	110.00
Transportation	420.89	539.32	380.68	520.95
Entertainment	124.71	183.89	46.57	134.16
Clothing & Personal Care	117.61	142.05	57.61	118.58
Utilities	329.46	399.84	221.25	394.58
Miscellaneous	1,312.79	1,260.63	1032.54	1,260.11
Adjustables Category	2,915.75	3,189.84	2183.71	3,036.89
All Consumption Expenses	3,672.43	3,864.21	2745.00	3,612.05
Total Observations	28	19	28	19

Notes: We follow the definition of Chetty and Szeidl (2007) for ‘commitments’ and ‘adjustables’ categories, and follow their Table 1 in identifying which expenses belong to each commitments and adjustables. Expenses for health, rent, and furnishings belong to commitments category, and rest of the expenses belong to adjustables category. Since our definition of transportation includes gas & maintenance, and clothing includes personal care items, so we assign these expenses to adjustables category.

Table 3.3. Differences-in-Differences Regression - Household Consumption Expenses with Income Shock as a Treatment Variable

	Regression Sample														
	Total	**Commitments**	**Health**	**Rent**	**Furnishings**	**Adjustables**	**Food**	**Education**	**Transport**	**Entertainment**	**Clothings**	**Utilities**	**Misc.**	**Commit-ments Share of Pre-Shock Income**	**Adjust-ables Share of Pre-Shock Income**
Treatment x Post-Shock	-675.3**	-41.77	-22.29	11.56	-31.04	-579.1*	-119.2*	9.549	-21.85	-28.41	-36.53	-103.0	-279.7**	-0.0345	-0.187**
	(203.20)	(66.48)	(36.57)	(32.95)	(19.25)	(226.25)	(47.53)	(21.60)	(60.89)	(41.58)	(28.82)	(78.33)	(92.84)	(0.02)	(0.06)
Model Evaluation															
N	94	94	94	94	94	94	94	94	94	94	94	94	94	94	94
Cluster Groups	47	47	47	47	47	47	47	47	47	47	47	47	47	47	47
R-squared (within)	0.49	0.04	0.02	0.00	0.20	0.30	0.31	0.05	0.02	0.19	0.17	0.07	0.27	0.10	0.35
F-statistic	17.07	3.70	0.78	0.54	7.69	7.97	7.98	1.23	0.95	4.91	4.28	1.08	5.39	4.23	10.47

Notes: In the above regression setup, there are two treatment groups, i.e., treatment and control groups, and two periods which are separated by an income shock event, which happens at the start of second year. The treatment group receives an income shock based on after-tax income from the past 12 months. There are five sub-treatment groups and each receives an income loss shock of 20%, 24%, 26%, 30%, or 32%. The five treatment groups are pooled together. We follow the definition of Chetty and Szeidl (2007) for 'commitments' and 'adjustables' categories, and follow their Table 1 in identifying which expenses belong to each commitments and adjustables. Expenses for health, rent, and furnishings belong to commitments category, and rest of the expenses belong to adjustables category. Since our definition of transportation includes gas & maintenance, and clothing includes personal care items, so we assign these to adjustables category. All regressions are fixed-effects (within) regressions with household-level fixed-effects. Cluster-robust standard errors are in parentheses - clustered at household-level. Significance level stars: *p<0.05, **p<0.01, ***p<0.001

Table 3.4. Producers' Risk Aversion before/after the Income Shock

	Pre-Shock Qualitative Risk		Post-Shock Quantitative Risk
	11-Point Risk Aversion β**/SE**	**11-Point Risk Aversion Odds Ratio/SE**	**Risk Premium ($)** β**/SE**
Treatment	-0.932	0.394	2307.0*
	(0.64)	(0.25)	(966.51)
Male	0.564	1.758	-697.2
	(1.18)	(2.08)	(1731.35)
Married	-0.101	0.904	-1407.3
	(0.96)	(0.87)	(1257.36)
Age	-0.0153	0.985	68.73
	(0.03)	(0.03)	(48.40)
Household Members	-0.113	0.893	787.7
	(0.40)	(0.36)	(454.43)
Total Acres	-0.0000437	1.000	-0.318
	(0.00)	(0.00)	(0.25)
Total Assets (÷ by $100K)	-0.00480	0.995	-5.317
	(0.01)	(0.00)	(7.24)
Model Evaluation			
Total Observations	40	40	40
Log Likelihood	-52.79	-52.79	-76.65
χ^2	2.81	2.81	9.87
p > χ^2	0.90	0.90	0.20

Notes: As discussed in the text, the qualitative risk measure elicits producers' willingness to take risk in the financial domain, following Dohmen et al. (2011) method. It is referred to as the measure of relative risk aversion in Guiso et al. (2018), and we model it using an ordered logit specification. The quantitative risk measure elicits producers' certainty equivalent in the face of a risky lottery ($10,000 vs $0) with equal chances. The quantitative risk measure is referred to as the absolute risk aversion measure in Guiso et al. (2018). We then calculate the risk premium of each producer which is the expected value of the lottery less certainty equivalent amount ($5000 - CE). We use the interval regression method to model the risk premium of producers. The qualitative risk measure is presented at the beginning of the survey (before income shock), and the quantitative measure is presented towards the end of the survey, after the shock. We dropped four observations because of inconsistency in response to risk questions. Two producers selected 5 or less (i.e., risk averse) on Likert scale for the qualitative measure, but they are extremely risk lovers after the shock (having risk premium -4000 or less). Two other producers started as high risk takers (choosing 9 and 10 on Likert scale), which dropped by two points each when asked the same question after the shock, however their choice of risk premium (-4000 or less) shows no indication of drop in risk taking. Robust standard errors are in parentheses. Significance level stars: *p<0.05, **p<0.01, ***p<0.001

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3.9 Appendix Tables

Table 3.A1. Indiana Specialty Crop Producers Demographics

	Mean	St. Deviation	2017 Census Mean
Respondent Age (n = 63)	57.79	15.03	55.5
Respondent Spouse Age (n = 47)	55.19	12.22	
Members Living in Household (n = 64)	3	1.4	3.6
Farm Assets (\$) (n = 56)	2,424,292	5,268,637	1,900,876
Household Monthly Income (\$) (n = 78)	6,055.29	5,593.37	
Household Assets (\$) (n = 55)	449,419	486,404	
	Frequency	Percentage (%)	2017 Census (%)
Gender (n = 82)			
Female	18	22.0	33.0
Male	64	78.0	67.0
Married (n = 64)			
No	16	25.0	
Yes	48	75.0	
Respondent Race (n = 62)			
American Indian	1	1.6	0.00
Other	1	1.6	0.70
White	60	96.8	99.30
Respondent's Spouse Race (n = 43)			
White	43	100	
Respondent Education (n = 63)			
HighSchool or Less	16	25.4	
Above HighSchool	47	74.6	
Respondent's Spouse Education (n = 47)			
HighSchool or Less	8	17	
Above HighSchool	39	83	
Respondent Occupation (n = 62)			
Not in Workforce	6	9.7	43.1
Work Other than Farming	15	24.2	
Farming	41	66.1	56.9
Respondent's Spouse Occupation (n = 42)			
Not in Workforce	8	19.0	
Work Other than Farming	25	59.5	
Farming	9	21.4	

Notes: Summary statistics are based on authors' survey of Indiana specialty crop producers. Relevant summary statistics for all Indiana agricultural producers are provided in the fourth column (subject to availability), using the USDA 2017 Census of Agriculture, i.e., 2017 Census Volume 1, Chapter 1: Indiana, Table 77. Census statistic for "Members Living in Household" is calculated using the formula: (Number of persons living in producers' household) / (Total Farms). Census statistic for farm assets value is based on estimated market value of land, buildings, all machinery, and equipment in Table 77. Census only reports sex of producers when there are 4 producers in an operation. Respondent occupation is based on majority time (50% or more time) spent at an occupation. Census statistic for producer occupation is based on "Days of work off farm" in Table 77.

Table 3.A2. Indiana Specialty Crop Producers Farm Operation Statistics

	Mean	St. Deviation	2017 Census Mean
Percent of Farm Owned (n = 63)	70.87	37.2	see notes
Acres of Vegetables & Melons (n = 84)	56.93	440.95	47.42
Acres of Fruits, Nuts & Berries (n = 84)	7.73	36.25	2.79
Acres of Other Crops (n = 84)	639.68	1,454	212.81
	Frequency	**Percentage (%)**	**2017 Census (%)**
Farm Operation Legal Status			
Family or Individual Operation (n = 62)			
(Yes/No)	(34 / 28)	(54.8 / 45.2)	85.04
Legal Partnership (n = 62)			
(Yes/No)	(13 / 49)	(21.0 / 79.0)	0.06
C- or S-Corporation (n = 62)			
(Yes/No)	(19 / 43)	(30.6 / 69.4)	0.07
Trust or Cooperative (n = 62)			
(Yes/No)	(2 / 60)	(3.2 / 96.8)	0.02
Available Financial Instrument to Run Farm			
Insurance (n = 83)			
(Yes/No)	(55 / 28)	(66.3 / 33.7)	
Government Loan (n = 83)			
(Yes/No)	(26 / 57)	(31.3 / 68.7)	
Bank Loan (n = 83)			
(Yes/No)	(53 / 30)	(63.9 / 36.1)	
Relatives Loan (n = 83)			
(Yes/No)	(9 / 74)	(10.8 / 89.2)	
Personal Savings (n = 83)			
(Yes/No)	(53 / 30)	(63.9 / 36.1)	
Supplier Credit (n = 83)			
(Yes/No)	(36 / 47)	(43.4 / 56.6)	
Credit Card (n = 83)			
(Yes/No)	(46 / 37)	(55.4 / 44.6)	
None Available (n = 83)			
(Yes/No)	(7 / 76)	(8.4 / 91.6)	

Notes: Summary statistics are based on authors' survey of Indiana specialty crop producers. Relevant summary statistics for all Indiana agricultural producers are provided in the fourth column (subject to availability), using the USDA 2017 Census of Agriculture, i.e., 2017 Census Volume 1, Chapter 1: Indiana, Table 77. In our survey, full owners represent 55.55% of all producers, and this percentage is 67% in the 2017 census. In calculating average acres per farm operation in the census, we only consider irrigated acres and farms. For 'other crops' we consider corn, corn for sillage, soybean, wheat, forage-land for hay and grass. In authors' survey, producers were allowed to select multiple categories of farm legal status, hence the percentages may not be directly comparable to census percentages.

Table 3.A3. Treatment/Control Balance - Household Income & Consumption Expenses before the Income Shock

	Regression Sample (N = 47)			
	Treatment Mean ($)	Control Mean ($)	Normalized Diff. Score	Mean Share of Income
Monthly:				
Income	5,827.18	5,422.37	0.09	1.00
Health	698.61	561.58	0.26	0.15
Rent	53.57	41.32	0.09	0.01
Household Furnishings	68.79	70.79	0.02	0.02
Commitments Category	820.96	673.68	0.25	0.18
Food	569.68	533.84	0.10	0.12
Education	40.61	130.26	0.34	0.02
Transportation	420.89	539.32	0.31	0.11
Entertainment	124.71	183.89	0.34	0.03
Clothing & Personal Care	117.61	142.05	0.18	0.03
Utilities	329.46	399.84	0.21	0.09
Miscellaneous	1,312.79	1,260.63	0.04	0.25
Adjustables Category	2,915.75	3,189.84	0.14	0.64
All Consumption Expenses	3,672.43	3,864.21	0.08	0.80
Total Observations	28	19		47
All Variables (Average)			0.17	

Notes: We follow the definition of Chetty and Szeidl (2007) for 'commitments' and 'adjustables' categories, and follow their Table 1 in identifying which expenses belong to each commitments and adjustables. Expenses for health, rent, and furnishings belong to commitments category, and rest of the expenses belong to adjustables category. Since our definition of transportation includes gas & maintenance, and clothing includes personal care items, so we assign these to adjustables category. Normalized difference scores are calculated based on Imbens and Rubin (2015) method. As a rule of thumb, a score above 0.25 or 0.5 signifies imbalance in treatment arms. The fifth column (mean share of income) pools both treatment and control households.

Table 3.A4. Indiana Specialty Crop Producers' Resiliency Against Natural Disasters

	Mean	St. Deviation
Insured Share of Planted Acres (n = 73)	0.42	0.47
	Frequency	Percentage (%)
Do you engage in farm financial planning for worst times like losses due to flood or drought? (Yes/No) (n=83)	(44 / 39)	(53.0 / 47.0)
Has an extreme event ever affected your farm? (Yes/No) (n = 84)	(67 / 17)	(79.8 / 20.2)
Financial Instrument You Would Use after Farm Losses		
Insurance (n = 83) (Yes/No)	(48 / 35)	(57.8 / 42.2)
Government Loan (n = 83) (Yes/No)	(27 / 56)	(32.5 / 67.5)
Bank Loan (n = 83) (Yes/No)	(47 / 36)	(56.6 / 43.4)
Relatives Loan (n = 83) (Yes/No)	(10 / 73)	(12.0 / 88.0)
Personal Savings (n = 83) (Yes/No)	(45 / 38)	(54.2 / 45.8)
Supplier Credit (n = 83) (Yes/No)	(21 / 62)	(25.3 / 74.7)
Credit Card (n = 83) (Yes/No)	(19 / 64)	(22.9 / 77.1)
If you needed $100,000 loan, who would you ask for it?		
Family (n = 63) (Yes/No)	(9 / 54)	(14.3 / 85.7)
Relatives (n = 63) (Yes/No)	(4 / 59)	(6.3 / 93.7)
Bank (n = 63) (Yes/No)	(53 / 10)	(84.1 / 15.9)
Farm Service Agency (n = 63) (Yes/No)	(23 / 40)	(36.5 / 63.5)
Climate Change Perception Question and Statements		
Is climate change important to your farm management decisions? (Yes/No) (n = 84)	(46 / 38)	(54.8 / 45.2)
Weather and climate change presents more risks than benefits to Indiana agriculture.		
Strongly Disagree	5	6.0
Somewhat Disagree	8	9.5
Neither Agree or Disagree	20	23.8
Somewhat Agree	26	31.0
Strongly Agree	25	29.8
I am worried about weather and climate change.		
Strongly Disagree	8	9.5
Somewhat Disagree	13	15.5
Neither Agree or Disagree	15	17.9
Somewhat Agree	25	29.8
Strongly Agree	23	27.4

Notes: Summary statistics are based on authors' survey of Indiana specialty crop producers.

3.10 Appendix Survey Questionnaire for Treatment Group

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Introduction and Consent

Welcome. Thanks for accepting our survey request. The approximate total time of this survey will be around 30 minutes. The information you provide will be used for research purposes only. In accordance with Purdue University policies, your responses will be kept confidential and will not be disclosed to anyone other than the two researchers working on this project. Next, please read the Consent Form.

Consent. **RESEARCH PARTICIPANT CONSENT FORM**

Key Information: Please take time to review this information carefully. This is a research study. Your participation in this study is voluntary which means that you may choose not to participate at any time without penalty. If you decide to take part in the study, please write your name at the end.

What is the purpose of this study? Our goal from this research survey is to understand the impact of natural disasters on Indiana specialty farmers' household spending and other financial decisions.

What will I do if I choose to be in this study? You will fill in financial information about your household and farm. Additionally, you will watch some pictures related to a disaster, and maybe other unpleasant pictures. Finally, there are some hypothetical financial questions and household characteristics.

What are the possible risks or discomforts? Some of the pictures might feel unpleasant. Secondly, breach of confidentiality is always a risk with data, but we will take precautions to minimize this risk as described in the confidentiality section.

Are there any potential benefits? We believe the results of this survey will help the government to further understand the needs of specialty crop growers in Indiana.

What alternatives are available? You can either fill the mail survey or the online version as described in the letter.

Will I receive payment or other incentive? You may receive one of the five $200 gift cards. Your odds of winning a gift card are 1 to 199. Please note that according to the rules of the Internal Revenue Service (IRS), payments that are made to you as a result of your participation in a study may be considered taxable income.

Are there costs to me for participation? There are no anticipated costs to participate in this research.

Will information about me and my participation be kept confidential? The project's research records may be reviewed by the US DHHS Office for Human Research Protections, and by departments at Purdue University responsible for regulatory and research oversight. Your research records will be only available to the research team. All paper and online records will be destroyed after we transfer data to Purdue computer.

What are my rights if I take part in this study? You have the right to withdraw from this study at any point, including any data that is collected. However, we recommend that you consider taking the whole survey, so our study can reflect the situation of specialty farmers with greater confidence. Meanwhile, you can't withdraw the collected data, once the data is transferred to Purdue University's computers.

Who can I contact if I have questions about the study?

If you have questions, comments or concerns about this research project, you can talk to one of the researchers. Please contact the research team key member:

Ahmad Zia Wahdat

Krannert Building, Office 777, 403 W. State Street, West Lafayette, IN 47907-2056

awahdat@purdue.edu, 617-548-4008

To report anonymously via Purdue's Hotline see www.purdue.edu/hotline

If you have questions about your rights while taking part in the study or have concerns about the treatment of research participants, please call the Human Research Protection Program at (765) 494-5942, email (irb@purdue.edu) or write to:

Human Research Protection Program - Purdue University

Ernest C. Young Hall, Room 1032, 155 S. Grant St., West Lafayette, IN 47907-2114

Documentation of Informed Consent

I have had the opportunity to read this consent form and have the research study understood. I am prepared to participate in the research study described above. (Please write your name below).

Introductory Questions

Q1. How do you see yourself: Are you generally a person who is willing to take risks in financial matters or do you try to avoid taking risks in financial matters?

(Please tick only one box on the scale, the value **0** means **completely unwilling to take risks** and the value **10** means **very willing to take risks**).

0 completely unwilling to take risks	1	2	3	4	5	6	7	8	9	10 very willing to take risks
○	○	○	○	○	○	○	○	○	○	○

Q2a. In the past 12 months, how many acres of these crops were planted and insured?

	Acres Planted	Acres Insured
Vegetables, Melons		
Fruits, Nuts, Berries		
All Other Crops		

Q2b. Do you engage in farm financial planning for worst times like farm/crop losses due to flood or drought?

- ○ Yes
- ○ No

Q2c. Has an extreme weather event ever affected your farm?

- ○ Yes
- ○ No

Q2d. Is climate change important to your farm management decisions?

- ○ Yes
- ○ No

Q2e. Indicate your level of agreement with the following statements (pick one choice for each row).

	Strongly Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
1. Weather and climate change presents more risks than benefits to Indiana agriculture.	○	○	○	○	○
2. I am worried about weather and climate change.	○	○	○	○	○

Q2f. Select below all the financial instruments that are available to you to run the farm operation.

Insurance	Government Loans	Bank Loans	Relatives Loans	Personal Savings	Supplier Credit	Credit Cards	Don't have access to any of these
☐	☐	☐	☐	☐	☐	☐	☐

Q2g. Which three financial instruments would you use after farm losses due to a disaster? (select three most important)

Insurance	Government Loans	Bank Loans	Relatives Loans	Personal Savings	Supplier Credit	Credit Cards
☐	☐	☐	☐	☐	☐	☐

Household Expenditure Questions

Q3. In the past 12 months, what was your **average monthly income** from **farm and non-farm** sources all together? (you can also divide annual **after-tax income** over 12 to get this)

Q4.

In the past 12 months, what were your **average monthly household expenses** for the following categories (don't include farm-related expenses)? Add all expenses and write the total in last cell (Total). Total expenses should be less than or equal to average monthly income in Q3, unless you took loans in the last 12 months and spent it on these categories.

1. Health Insurance Cost and Out-of Pocket Health Expenses	
2. Food (including Food Away from Home)	
3. Education and Child Care	
4. Rent Expenses for Household Use	
5. Mortgage Interest and Property Taxes	
6. Transportation Expense for Household Use	
7. Vehicle (Fuel, Maintenance, Insurance) for Household Use	
8. Entertainment	

9. House Furnishing (internal home decor)	
10. Clothing and Personal Care	
11. Utilities and Household Supply	
12. Contributions to Outside Alimony and Charity	
13. Life/Disability Insurance and Retirement Expense (or Savings)	
Total	

Q5. Please multiply your **average monthly income in Q3** by **(0.74)** and write your answer in the empty box:

(Income in Q3) x 0.74 =

A Scenario. Following are two images showing the impact of crop freeze and flooding. Imagine you were first hit by a crop freeze in late spring, and then recently by heavy flooding. Due to these events, you suffered crop losses and home damages. These losses affect your average monthly income. Your average monthly income in each of the next 12 months will be **equal to the amount calculated in Q5** previously, which is 26 percent less than **the income in Q3**. Please note that the **income in Q5** is all you have got for monthly spending, even after receiving insurance money, or partial loan acceptance, or using a part of your savings. And there is no opportunity or time to earn extra non-farm income. And you run the same size farm operation in the next 12 months as in the last 12 months.

Crop Freeze

Flooding

Q6.
In each of the next 12 months, your **average monthly income** will be **equal to the amount in Q5**. How would you spend **this new lower amount** on the following categories?

1. Health Insurance Cost and Out-of-Pocket Health Expenses	
2. Food (including Food Away from Home)	
3. Education and Child Care	
4. Rent Expenses for Household Use	
5. Mortgage Interest and Property Taxes	
6. Transportation Expense for Household Use	
7. Vehicle (Fuel, Maintenance, Insurance) for Household Use	
8. Entertainment	
9. House Furnishing (internal home decor)	
10. Clothing and Personal Care	
11. Utilities and Household Supply	
12. Contributions to Outside Alimony and Charity	
13. Life/Disability Insurance and Retirement Expense (or Savings)	
Total	

Financial Decision Questions

Q7.
Imagine you need a loan of **$100,000** for farm investment and household expenses in the next 12 months. Think about who would you ask for such a loan: family, relatives, bank, farm service agency? Keep thinking about this question as you will answer it later. Now move to the next question, Q8.

Q8. Imagine you are offered a farm investment opportunity, called the "first opportunity," that will pay you an **annual net return of either $10,000 or nothing** (**$0).** The chances are half-and-half like a coin toss: $10,000 when heads turn up and $0 when tails turn up. Alternatively, you are offered a "second opportunity" that has a **fixed annual net return all the time**.
If the fixed annual net return of the second opportunity is **$100**, would you choose such opportunity instead of the first opportunity?

- ◯ **Yes, I select second opportunity**. (move to Q18 if you select Yes)
- ◯ **No, I don't select second opportunity** (move to next question, Q9, if you select No)

Q9. If the fixed annual net return of the second opportunity is **$500**, would you choose such opportunity instead of the first opportunity?

- ◯ **Yes, I select second opportunity**. (move to Q18 if you select Yes)
- ◯ **No, I don't select second opportunity** (move to next question, Q10, if you select No)

Q10. If the fixed annual net return of the second opportunity is **$1,500**, would you choose such opportunity instead of the first opportunity?

- ◯ **Yes, I select second opportunity**. (move to Q18 if you select Yes)
- ◯ **No, I don't select second opportunity** (move to next question, Q11, if you select No)

Q11. If the fixed annual net return of the second opportunity is **$3,000**, would you choose such opportunity instead of the first opportunity?

- ◯ **Yes, I select second opportunity**. (move to Q18 if you select Yes)
- ◯ **No, I don't select second opportunity** (move to next question, Q12, if you select No)

Q12. If the fixed annual net return of the second opportunity is **$4,000**, would you choose such opportunity instead of the first opportunity?

- ◯ **Yes, I select second opportunity**. (move to Q18 if you select Yes)
- ◯ **No, I don't select second opportunity** (move to next question, Q13, if you select No)

Q13. If the fixed annual net return of the second opportunity is **$5,000**, would you choose suhc opportunity instead of the first opportunity?

- ◯ **Yes, I select second opportunity**. (move to Q18 if you select Yes)
- ◯ **No, I don't select second opportunity** (move to next question, Q14, if you select No)

Q14. If the fixed annual net return of the second opportunity is **$5,500**, would you choose such opportunity instead of the first opportunity?

- ◯ **Yes, I select second opportunity**. (move to Q18 if you select Yes)
- ◯ **No, I don't select second opportunity** (move to next question, Q15, if you select No)

Q15. If the fixed annual net return of the second opportunity is **$7,000**, would you choose such opportunity instead of the first opportunity?

- ◯ **Yes, I select second opportunity**. (move to Q18 if you select Yes)
- ◯ **No, I don't select second opportunity** (move to next question, Q16, if you select No)

Q16. If the fixed annual net return of the second opportunity is **$9,000**, would you choose such opportunity instead of the first opportunity?

- ◯ **Yes, I select second opportunity**. (move to Q18 if you select Yes)
- ◯ **No, I don't select second opportunity** (move to next question, Q17, if you select No)

Q17. If the fixed annual net return of the second opportunity is **greater than $9,000**, would you choose such opportunity instead of the first opportunity?

- ◯ **Yes, I select second opportunity**. (move to Q18 if you select Yes)
- ◯ **No.** (If you select No, move to next question, Q18)

Q18. Who would you ask for a **$100,000** loan as mentioned before? (you can select multiple choices)

- ◯ Family
- ◯ Relatives
- ◯ Bank
- ◯ Farm Service Agency

Q19. How do you see yourself in the next 12 months: Are you generally a person who is willing to take risks in financial matters or would you try to avoid taking risks in financial matters?

(Please tick only one box on the scale, the value **0** means **completely unwilling to take risks** and the value **10** means **very willing to take risks**).

0 completely unwilling to take risks	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10** very willing to take risks
◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯

Household Characteristics Questions

Q20. What is your Gender?

- ◯ Male
- ◯ Female

Q21. Are you married?

- ◯ Yes
- ◯ No (If you answer No, then don't fill "Your Spouse" part in Q22, Q23, Q24, Q25.)

Q22. What is your and your spouse's race?

You	White ◯	American Indian ◯	Asian ◯	Black or African American ◯	Other ◯
Your Spouse	White ◯	American Indian ◯	Asian ◯	Black or African American ◯	Other ◯

Q23. What is your and your spouse's education?

You	4 year degree and beyond ◯	Some college or associates ◯	High school ◯	Less than high school ◯
Your Spouse	4 year degree and beyond ◯	Some college or associates ◯	High school ◯	Less than high school ◯

Q24. At which occupation did you and your spouse spend the majority (50 percent or more) of your work time in the past 12 months?

You	Work other than farming ◯	Farming ◯	Not in workforce ◯
Your Spouse	Work other than farming ◯	Farming ◯	Not in workforce ◯

Q25. What is your and your spouse's age?

Your	
Your Spouse	

Q26. How many people lived in your household in the past 12 months?

(include yourself, spouse, children, and any other living in your household)

Concluding Questions and Notes

Q27. In the past 12 months, what was your farm operation's legal status for tax purposes?

(you can select multiple choices)

- Family or Individual Operation
- Legal Partnership
- C-corporation or S-Corporation
- Other such as Trust or Cooperative

Q28. In the past 12 months, what percentage of farm operation business did your household own?

Q29. In the past 12 months, what was the total amount of your

Household Assets (like financial accounts, personal home, vehicle, and other assets).	
Farm Assets (like financial accounts, farm land, trees, property, vehicles, livestock).	

Final Note. Thank you for your valuable time. Your answers will be of great help to understand Indiana specialty farmers' vulnerability. Please **provide your phone number** in space below so we can contact you, in case you win **$200 prize**.
In a couple of months, you can start checking this link (https://bit.ly/2J8rGkm) to see the winners of $200 prizes. We only provide the first name of the winners for confidentiality reasons. If the above link doesn't work, please send an email to awahdat@purdue.edu

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3.11 Appendix Survey Questionnaire for Control Group

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Introduction and Consent

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What are the possible risks or discomforts? Some of the pictures might feel unpleasant. Secondly, breach of confidentiality is always a risk with data, but we will take precautions to minimize this risk as described in the confidentiality section.

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Are there costs to me for participation? There are no anticipated costs to participate in this research.

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Krannert Building, Office 777, 403 W. State Street, West Lafayette, IN 47907-2056
awahdat@purdue.edu, 617-548-4008

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Ernest C. Young Hall, Room 1032, 155 S. Grant St., West Lafayette, IN 47907-2114

Documentation of Informed Consent

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Introductory Questions

Q1. How do you see yourself: Are you generally a person who is willing to take risks in financial matters or do you try to avoid taking risks in financial matters?

(Please tick only one box on the scale, the value **0** means **completely unwilling to take risks** and the value **10** means **very willing to take risks**).

0 completely unwilling to take risks	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10** very willing to take risks
◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯

Q2a. In the past 12 months, how many acres of these crops were planted and insured?

	Acres Planted	Acres Insured
Vegetables, Melons		
Fruits, Nuts, Berries		
All Other Crops		

Q2b. Do you engage in farm financial planning for worst times like farm/crop losses due to flood or drought?

- ◯ Yes
- ◯ No

Q2c. Has an extreme weather event ever affected your farm?

- ◯ Yes
- ◯ No

Q2d. Is climate change important to your farm management decisions?

- ◯ Yes
- ◯ No

Q2e. Indicate your level of agreement with the following statements (pick one choice for each row).

	Strongly Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
1. Weather and climate change presents more risks than benefits to Indiana agriculture.	○	○	○	○	○
2. I am worried about weather and climate change.	○	○	○	○	○

Q2f. Select below all the financial instruments that are available to you to run the farm operation.

Insurance	Government Loans	Bank Loans	Relatives Loans	Personal Savings	Supplier Credit	Credit Cards	Don't have access to any of these
☐	☐	☐	☐	☐	☐	☐	☐

Q2g. Which three financial instruments would you use after farm losses due to a disaster? (select three most important)

Insurance	Government Loans	Bank Loans	Relatives Loans	Personal Savings	Supplier Credit	Credit Cards
☐	☐	☐	☐	☐	☐	☐

Household Expenditure Questions

Q3. In the past 12 months, what was your **average monthly income** from **farm and non-farm** sources all together? (you can also divide annual **after-tax income** over 12 to get this)

Q4.
In the past 12 months, what were your **average monthly household expenses** for the following categories (don't include farm-related expenses)? Add all expenses and write the total in last cell (Total). Total expenses should be less than or equal to average monthly income in Q3, unless you took loans in the last 12 months and spent it on these categories.

1. Health Insurance Cost and Out-of Pocket Health Expenses	
2. Food (including Food Away from Home)	
3. Education and Child Care	
4. Rent Expenses for Household Use	
5. Mortgage Interest and Property Taxes	
6. Transportation Expense for Household Use	
7. Vehicle (Fuel, Maintenance, Insurance) for Household Use	
8. Entertainment	
9. House Furnishing (internal home decor)	
10. Clothing and Personal Care	

11. Utilities and Household Supply	
12. Contributions to Outside Alimony and Charity	
13. Life/Disability Insurance and Retirement Expense (or Savings)	
Total	

Q5. Please subtract **$10** from your **average monthly income in Q3** and write your answer in the empty box:

(Income in Q3) - $10 =

A Scenario. Following are two images showing the impact of crop freeze and flooding. Imagine your county was first hit by a crop freeze in late spring, and then recently by heavy flooding. Some of the farms in your county suffered serious damages. Thankfully, some of the neighborhoods, including your farm and home remained safe. You had a very small amount of farm equipment damage. Because of the damage, your average monthly income in each of the next 12 months will be **equal to the income calculated in Q5** previously, which is only $10 less than the **income in Q3**. Please note that the **income in Q5** is all you have for monthly spending for each of the next 12 months. And you run the same size farm operation in the next 12 months as in the last 12 months. And your non-farm work hours and income remain the same. Now go to the next question.

Crop Freeze

Flooding

Q6.
In each of the next 12 months, your **average monthly income** will be **equal to the amount in Q5**. How would you spend **this new lower amount** on the following categories?

1. Health Insurance Cost and Out-of-Pocket Health Expenses	
2. Food (including Food Away from Home)	
3. Education and Child Care	
4. Rent Expenses for Household Use	
5. Mortgage Interest and Property Taxes	
6. Transportation Expense for Household Use	
7. Vehicle (Fuel, Maintenance, Insurance) for Household Use	
8. Entertainment	
9. House Furnishing (internal home decor)	
10. Clothing and Personal Care	
11. Utilities and Household Supply	
12. Contributions to Outside Alimony and Charity	
13. Life/Disability Insurance and Retirement Expense (or Savings)	
Total	

Financial Decision Questions

Q7. Imagine you are offered a farm investment opportunity, called the "first opportunity," that will pay you an **annual net return of either $10,000 or nothing ($0).** The chances are half-and-half like a coin toss: $10,000 when heads turn up and $0 when tails turn up. Alternatively, you are offered a "second opportunity" that has a **fixed annual net return all the time**.
If the fixed annual net return of the second opportunity is **$100**, would you choose such opportunity instead of the first opportunity?

- ◯ **Yes, I select second opportunity**. (move to Q17 if you select Yes)
- ◯ **No, I don't select second opportunity** (move to next question, Q8, if you select No)

Q8. If the fixed annual net return of the second opportunity is **$500**, would you choose such opportunity instead of the first opportunity?

- ◯ **Yes, I select second opportunity**. (move to Q17 if you select Yes)
- ◯ **No, I don't select second opportunity** (move to next question, Q9, if you select No)

Q9. If the fixed annual net return of the second opportunity is **$1,500**, would you choose such opportunity instead of the first opportunity?

- ◯ **Yes, I select second opportunity**. (move to Q17 if you select Yes)
- ◯ **No, I don't select second opportunity** (move to next question, Q10, if you select No)

Q10. If the fixed annual net return of the second opportunity is **$3,000**, would you choose such opportunity instead of the first opportunity?

- ◯ **Yes, I select second opportunity**. (move to Q17 if you select Yes)
- ◯ **No, I don't select second opportunity** (move to next question, Q11, if you select No)

Q11. If the fixed annual net return of the second opportunity is **$4,000**, would you choose such opportunity instead of the first opportunity?

- ◯ **Yes, I select second opportunity**. (move to Q17 if you select Yes)
- ◯ **No, I don't select second opportunity** (move to next question, Q12, if you select No)

Q12. If the fixed annual net return of the second opportunity is **$5,000**, would you choose such opportunity instead of the first opportunity?

- ◯ **Yes, I select second opportunity**. (move to Q17 if you select Yes)
- ◯ **No, I don't select second opportunity** (move to next question, Q13, if you select No)

Q13. If the fixed annual net return of the second opportunity is **$5,500**, would you choose such opportunity instead of the first opportunity?

- ◯ **Yes, I select second opportunity**. (move to Q17 if you select Yes)
- ◯ **No, I don't select second opportunity** (move to next question, Q14, if you select No)

Q14. If the fixed annual net return of the second opportunity is **$7,000**, would you choose such opportunity instead of the first opportunity?

- ◯ **Yes, I select second opportunity**. (move to Q17 if you select Yes)
- ◯ **No, I don't select second opportunity** (move to next question, Q15, if you select No)

Q15. If the fixed annual net return of the second opportunity is **$9,000**, would you choose such opportunity instead of the first opportunity?

- ◯ **Yes, I select second opportunity**. (move to Q17 if you select Yes)
- ◯ **No, I don't select second opportunity** (move to next question, Q16, if you select No)

Q16. If the fixed annual net return of the second opportunity is **greater than $9,000**, would you choose such opportunity instead of the first opportunity?

- ◯ **Yes, I select second opportunity**. (move to Q17 if you select Yes)
- ◯ **No, I don't select second opportunity** (move to next question, Q17, if you select No)

Q17. If you needed **$100,000** loan, who would you ask for it? (you can select multiple choices)

- ◯ Family
- ◯ Relatives
- ◯ Bank
- ◯ Farm Service Agency

Q18. How do you see yourself in the next 12 months: Are you generally a person who is willing to take risks in financial matters or would you try to avoid taking risks in financial matters?

(Please tick only one box on the scale, the value **0** means **completely unwilling to take risks** and the value **10** means **very willing to take risks**).

0 completely unwilling to take risks	1	2	3	4	5	6	7	8	9	10 very willing to take risks
◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯

Household Characteristics Questions

Q19. What is your Gender?

◯ Male

◯ Female

Q20. Are you married?

◯ Yes

◯ No (If you answer No, then don't fill "Your Spouse" part in Q21, Q22, Q23, Q24.)

Q21. What is your and your spouse's race?

You	White ◯	American Indian ◯	Asian ◯	Black or African American ◯	Other ◯
Your Spouse	White ◯	American Indian ◯	Asian ◯	Black or African American ◯	Other ◯

Q22. What is your and your spouse's education?

You	4 year degree and beyond ◯	Some college or associates ◯	High school ◯	Less than high school ◯
Your Spouse	4 year degree and beyond ◯	Some college or associates ◯	High school ◯	Less than high school ◯

Q23. At which occupation did you and your spouse spend the majority (50 percent or more) of your work time in the past 12 months?

You	Work other than farming ◯	Farming ◯	Not in workforce ◯
Your Spouse	Work other than farming ◯	Farming ◯	Not in workforce ◯

Q24. What is your and your spouse's age?

Your __________

Your Spouse __________

Q25. How many people lived in your household in the past 12 months?

(include yourself, spouse, children, and any other living in your household)

Concluding Questions and Notes

Q26. In the past 12 months, what was your farm operation's legal status for tax purposes?

(you can select multiple choices)

- Family or Individual Operation
- Legal Partnership
- C-corporation or S-Corporation
- Other such as Trust or Cooperative

Q27. In the past 12 months, what percentage of farm operation business did your household own?

Q28. In the past 12 months, what was the total amount of your

Household Assets
(like financial accounts, personal home, vehicle, and other assets).

Farm Assets
(like financial accounts, farm land, trees, property, vehicles, livestock).

Final Note. Thank you for your valuable time. Your answers will be of great help to understand Indiana specialty farmers' vulnerability. Please **provide your phone number** in space below so we can contact you, in case you win **$200 prize**.
In a couple of months, you can start checking this link (https://bit.ly/ 2J8rGkm) to see the winners of $200 prizes. We only provide the first name of the winners for confidentiality reasons. If the above link doesn't work, please send an email to awahdat@purdue.edu

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4. INCOME SHOCKS AND LOSS AVERSION IN CONSUMPTION EXPENDITURES

A reality of households in any economy is that they can possibly lose income for a multitude of reasons, for instance, unemployment, poor health, business loss, or property damage. An income loss can result in less spending on goods and services that are crucial to households' well-being. From a household's perspective, a loss in consumption expenditures after an income loss can be an unpleasant experience, one that the household tries to avoid if it can. In models of consumer behavior with reference-dependent preferences, consumer well-being depends not only on the level of consumption, but also on the comparison between consumption and its reference level (Kahneman et al., 1991; Kőszegi and Rabin, 2006). When consumption level falls below (rises above) the reference level of consumption, it leads to a sensation of loss (gain). A manifestation of reference-dependent preferences is the concept of "loss aversion", i.e., people tend to prefer avoiding losses compared to receiving equal value gains (Kahneman and Tversky, 1979; Kahneman et al., 1991).

The objective of this study is to estimate the size of loss aversion in consumption expenditures when households experience income shocks. I assume that households' reference level (or reference point) of consumption expenditures is based on the status quo (the recent past). I model status quo-based consumption expenditures as last period's expenditures. Specifically, I study households whose consumption expenditures fall below or rise above the reference level after a decrease or increase in disposable income, respectively.[1] From the perspective of consumption response to income shocks, this study explores whether households exhibit symmetric or asymmetric consumption behavior after experiencing income shocks, and if such behavior holds true across different age brackets. For instance, for a $1,000 increase or decrease in disposable income, the magnitude of respective spending increase or decrease is the same (symmetric) or different (asymmetric). As the main objective of many government support policies is to protect household spending for the sake of household well-being and a strong functioning economy, estimating loss aversion in consumption

[1] ↑Throughout this study, both disposable income and consumption expenditures are expressed in terms of real 2018 Australian dollars.

expenditures provides an understanding of households' tendency to prefer avoiding consumption expenditure losses, which can be detrimental to household well-being.

Since the early days of the prospect theory of Kahneman and Tversky (1979) and the reference-dependent preferences model of Kőszegi and Rabin (2006), behavioral models with reference point have helped explain individual behavior in various economic settings, especially when choice outcome is close to the reference point. Prospect theory and the implications of loss aversion for choice behavior have been studied in a number of areas of economics, i.e., finance, insurance, consumption-savings, industrial organization, labor supply, and consumer choice (see Barberis (2013), DellaVigna (2018), and Karle et al. (2015) for a literature review). Technically, people are considered loss averse if the slope of their prospect theory-based value function is steeper in the loss domain than in the gain domain. Whenever the loss aversion coefficient (λ) is greater than 1, i.e., the ratio of value function's slope in the loss and gain domains is greater than 1, it signifies loss aversion. Regarding the size of loss aversion coefficient, the classic study of Tversky and Kahneman (1992) reports a median coefficient of 2.25, i.e. losses loom twice as large as equal value gains. However, depending on the context and the area of study, loss aversion coefficients can vary in size: 3.11 (Pagel, 2017), 2.2 (Merkle, 2019), 1.8 (Pennings and Smidts, 2003), 1.43 (Schmidt and Traub, 2002).

Although reference point is forward-looking (expectations based) in some of the models (Kőszegi and Rabin, 2006, 2009), other models assume a status quo-based reference point, i.e., reference point is backward-looking and based on the recent past (Bowman et al., 1999). When the reference point of consumption is forward-looking and income is anticipated, a decision maker exhibits an interesting behavior regarding her consumption relative to the reference point: upon receiving bad news (i.e., income shock), she will overconsume in the present and underconsume in the future because consuming less in the present is more painful than consuming less in the future (Kőszegi and Rabin, 2009; Pagel, 2017). Although Bowman et al. (1999) choose past consumption as a reference point for consumption, they similarly show that anticipated income gains (losses) lead to an increase (no change) in consumption today – i.e., people exhibit an asymmetric consumption response to anticipated income changes. In other words, people will cut consumption whenever the anticipated income shock is actually realized. An important feature of the current study is the evaluation of households' consumption behavior in response to realized income changes rather than anticipated income changes. In doing so, this study presents evidence whether households exhibit symmetric or asymmetric consumption behavior in response to realized income changes.

In my model's setup, a household's total consumption utility is composed of an intrinsic utility ("consumption utility" from consumption expenditures) and a "gain-loss utility" originating from the change in consumption expenditures relative to the reference level of consumption expenditures (Kőszegi and Rabin, 2006). I consider the reference level of consumption expenditures to be the status quo, i.e., last period's expenditures. Household enters a decision period (a financial year) and expects its disposable income to be the same as during the last period, and when this turns out to be true, the household's consumption expenditures coincide with the reference level of consumption expenditures and the gain-loss utility term becomes irrelevant. When disposable income in a decision period is more (less) than last period's disposable income, the household maximizes total consumption utility with respect to the new disposable-income constraint by choosing consumption expenditures that are more (less) than the reference level of consumption expenditures. Now, the household's total consumption utility has both intrinsic utility and gain-loss utility components. Since the household's total consumption utility changes between the two scenarios of (i) no change in disposable income, and (ii) an increase or decrease in disposable income relative to the last period, I estimate consumption loss aversion in a regression of consumption change over disposable income change variables, i.e., positive and negative income change variables.

In the estimation of loss aversion parameter, I choose the reference level of consumption expenditures to be status quo-based or equal to last period's consumption expenditures. I use longitudinal household data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey and restrict analysis to Australian financial years 2005-06 to 2009-10. Consistent with the prediction of prospect theory that losses weigh more than equal value gains, I expect that household consumption losses loom larger than equal amount of gains. In my results, I find the evidence that, on average, losses in consumption expenditures loom about 1.4 times larger than equal value gains, i.e., the loss aversion parameter has an estimated value of $\hat{\lambda} = 1.4$. My estimation results are robust to an alternative reference level of consumption expenditures, i.e., the reference level being the average consumption expenditures of last two periods. Furthermore, I find that retirement-age households are loss neutral in consumption expenditures, i.e., $\hat{\lambda} = 1$. However, for working-age households, loss aversion in consumption increases as they get younger, i.e., $\hat{\lambda} = 2.02$ for households younger than 30 years of age. Finally, regarding households' consumption response to income shocks, I find that retirement-age households exhibit a symmetric consumption behavior, however, working-age younger households exhibit an asymmetric consumption behavior.

The main contribution of this study is the empirical estimation of consumption loss aversion when households experience income shocks. Additionally, this study estimates consumption loss aversion by different age groups, to show heterogeneity in loss aversion behavior between retirement-eligible households and working-age households. The above contributions add to the literature on estimating loss aversion (Tversky and Kahneman, 1992), and enrich the discussion around consumption behavior under loss aversion (Kőszegi and Rabin, 2009; Pagel, 2017). This study also contributes to the literature on consumption response to income shocks (Christelis et al., 2019). Using household panel data and panel fixed-effects methods, I show that retirement-age households (working-age households) have a symmetric (asymmetric) consumption response to realized income shocks.

Meanwhile, how reference point is formed in various decision environments, and whether reference point is "forward-looking" (expectations based) or "backward-looking" (status quo based) remain important research topics (DellaVigna, 2018). In the current study, I present an empirical method for estimating household loss aversion in consumption expenditures when the reference point is based on the status quo and income shock is experienced.

The implications of this study for household consumption-based well-being and economic policy are twofold. First, since Australian household consumption has become more vulnerable to macroeconomic shocks since 2009-10 (partially due to household leverage) (Kearns et al., 2020), it suggests that in recent years, experienced loss aversion in consumption expenditures could be stronger than what we report in this study ($\hat{\lambda} = 1.4$) because households suffer in well-being. Second, a policy response to boost household spending can benefit from targeting households that are more consumption responsive (see, Andreolli and Surico (2021)). I find in Australian household data that, after an income shock, the decrease in consumption among retirement-age households is subdued compared to working-age households (24 cents versus 32-44 cents), so younger households would benefit relatively more from income support programs.

4.1 Household Consumption with Reference-Dependent Preferences

In this section, I present utility of a household with reference-dependent consumption under two scenarios of disposable income Y in year t: (i) when disposable income Y in year t is the same as during the last year $(t-1)$ and consumption level c is equal to reference consumption r, and (ii) when disposable income Y in year t increases or decreases compared to the last year and consumption level c is more or less than the reference consumption r. I then evaluate the change in household's total consumption utility under the two scenarios of disposable income to arrive at a model that I use for estimating loss aversion in consumption expenditures. The following variables are expressed in real terms (real 2018 Australian dollars) throughout this study, i.e., disposable income Y, consumption expenditures c, and reference level of consumption expenditures r. I also make simplifying assumptions regarding the economic environment in which households make decisions: (i) similar to the assumption in Chetty and Szeidl (2016), relative prices of goods and services in the market basket are constant and exogenous, i.e., idiosyncratic shocks in terms of income are smaller than any aggregate shock to disturb the partial equilibrium of goods and services markets, (ii) in a given year t, households expect that their disposable income will be the same as during the last year, and (iii) households are modeled as individuals regarding their decision makings about consumption expenditures.

Following the reference-dependent preferences framework of Kőszegi and Rabin (2006), a household's total consumption utility is composed of two parts: (i) the intrinsic utility $u(.)$ from consumption level c, and (ii) a value function $\mu(.)$ that captures the "gain-loss utility" when consumption c is above or below the reference consumption point r. Although reference point formation is based on rational expectations in Kőszegi and Rabin (2006), I consider households to form expectations about their real consumption expenditures based on the status-quo. Specifically, I consider a household's reference level of consumption expenditures in year t to be equal to last period's $(t-1)$ consumption expenditures. In other words, a household's reference point of consumption expenditures is backward-looking (based on the status quo).

Per Kőszegi and Rabin (2006), I consider a linear intrinsic utility function $u(c) = \delta c$ and a linear value function with kink at the reference point, i.e., $\mu(x) = \eta x$ for $x \geq 0$, and $\mu(x) = \eta\lambda x$ for $x < 0$, where $x = (c - r)$, r is the reference consumption level, and λ is the loss aversion parameter per the prospect theory of Kahneman and Tversky (1979). Households are loss averse in consumption whenever $\lambda > 1$.

In the scenario when household's disposable income in year t is the same as in year $(t-1)$, it will choose its consumption level c to be equal to the reference consumption level r. When a household realizes that its disposable income has not changed since last year, choosing reference consumption level r is the "preferred equilibrium" because it maximizes utility (see Kőszegi and Rabin (2006) for preferred equilibrium definition). Therefore, replacing c with r in household i's utility in year t we get

$$\overline{U}_{it} = u(r_{it}) + \mu(r_{it} - r_{it}) = \delta r_{it}, \tag{4.1}$$

where $\overline{U}$ denotes household's total consumption utility when disposable income is the same as during the last year.

In the scenario when household's disposable income in year t increases or decreases compared to year $(t-1)$, it chooses a consumption level c that maximizes household's total consumption utility with respect to the new disposable income constraint. Since consumption level c for household i in year t is going to be more or less than the reference consumption level r, the household's total consumption utility will have a gain-loss utility part in addition to the intrinsic utility from c, i.e.,

$$U_{it} = u(c_{it}) + \mu(c_{it} - r_{it}) = \delta c_{it} + \eta(c_{it} - r_{it}) * I[c_{it} \geq r_{it}] + \eta\lambda(c_{it} - r_{it}) * I[c_{it} < r_{it}], \tag{4.2}$$

where $I[.]$ is the indicator function, and δ, η, and λ are positive parameters.

Subtracting (4.1) from (4.2) gives the change in household's total consumption utility when household's disposable income in year t deviates from the expected level (i.e., last year's disposable income)

$$\Delta U_{it} = \delta(c_{it} - r_{it}) + \eta(c_{it} - r_{it}) * I[c_{it} \geq r_{it}] + \eta\lambda(c_{it} - r_{it}) * I[c_{it} < r_{it}]. \tag{4.3}$$

In order to empirically estimate the consumption loss aversion parameter λ, I estimate the following panel fixed-effects regression equation,

$$\Delta c_{it} = \eta(\Delta Y_{it}) * I_{[Y_{it} \geq Y_{it-1}]} + \eta\lambda(\Delta Y_{it}) * I_{[Y_{it} < Y_{it-1}]} + \beta X_{it} + \alpha_i + \rho_t + \varepsilon_{it}, \tag{4.4}$$

where $\Delta c_{it} = (c_{it} - r_{it})$, r_{it} is the reference consumption level (equal to c_{it-1}), $\Delta Y_{it} = (Y_{it} - Y_{it-1})$, X_{it} is a vector of time-varying household socio-demographics, α_i is household fixed-effects, ρ_t is year fixed-effects, and ε_{it} is the error term. I compute standard errors that are robust and clustered at the household level. I am able to identify the η and $\eta\lambda$ coefficients by exploiting variation within each household across time in a panel fixed-effects regression. I also estimate equation (4.4) through pooled ordinary least squares and panel random-effects. I aim to test the following hypothesis.

Hypothesis: Households with reference-dependent preferences will exhibit loss aversion in consumption expenditures ($\lambda > 1$) when the experience of disposable income loss leads to a decrease in consumption expenditures below the reference level.

4.2 Data

The data for my analysis comes from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, General Release 18 (Summerfield et al., 2019). The HILDA Survey is a longitudinal household survey – based on a national probability sample of Australian households – covering broad social and economic topics since 2001. In my analysis, I use the HILDA Survey waves 5-10, which correspond to Australian financial years 2005-06 to 2009-10.[2] I restrict analysis to the five financial years from 2005-06 to 2009-10 because the

[2]↑Australian financial year starts July 1 and ends on June 30 of the next year.

HILDA Survey data on household expenditures is the most comprehensive during these five financial years. The total spending on household goods and services in each of the HILDA Survey waves 6 to 9 represent about 80% of total expenditures in the Household Expenditure Survey (HES) 2003-04, where HES is managed by the Australian Bureau of Statistics (ABS) and serves as a benchmark for household expenditures in Australia (Wilkins and Sun, 2010). Overall, the HILDA Survey performs well in capturing quality panel data on household expenditures (Wilkins and Sun, 2010).

To stay consistent with the model from previous section, I restrict analysis to households that have a decrease (increase) in disposable income in year t and a decrease (increase) in consumption expenditures relative to the reference level. I use ABS's Consumer Price Index (CPI) by 11 groups (i.e., health, transport, etc.) and by eight Australian capital cities to express HILDA expenditure items in real 2018 dollars. Household disposable income is also expressed in real 2018 Australian dollars. I add all available expenditure items at the household level to get the aggregate variable for household consumption expenditures. Since I focus on consumption expenditures in this study, I do not include household investment expenditures (i.e., mortgage and home repair expenses) in the aggregate household expenditures variable.

I only use the data from three financial years for estimation purposes, i.e., 2007-08, 2008-09, and 2009-10. The data from financial years 2005-06 and 2006-07 are only used to provide the reference level of consumption expenditures for financial year 2007-08. The starting financial year in my analysis is 2007-08.

Table 4.1 presents the descriptive summary statistics for (i) household socio-economic variables, (ii) change in household disposable income since last financial year, and (iii) change in household consumption expenditures compared to the reference level of consumption expenditures. Except for the variables from (ii) and (iii) that require additional data from financial year 2006-07, the socio-economic variables are primarily based on data from the three financial years, 2007-08 to 2009-10. The descriptive summary statistics are organized by (i) all households, which are sub-divided into (ii) households with a decrease in income and consumption expenditures, and (iii) households with an increase income and consumption expenditures. Half of the households are run by females. Most of the household heads are legally married (47.39%), the rest are either never married or have 'Other Status', i.e., widowed, divorced, separated, or in a de facto relationship. Most of the household heads have an advanced diploma or below that, hence representing about 77% of the sample households. The average age of household heads is about 49 years.

The average disposable income and consumption expenditures for all households are about \$91,087 and \$46,997, respectively. However, these two figures are obviously lower among households with a decrease in disposable income (\$74,982; \$38,683) when compared to the households with an increase in disposable income (\$103,241; \$53,271). Meanwhile, on average, the change in disposable income compared to the last financial year is about \$3,689 for all households; and the change in consumption expenditures compared to the reference level of expenditures is about \$2,035 for all households. When we focus on the households that had a decrease (increase) in disposable income and consumption expenditures, the average change in disposable income is about -\$26,136 (\$26,195), and the average change in consumption expenditures is about -\$14,591 (\$14,581). In absolute terms, the change in each disposable income and consumption expenditures is almost the same in the two group of households.

4.3 Results

In this section I present the results from estimating equation (4.4); and I use the data described in the Data section. The dependent variable in equation (4.4) captures change in consumption expenditures compared to the reference level. Specifically, I aim to present the estimated coefficients associated with disposable income increase or decrease since last period (i.e., η and $\eta\lambda$, respectively) which allow me to calculate the loss aversion parameter λ, i.e., ($\frac{\eta\lambda}{\eta} = \lambda$).

In Column 1 in Table 4.2, I present the estimates from a pooled ordinary least squares (OLS) regression with robust standard errors. In the pooled OLS regression, I control for household head's age and other time-invariant characteristics, i.e., gender, marital status, and education. The base category for each categorical variable is as following: 'male' for gender; 'legally married' for marital status; and 'advanced diploma or below that' for education. I also estimate equation (4.4) in a panel random-effects regression in Column 2. The panel fixed-effects regression in Column 3 of Table 4.2 is the preferred specification, which accounts for household fixed-effects and robust standard errors, which are clustered at the household level. The model fit of panel fixed-effects regression is better than that of pooled OLS as evidenced by the lower Akaike Information Criterion (AIC) score, i.e., 202,554 versus 208,949, respectively. The R^2 statistical measure is also higher (0.3) in the panel fixed-effects regression compared to the R^2 of pooled OLS (0.26), however, the two R^2 measures are not directly comparable. The R^2 in panel fixed-effects regression is a within-household measure, i.e., how much of variation in the dependent variable within each household is explained by the model variables.

In Table 4.2, the first two variables measure an increase or decrease in disposable income since last period, and their coefficients provide estimates of gain (η) and loss ($\eta\lambda$) parameters, respectively. In Columns 1 and 2 of Table 4.2, the estimates of η and $\eta\lambda$ are 0.21 and 0.29, respectively, and both estimates are statistically significant ($p < 0.01$). An estimate of η at 0.21 means that when disposable income increases by 1 dollar since last period, household consumption expenditures increase by 0.21 dollars. An estimate of $\eta\lambda$ at 0.29 means that when losses in disposable income increase by 1 dollar, household consumption expenditures decrease by 0.29 dollars, hence the asymmetric consumption response to realized income shock. In the panel fixed-effects results in Column 3, the significant estimates of η and $\eta\lambda$ are 0.23 and 0.32, respectively. In the second last row of Table 4.2, I calculate the loss aversion parameter λ, which is equal to 1.41 ($\frac{\eta\lambda}{\eta} = 1.41$).

My findings about the estimates of gain and loss coefficients are consistent with the findings of prospect theory, i.e., losses loom larger than gains (Kahneman and Tversky, 1979). However, the loss aversion parameter is less than 2. I show the p-value for a Wald-test of ($\hat{\lambda} = 1$) in the last row of Table 4.2 following Merkle (2019). I am able to reject the null hypothesis that the loss aversion parameter λ is equal to unity ($p < 0.01$). I find that losses loom about 1.4 times larger than gains. Therefore, I consider households in my study to be loss-averse in real consumption expenditures based on the loss aversion parameter ($\hat{\lambda}$ = 1.41) from the estimation results in Table 4.2. Karle et al. (2015) categorize $\lambda \in (1.8, 3]$ as "loss-averse" and $\lambda > 3$ as "strongly loss-averse". The results in Table 4.2 also suggest that, on average, households exhibit asymmetric consumption response after experiencing income shocks.

4.3.1 Consumption Loss Aversion by Retirement-Eligible Households and Working-Age Households

In this subsection, I estimate the same panel fixed-effects regression as in Table 2, however I focus my analysis on retirement-eligible and working-age households. In Australia, people become eligible for pension at the age of 65 up to 67. To be conservative, I define households to be retirement-eligible if the survey respondent is of age 70 or above. Households are considered working-age if survey respondents are below 70 years of age.

In Columns 1-5 of Table 4.3, the most interesting finding is that working-age households of different age ranges are loss averse in consumption expenditures (i.e., $\hat{\lambda} > 1$), however, retirement-eligible households are loss neutral in consumption expenditures (Column 6), i.e., $\hat{\lambda} = 1$. More importantly, the loss aversion parameter (λ) is decreasing in size as household age group becomes older. For instance, $\hat{\lambda} = 2.02$ for age < 30 (Column 1); $\hat{\lambda} = 1.64$ for age < 40 (Column 2); $\hat{\lambda} = 1.54$ for age < 50 (Column 3); $\hat{\lambda} = 1.48$ for age < 60 (Column 4) $\hat{\lambda} = 1.46$ for age < 70 (Column 5); however, λ is not different than 1 for retirement-eligible households in Column 6. Specifically, for working-age households that are less than 30 years old, consumption losses loom twice as large as equal value gains, i.e., $\hat{\lambda} = 2.02$ (Column 1). The results in Table 4.3 further signify that retirement-eligible households exhibit symmetric response to realized income shock, however, working-age households exhibit asymmetric response. The results in Table 4.2 mask the contrasting consumption behavior as seen in Table 4.3 because Table 4.2 reports consumption response for the average household which is asymmetric in nature.

A potential explanation for why retirement-eligible households have symmetric consumption response to realized income shock as opposed to the asymmetric response of working-age households can be the extra leisure time that retirement-eligible people have at hand. Extra leisure time allows the flexibility that retirement-eligible people could shop efficiently and also engage in home production activities like laundry, house cleaning, and cooking (Aguiar and Hurst, 2005, 2007; Hurd and Rohwedder, 2006). If retirement-eligible households are already efficient in their consumption, they would not have the flexibility to cut expenditures by as much as working-age households (compare 24 cents decrease versus 44 cents decrease in expenditures in the second row of Columns 6 and 1 of Table 4.3). So, a \$1 negative income shock would push retirement-eligible households to cut expenditures by a smaller magnitude when compared to working-eligible households.

4.3.2 Loss Aversion for an Alternative Reference Level of Consumption Expenditures

In this subsection I check whether the estimated loss aversion parameters in Table 4.2 are robust to an alternative reference level of consumption expenditures, i.e., the average consumption expenditures of last two financial years. In Table 2, the reference level of consumption expenditures is equal to last financial year's consumption expenditures. I replicate the results in Table 4.2 with the alternative reference level of consumption expenditures and present the new results in Table 4.4.

In Table 4.4, the model fit of panel fixed-effects regression (AIC = 200,467) is better than that of pooled OLS (AIC = 208.033). The loss aversion parameter from Columns 1 and 2 in Table 4.4 is equal to 1.28 ($p < 0.01$). The loss aversion parameter from the panel fixed-effects regression in Column 3 is equal to 1.37 ($p = 0.01$). Obviously, the loss aversion parameters slightly differ in value compared to those presented in Table 4.2, it is still the case that losses loom larger than gains, i.e., the p-value for a Wald-test of ($\hat{\lambda} = 1$) is less than or equal to 0.01. Households in this study are loss-averse in real consumption expenditures – even with the alternative reference level. And, on average, households exhibit an asymmetric consumption response after experiencing an income shock, i.e., a \$1 increase (decrease) in disposable income leads to 0.21 dollars increase (0.29 dollars decrease) in expenditures. [3]

[3]↑The number of observations in Table 4.4 slightly differ than that of Table 4.2. This happens because I always restrict my analysis to households that have a decrease (increase) in real disposable income in year t and a decrease (increase) in real consumption expenditures relative to the reference level. So as the reference level of consumption expenditures changes, the analysis sample will also change. Despite the above change, about 84% of the unique household-year observations in Table 4.2 still show up in Table 4.4.

4.4 Discussion and Conclusion

Not all households in an economy can be fortunate enough to have stable streams of disposable income. An income shock in a given year can potentially push households to cut upon their consumption expenditures. It is not just the level of consumption expenditures that the household cares about, it is also about how far consumption expenditures fall below the reference level of expenditures. In this study I aim to identify whether households with reference-dependent preferences experience loss aversion in real consumption expenditures. Although reference point formation is based on rational expectations in Kőszegi and Rabin (2006), I consider households' reference point for consumption expenditures to be based on the status-quo, i.e., last period's consumption expenditures.

I use survey data for financial years 2005-06 to 2009-10 from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, which is a longitudinal household survey. I study households that have a decrease (increase) in real disposable income in year t and a decrease (increase) in real consumption expenditures relative to its reference level. Since the disposable income and consumption expenditures in the survey are already realized by households, an estimation of the degree of loss aversion in consumption expenditures reflects the actual, experienced loss aversion.

In the Results section (Tables 4.2 and 4.4), I provide the evidence that losses in real consumption expenditures loom about 1.4 times larger than gains, i.e., the loss aversion parameter has an estimated value of about 1.4 ($\hat{\lambda} = 1.4$). My results are robust to an alternative reference point of consumption expenditures, i.e., the reference point being the average consumption expenditures of last two financial years. The results further highlight the asymmetric consumption behavior of households in response to realized income shocks. This asymmetry means that, in absolute terms, for a \$1 change in income, the decrease in consumption expenditures is 9 cents greater than the increase in expenditures (Column 3 of Table 4.2). My results are consistent with recent literature findings, i.e., consumption response to negative income shock is larger than the one from positive income shock (Christelis et al., 2019).

Interestingly, I also find in my results (Table 4.3) that retirement-eligible households (age 70 and above) are loss neutral in consumption expenditures (i.e., $\hat{\lambda} = 1$), however, working-age younger households are consumption loss averse (i.e., $\hat{\lambda} > 1$). In particular, for working-age households who are less than 30 years of age, losses loom twice as large as as equal value gains ($\hat{\lambda} = 2.02$). Table 4.3 further shows that retirement-eligible households have a symmetric consumption response to income shocks as opposed to the asymmetric response of younger households. Finally, the consumption response to negative income shock is smaller for retirement-eligible households than that of younger households (i.e., 24 cents versus 32-44 cents, see second row of Table 4.3). This last finding is in contrast to the findings of Christelis et al. (2019), who show that the hypothetical consumption response of older Dutch people at age 70 is larger than that of younger people, regardless of income shock sign. It is possible that the contrast in our findings regarding consumption behavior of older households could be due to different survey populations (Dutch versus Australian) or survey data (hypothetical versus non-hypothetical). It is also possible that since older households are already efficient with their consumption expenditures (Aguiar and Hurst, 2005, 2007), there would hardly be much room to cut spending further.

An implication of this study is that losses in consumption expenditures are psychologically taxing for Australian working-age households, and the psychological burden of losses weigh about 1.4 times larger than the pleasure of equal value gains. If anything, experienced loss aversion in consumption expenditures could be stronger in recent years than what we report in this study ($\hat{\lambda} = 1.4$) because Australian household consumption has become more vulnerable to macroeconomic shocks since 2009-10 (partially due to household leverage) (Kearns et al., 2020). Losses in consumption expenditures can be indeed painful for working-age younger households who have to meet a range of needs at the household level (i.e., education, health, food, etc.). Although household consumption response to income shock is one of those issues that governments care about, having an understanding of the degree of psychological burden that goes along with consumption loss can provide additional insight into the consumption response behavior. A further implication of this study is that a targeted policy response can be more effective when households suffer income loss. Although all age groups in this study suffer from reducing consumption expenditures after an income loss, younger working-age households are pressed hard. An extension of the current research can focus on replicating this study's results with household panel data from other countries such as Canada, Germany, Great Britain, and the United States, to evaluate whether the loss aversion in household consumption differ across countries and age groups.

4.5 Tables

Table 4.1. Household Summary Statistics for Socio-Economic Variables

	All Households (N = 9,301)		Households with a Decrease in Income & Consumption Expenditures (N = 4,000)		Households with an Increase in Income & Consumption Expenditures (N = 5,301)	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
Gender						
Male	4,616	49.63	2,017	50.42	2,599	49.03
Female	4,685	50.37	1,983	49.58	2,702	50.97
Marital Status						
Legally Married	4,408	47.39	2,005	50.13	2,403	45.33
Never Married & Not De Facto	1,591	17.11	579	14.47	1,012	19.09
Other Status	3,302	35.50	1,416	35.40	1,886	35.58
Education						
Advanced Diploma or Below It	7,164	77.02	3,108	77.70	4,056	76.51
Bachelors or Graduate Diploma	1,773	19.06	743	18.57	1,030	19.43
Master's or Doctorate	364	3.91	149	3.72	215	4.06
	Mean	SD	Mean	SD	Mean	SD
Age	48.89	(17.4)	50.66	(17.1)	47.56	(17.6)
Disposable Income	91,087.67	(65,270.90)	74,981.92	(54,585.80)	103,240.66	(69,884.90)
Consumption Expenditures	46,997.49	(27,587.80)	38,682.89	(22,171.20)	53,271.48	(29,547.30)
Δ in Disposable Income	3,689.62	(44,377.90)	-26,135.86	(34,781.70)	26,195.16	(36,945.50)
Δ in Consumption Expenditures	2,035.28	(21,289.10)	-14,590.87	(15,287.30)	14,580.94	(15,902.90)

Notes: Summary statistics (unweighted) are presented by (i) all households, (ii) households with a decrease in income and consumption expenditures, and (iii) household with an increase in income and consumption expenditures. The 'Other Status' category under 'Marital Status' represents people who are widowed, divorced, separated, or in a de facto relationship. SD stands for standard deviation. Δ means change. The data for this table comes from the HILDA Survey for financial years 2007-08, 2008-09, and 2009-10. The last two variables (i.e., Change in Disposable Income and Change in Consumption Expenditures) also require data for financial year 2006-07. The last four variables on income and consumption expenditures are in real 2018 Australian dollars and winsorized at 1% and 99% levels. A change (increase or decrease) in disposable income or consumption expenditures in year (t) is with respect to year (t-1).

Table 4.2. Household Consumption Expenditures Loss Aversion

	$\Delta c_t = c_t - r_t$		
	Pooled OLS	Panel Random-Effects	Panel Fixed-Effects
	(1)	(2)	(3)
Income$_t$ - Income$_{t-1} \geq 0$	0.21***	0.21***	0.23***
	(0.01)	(0.01)	(0.02)
Income$_t$ - Income$_{t-1} < 0$	0.29***	0.29***	0.32***
	(0.01)	(0.01)	(0.02)
Never Married and Not De Facto	-1,521.59***	-1,521.59***	-4,699.32
	(549.29)	(486.26)	(3,642.00)
Other Marital Status	-736.62*	-736.62**	9.57
	(433.21)	(375.70)	(2,483.53)
Bachelors or Graduate Diploma	455.92	455.92	-1,781.40
	(532.62)	(458.67)	(4,110.32)
Master's or Doctorate	1,345.38	1,345.38	3,454.03
	(1,126.84)	(993.28)	(5,780.44)
Age	-43.41***	-43.41***	-1,109.01***
	(11.20)	(9.83)	(329.05)
Female	434.54	434.54	
	(388.96)	(336.72)	
Constant	4,750.44***	4,750.44***	56,726.53***
	(786.65)	(697.21)	(16,137.58)
Observations	9,301	9,301	9,301
Year Fixed-Effects	Yes	Yes	Yes
R^2	0.26	0.30	0.30
Akaike information criterion	208,949		202,554
Loss aversion parameter (λ)	1.41	1.41	1.41
P-value for a test of ($\lambda = 1$)	< 0.01	< 0.01	< 0.01

Notes: Dependent variable represents change in household consumption expenditures (i.e., $c_t - r_t$), where r_t is the reference-level of expenditures, which is equal to c_{t-1}. All specifications include year fixed-effects. Standard errors (SEs) are parentheses. SEs are robust in pooled OLS, and cluster-robust in panel random-effects and fixed-effects (SE clustering is at household level). Coefficients are significant at *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 4.3. Household Consumption Expenditures Loss Aversion by Age Groups

	$\Delta c_t = c_t - r_t$					
	Age <30	Age <40	Age <50	Age <60	Age <70	Age ≥70+
	(1)	(2)	(3)	(4)	(5)	(6)
Income_t - $\text{Income}_{t-1} \geq 0$	0.22***	0.24***	0.24***	0.23***	0.22***	0.24***
	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.05)
Income_t - $\text{Income}_{t-1} < 0$	0.44***	0.40***	0.37***	0.34***	0.32***	0.24***
	(0.06)	(0.04)	(0.03)	(0.02)	(0.02)	(0.05)
Never Married & Not De Facto	-10,317.18*	-7,082.07	-5,251.98	-4,150.76	-4,544.02	
	(6,011.10)	(4,396.45)	(3,953.54)	(3,801.29)	(3,734.88)	
Other Status	-3,638.13	-409.85	410.03	734.84	296.91	-7,739.95
	(5,021.75)	(3,251.77)	(2,868.60)	(2,712.41)	(2,634.46)	(6,645.83)
Bachelors or Graduate Diploma	2,405.03	1,490.50	-2,695.84	-1,568.87	-1,650.52	
	(4,698.02)	(3,947.19)	(4,057.95)	(3,984.32)	(4,092.91)	
Master's or Doctorate	8,528.96	10,184.70	4,999.62	3,964.53	3,797.84	
	(6,992.10)	(6,481.64)	(5,669.79)	(5,661.40)	(5,762.23)	
Age	-1,910.43*	-1,398.59**	-1,603.42***	-1,336.13***	-1,233.53***	6.37
	(1,103.03)	(668.91)	(495.04)	(416.53)	(370.10)	(665.87)
Constant	55,010.92**	46,304.37**	60,956.97***	56,533.30***	56,951.89***	4,521.56
	(27,916.22)	(20,236.00)	(17,759.15)	(16,842.15)	(16,395.65)	(51,023.85)
Observations	1,451	3,064	4,998	6,684	7,970	1,331
Household Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.32	0.33	0.33	0.33	0.31	0.24
Akaike information criterion	31,312	66,607	108,966	145,958	174,157	27,906
Loss aversion parameter (λ)	2.02	1.64	1.54	1.48	1.46	1.02
P-value for a test of ($\lambda = 1$)	0.04	0.02	0.01	0.00	0.00	0.94

Notes: Dependent variable represents change in household consumption expenditures (i.e., $c_t - r_t$), where r_t is the reference-level of expenditures, which is equal to c_{t-1}. All specifications include year fixed-effects. FE stands for fixed-effects. Standard errors (SEs) are parentheses. SEs are robust in pooled OLS, and cluster-robust in panel random-effects and fixed-effects (SE clustering is at household level). Coefficients are significant at $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4.4. Household Consumption Expenditures Loss Aversion with Alternative Reference Point

	$\Delta c_t = c_t - r_t$		
	Pooled OLS	Panel Random-Effects	Panel Fixed-Effects
	(1)	(2)	(3)
Income_t - $\text{Income}_{t-1} \geq 0$	0.21***	0.21***	0.21***
	(0.01)	(0.01)	(0.02)
Income_t - $\text{Income}_{t-1} < 0$	0.26***	0.26***	0.29***
	(0.01)	(0.01)	(0.02)
Never Married & Not De Facto	-1,839.41***	-1,839.41***	-6,529.01*
	(527.38)	(494.99)	(3,540.77)
Other Status	-849.67**	-849.67**	1,308.54
	(408.92)	(383.02)	(2,441.29)
Bachelors or Graduate Diploma	112.83	112.83	-2,224.00
	(502.57)	(463.18)	(3,512.97)
Master's or Doctorate	1,883.41*	1,883.41*	-4,327.08
	(1,051.51)	(1,052.32)	(5,550.78)
Age	-49.58***	-49.58***	-1,643.43***
	(10.68)	(10.01)	(323.19)
Female	626.21*	626.21*	
	(368.78)	(343.32)	
Constant	5,806.15***	5,806.15***	84,019.62***
	(740.91)	(692.62)	(15,864.71)
Observations	9,302	9,302	9,302
Year Fixed-Effects	Yes	Yes	Yes
R^2	0.26	0.29	0.29
Akaike information criterion	208,033		200,467
Loss aversion parameter (λ)	1.28	1.28	1.37
P-value for a test of ($\lambda = 1$)	< 0.01	< 0.01	0.01

Notes: Dependent variable represents change in household consumption expenditures (i.e., $c_t - r_t$), where r_t is the reference-level of expenditures, which is equal to the average of last two years' consumption expenditures $(c_{t-1} + c_{t-2})/2$. All specifications include year fixed-effects. Standard errors (SEs) are parentheses. SEs are robust in pooled OLS, and cluster-robust in panel random-effects and fixed-effects (SE clustering is at household level). Coefficients are significant at $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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5. CONCLUSION

In my dissertation, I study household consumption expenditures in the aftermath of transitory income shocks. Consumption expenditures are relevant both for household well-being and the gross domestic product. Although the permanent income hypothesis predicts that households smooth consumption over their lifetimes, credit-constrained households may find consumption smoothing impractical. When a low-asset household faces a negative income shock, a decrease in household expenditures may potentially jeopardize household well-being, for instance, through low food intake, less spending on kids' education, or less savings for retirement.

Overall, I find that transitory income shocks negatively affect household consumption expenditures. More importantly, I find that households' consumption response to transitory income shocks is context- and population-dependent. For instance, hurricanes have a larger impact on food-at-home expenditures than floods; only low-income households' food-at-home expenditures suffer after natural disasters; Indiana specialty farm households reduce only the expenditures of food and miscellaneous categories after an income loss of 20%-32%; Australian households exhibit an asymmetric consumption response to transitory income shocks. Understanding how consumption response may vary across contexts and populations can help in making post-disaster aid and fiscal policy response more efficient through better targeting.

In the first essay (Chapter 2), my co-author and I exploit spatial and temporal variation in natural disasters in the United States to identify disasters' impact on households' food-at-home (FAH) expenditures and FAH quality. Across the U.S., highly damaging natural disasters remain a constant threat since 1980. Natural disasters can easily disrupt livelihoods and infrastructure. We study FAH expenditures and FAH quality because both are relevant for household health and well-being. We find that there is heterogeneity in the impact of floods and hurricanes on FAH expenditures. We find that the average 15-day decrease in FAH spending is about \$2 in the 90 days after a flood and about \$7 in the 30 days after a hurricane. In other words, floods have a prolonged effect and hurricanes have an immediate effect. We find evidence that floods and hurricanes remain a threat to the FAH expenditures of vulnerable households, for instance, low-income households and households in coastal states. However, natural disasters have an inconsequential impact on FAH quality. Our findings could help relief organizations to plan for a customized distribution of food items and non-alcoholic beverages after each flooding and hurricane, hence making post-disaster aid allocation more efficient.

In the second essay (Chapter 3), my co-authors and I focus on specialty producers in the state of Indiana and study the impact of natural disasters on their household expenditures. The objective of second essay is twofold, first, to determine how specialty producers' household consumption responds to adverse income shock due to natural disasters, and second, to evaluate whether an income loss experience affects specialty producers' risk-taking behavior. Compared to commodity crops, specialty crops' production is more vulnerable to adverse weather shocks, labor shortages, and perishability. Using a split-sample survey, we find that our sample farm households reduce their monthly expenses of food and miscellaneous categories by ∼\$119 and ∼\$280, respectively, after an income loss of 20%-32%. We also find that sample producers are less willing to take financial risk after an income loss experience, i.e., they have decreasing absolute risk aversion. These findings imply that, after an income shock, specialty producers may have to (i) sacrifice food intake and retirement savings, and (ii) hold off investing in their farms. Since specialty crops play a vital role in the U.S. farm sector due to their contribution to farm income and U.S. households' nutrition, the results of this study are relevant for U.S. agricultural policy.

Although the first two essays look into the impact of negative income shocks on household consumption expenditures, the third essay (Chapter 4) looks into both positive and negative income shocks. In the third essay, I assume that households have reference-dependent preferences, i.e., households' well-being depends not only on the level of consumption, but also on the comparison of consumption level compared to the reference level of consumption. A manifestation of reference-dependent preferences is the concept of "loss aversion", i.e., people tend to prefer avoiding losses compared to receiving equal value gains. Using the Household, Income and Labour Dynamics in Australia (HILDA) Survey for financial years 2005-06 to 2009-10, I find that losses in consumption expenditures loom about 1.4 times larger than gains, i.e., the loss aversion parameter has an estimated value of about 1.4 ($\hat{\lambda}$

= 1.4). Interestingly, retirement-eligible households (age 70 and above) are loss neutral in consumption expenditures (i.e., $\hat{\lambda} = 1$), however, working-age younger households are consumption loss averse (i.e., $\hat{\lambda} = 2.02$). These results further show that retirement-eligible households have a symmetric consumption response to income shocks as opposed to the asymmetric response of younger households. An implication of this study is that losses in consumption expenditures are psychologically taxing for Australian working-age households. Furthermore, younger households would benefit relatively more from income support programs than retirement-age households as the former group is more consumption responsive to negative income shocks.