Essays on Consumer Decision Making and Policy

by

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DISSERTATION ABSTRACT

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When consumers first learn of an impending natural disaster, they may be faced with substantial uncertainty regarding their future consumption and demand. As the exact location and severity of the event comes into focus, this uncertainty lessens and those who will be directly impacted tend to purchase emergency supplies all at once. This behavior, known as "panic buying", often leads to increased burdens on supply chains and market failures. Using various econometric techniques, I aim to unravel the primary factors that determine the magnitude of panic buying. In the first chapter of my dissertation, I use event study analysis to determine that the overall history of an area reduces the amount of panic buying that is observed. In the second chapter I structurally estimate how the sudden announcement of a natural disaster influences the consumer's decision to purchase, consume, and store emergency supplies. I find the cost of storing emergency supplies for future disasters is significant to consumers, further encouraging the behavior of "panic buying". Finally, I estimate the effect of prior forecast accuracy on current panic buying using various econometric techniques. I find that sales of emergency supplies are significantly affected by past inaccurate forecasts through both recency bias and the hot-hand fallacy.

ACKNOWLEDGMENTS

I thank Keaton Miller for being my adviser throughout the dissertation process. You have been a wonderful mentor to me as I have learned to navigate the academic landscape. I look forward to using all the tools you have taught me as I go forward to teach students of my own and conduct new and exciting research.

I thank John Chalmers at the University of Oregon for providing access to the NielsenIQ Datasets and helping make my research process. I am grateful for your help and that you also saw the excitement and importance of my research.

This paper represents my own analyses derived in part from 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 my 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.

DEDICATION

I would like to dedicate this work to Brandon Jurrens. Thank you for pushing me to not give up and listening to all of my ramblings about economics and natural disasters. I appreciate you being there to challenge me with new ideas and allowing me to bounce ideas off of you. This would have been much more difficult without your love and support.

Contents

List of Figures

List of Tables

1 Overview of Hurricane Preparation and Forecasts

Natural disasters are becoming more frequent and severe (Anderson and Bausch, 2006; Van Aalst, 2006). This trend has led to broad impacts on the economy as natural disasters cause poorer labor market outcomes, decreased land values, stalls in international trade, and increased government transfer payments (Ibarrarán et al., 2009; Deryugina, 2017; Deryugina et al., 2018; Sytsma, 2020). However, natural disasters also affect people at a more individual level. Prior research has focused on how individuals respond to disasters through either channels of insurance or migration (Gallagher, 2014; McCoy and Walsh, 2018; Bakkensen et al., 2019). Less work has been done on how individuals respond during the forecast leading up to a disaster. Primary work in this field has been on gasoline purchases (Beatty et al., 2021; Bian et al., 2024) and purchases of emergency supplies (Norris et al., 1999; Baker, 2011; Kelly et al., 2012; Meyer et al., 2014). Beatty et al. (2019) find that there is a significant uptick in sales of bottled water, flashlights, and batteries during the time surrounding a hurricane. This uptick is often referred to in the media a "panic buying."

Although panic buying is a well established and documented phenomenon, little research has been done on its driving forces. There are many factors that could potentially influence how people choose to respond to a hurricane forecast: experience, knowledge, beliefs, and many more. By combining hurricane forecast data with data on sales of emergency supplies I gain a better understanding of the elements that drive panic buying. I focus on elements from behavioral and industrial organization literature as a basis for my research.

Chapter 2 of this work takes a behavioral approach and studies the effects of experience and memory on panic buying behaviors. I use a series of event studies to estimate the effects of living in an area that is more prone to hurricanes. I show that counties with fewer historical hurricanes see much larger instances of panic buying than other hurricane prone counties. I also show results of memory that are consistent with prior literature. I find that the strongest decline in panic buying occurs in the years immediately after a hurricane.

Chapter 3 takes a structural approach to the problem, by estimating a dynamic consumer choice model. By utilizing household scanner data, I estimate a dynamic model where consumers choose how much to purchase, store, and consume in each time period. I estimate multiple versions of this model. First, I assume that hurricanes do not influence the household's decision. The results of this estimation show that the expected cost of storing water is quite low (around $5 per week for the average family) and does not help to explain any panic buying behavior. I then add hurricane forecasts and landfalls to the model. In this version the expected cost of remaining prepared becomes quite high for households. This high cost in the model shows that households are optimizing their behavior by waiting until they are more certain they will consume the water before making a purchase.

Chapter 4 takes a more behavioral approach to panic buying. The error in modern hurricane forecasting forces people to decide how much risk they believe they will face. It is likely that individuals will use past outcomes as a basis for updating their beliefs. In gambling and behavioral literature, there is evidence of people falling for recency bias or the hot-hand fallacy when using past information to inform current decisions. Using past hurricane forecasts and outcomes, I test to see if panic buying behaviors show any evidence of these common biases. I find that panic buying is significantly worse when the last forecast resulted in no hurricane landfall. I also find the hot-hand fallacy holds the strongest for areas with streaks on inaccurate forecasts. Specifically, panic buying gets marginally worse once a hurricane is finally realized after a string of past inaccurate forecasts. Finally, I show that improved forecasting technology would serve to reduce large amounts of panic buying that is currently happening. This reduction would lead to a more efficient outcome and one that is more in line with the goals of state and national emergency management agencies.

2 The Effects of Experience on Hurricane Preparation

2.1 Introduction

Natural disasters are becoming more frequent and severe (Anderson and Bausch, 2006; Van Aalst, 2006). This trend has led to broad impacts on the economy as natural disasters cause poorer labor market outcomes, decreased land values, stalls in international trade, and increased government transfer payments (Ibarrarán et al., 2009; Deryugina, 2017; Deryugina et al., 2018; Sytsma, 2020). As disasters become more frequent, individuals living in threatened areas may experience an increasing number of disasters during their lifespan. This frequency allows people more opportunities to learn from disasters and use that information when preparing for future disasters. However, as storm patterns change, people who live in areas which previously experienced few storms may face disasters without having had the opportunity to learn to prepare. This lack of experience and information could lead to people not properly preparing when a disaster finally affects them. Additionally, because many years can pass before a person faces a repeat disaster, the average person may face a salience problem. If significant time has passed, the people may forget the extent of preparation that is required to properly prepare for a disaster. The destruction caused by natural disasters can pose difficulties for people purchasing emergency supplies after the fact and in some cases even hazardous. Hazardous road conditions after natural disasters can also make it more difficult for relief efforts to provide support for those who were not able to properly prepare (Horner and Widener, 2011). In some areas, a lack of experience with storms (or a lack of salience for the experiences that do exist) may lead to an increased impact of a given storm as those individuals may not be as prepared as they would have been with experience. Thus, it is important to understand how exposure to past disasters influences how individuals prepare for future disasters and any gaps in preparation purchases that these historical characteristics may cause.

In this paper, I explore how experience with tropical disturbances and the time between storms affects purchasing patterns of emergency supplies in the Atlantic and Gulf Coast regions of the United States (i.e. those areas subject to the annual Atlantic hurricane season). To understand this relationship, I combine NielsenIQ Scanner Data with hurricane forecast and historical landfall data from the National Oceanic and Atmospheric Association (NOAA) from 2008-2019. With modern forecasting techniques, consumers can respond to the threat of a storm before it lands.[1] This allows them to purchase emergency supplies in response to the forecast. The scanner data allows me to test for significant changes in the sale of emergency supplies during the weeks surrounding a storm for a given county. I also explore heterogeneity in these changes across counties conditional on their storm histories.

My analysis begins with a baseline exploration of the effect of storm forecasts and landfalls on the sales of different emergency supplies in the style of Beatty et al. (2019). I focus on the sales of purified drinking

[1] Hurricane seasons produce cyclonic storms of different intensities, including storms labeled by NOAA as "disturbances", "tropical depressions", "tropical storms", and "hurricanes", all of which can cause damage to infrastructure and housing. For simplicity I refer to all these categories of weather events as "storms" throughout this paper.

water, flashlights, and batteries as they are named specifically by the Department of Homeland Security as emergency supplies for all natural disasters and are available at a wide variety of stores in the scanner data. I find that sales of all three goods increase by roughly 20% in the week before landfall and the week of landfall. These estimates correspond to those of Beatty et al. (2019). I then diverge from their analysis by exploring the effects of county specific historical tropical disturbance variables on sales of emergency supplies during a current tropical disturbance. The first historical variable I analyze is the county's total historical landfall count since 1983. This allows me to test for the possibility of learning behavior by understanding how the sales in counties change as the exposure to tropical disturbances increases[2]. I find that for each additional hurricane a county previously faced, sales of batteries increase by 2.67% and sales of flashlights increase by 5.37% when the county faces a current tropical disturbance. Sales of bottled water at this time also increase, but the change is insignificant.

The second historical variable, years since the last storm, allows me to test for signs of salience of the disasters risk. If a county has not been hit for many years, regardless of its historical exposure, people's perceptions of the risk may start to fade. I find that sales of emergency supplies are significantly higher when storm follows a tropical storm or hurricane within the next six years. However, if a storm follows a major hurricane the largest increase in sales is only within the next 3 years. I also run a regression to test the effect of a single additional year since the last hurricane and find that sales of water increase by 1.34% and sales of flashlights increase by 2.68% when a county is in the predicted path of a later storm. Sales of batteries increase during this time, but the change is not significant.

Much of the current literature on natural disasters focuses on changes in markets after a disaster. Such literature includes effects of insurance take-up rates, labor market impacts, and government assistance applications (Hallstrom and Smith, 2005; Gallagher, 2014; McCoy and Walsh, 2018; Bakkensen et al., 2019; Groen and Polivka, 2008; Deryugina, 2017; Deryugina et al., 2018). Others focus on how markets and decisions are made in the days leading up to a singular disaster through the use of phone surveys (Kelly et al., 2012; Meyer et al., 2014). I focus on the intersection of this literature by studying how past experiences with hurricanes affect the responses in the current period. I find that the historical exposure of a area to hurricanes increases the rate at which emergency supplies are sold in a county.

The literature on the salience of disasters tends to use variables with lower purchasing frequencies such as houses and insurance or changes in financial markets to understand how recent disasters affect decisions (McCoy and Walsh, 2018; Bakkensen et al., 2019; Bourdeau-Brien and Kryzanowski, 2020). Others that focus on a more individual response rely on either general surveys or surveys after disasters to understand feelings around risk and preparation steps that had been taken (Lazo et al., 2010; Baker, 2011; Meyer et al., 2014). The closest research to mine is that in the wildfire literature which looks at people's interest in home air purifiers, and the decision to stay indoors (Burke et al., 2022). I add to this literature by utilizing

[2]While this test can reject learning behavior, it is likely limited to confirm learning behavior, in part because I do not observe individual-level exposure. Additionally, migration between counties would imply that the average resident will have less exposure than the county itself which would reduce power and would skew the results to reject learning even if it exists. I assume that the results are representative of an average consumer that has lived in the county during the 12 years for which I have scanner data.

sales data of emergency supplies that are more liquid than a home or insurance and can be purchased much more frequently. Additionally, emergency supplies are relatively inexpensive, allowing me to capture the salience of hurricanes for a larger portion of the affected population. My findings are similar to those of prior literature in that the largest effect of hurricanes falls off after only a few years.

The rest of the paper proceeds as follows. Section II discusses the background of hurricane preparation. Section III explains the data. Section IV goes over the main results and section V concludes.

2.2 Background

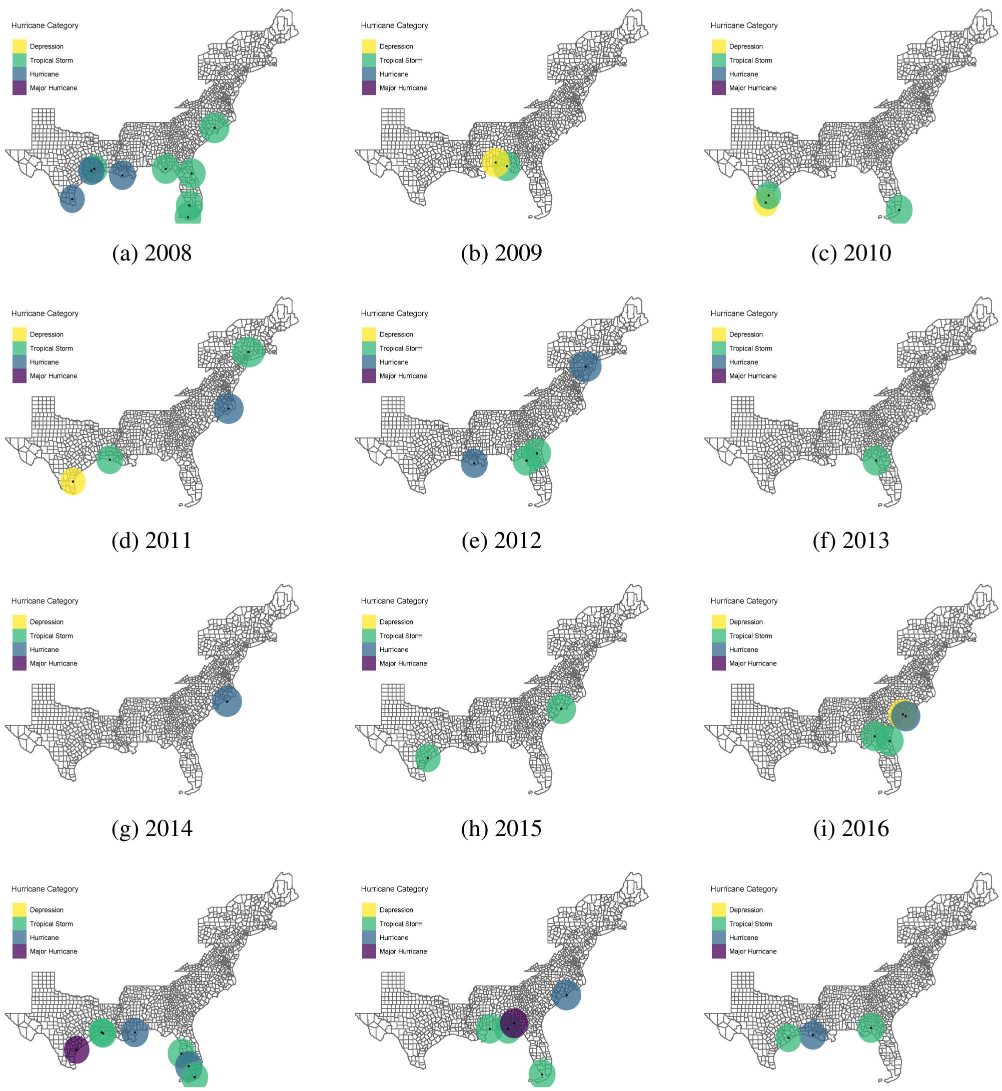
The Department of Homeland Security (DHS) and other agencies publish and distribute information about hurricane preparation and what goods individuals should have on hand in case of emergency. These recommended actions and emergency supplies to have on hand are nearly identical between state and local agencies with many referring individuals to the DHS website, ready.gov, for more information. I use the checklist from ready.gov as a reference to identify which goods individuals may choose to purchase when preparing for a hurricane.

The goods recommended for an emergency supply kit are one gallon of water per person per day for a minimum of 3 days, enough non-perishable ready-to-eat food for at least three days, a battery powered radio, a flashlight, a first aid kit, extra batteries, a whistle, masks, plastic sheeting and tape, garbage bags and ties, a manual can opener, maps, and a cell phone and charger. There are also other additional items listed which may be applicable in particular situations but which not everyone is recommended to have on hand. Because I observe sales in grocery and mass merchandiser stores, I limit my analysis to only those items that are frequently bought in such locations. Additionally, a wide variety of foods are listed as non-perishable and ready-to-eat. Some specifically mentioned on the DHS list are canned meats, fruits, vegetables, dried meats, dry cereal, granola, and peanut butter. Thus, food is still very heterogeneous, and sales will largely depend on personal preferences. I focus on sales of bottled water, flashlights, and batteries as these can be purchased at most grocery and mass merchandise retailers, and they are more homogeneous in nature.

If hurricane season were perfectly predictable, and households did not face credit or inventory constraints, households would be able to perfectly smooth their consumption of emergency supplies. However, there are currently no models to predict how many hurricanes will form each year, or how many will make landfall. Figure 1 shows maps of landfall locations for all tropical disturbances from 2008 - 2019. The number and intensity of storms that make landfall varies significantly from year to year. Additionally, some counties are hit in back-to-back years and then not hit again in the data where others are hit quite frequently. This variation from year to year could make it difficult for consumers to know if and how much they should prepare in advance for a hurricane.

Once a hurricane begins to form, meteorologists at the National Hurricane Center of NOAA predict the potential wind speeds and path of the storm. The predictions published by NOAA provide a projected storm path for the next 120 hours (5 days) with new advisories being published every six hours. These

Figure 1: Tropical Cyclone Landfall Locations



(a) 2008 (b) 2009 (c) 2010

(d) 2011 (e) 2012 (f) 2013

(g) 2014 (h) 2015 (i) 2016

(j) 2017 (k) 2018 (l) 2019

Note: The maps in this figure represent each year of data and the corresponding tropical cyclone landfalls for that year. Some storms made landfall, went back out to sea, and then made landfall again. The definition of the landfall variable allows some storms to make multiple landfalls. The radius of each circle is 100 nautical miles, as this is the average radius of tropical cyclones in the Atlantic Basin and is the distance used for creating the landfall variable. The category of the storm is the category upon landfall.

predictions are most accurate for the next 24 hours with the margins of error increasing for each following 24-hour increment. Even then these forecasts are not perfect, and storms can often make landfall within 100 miles of where they had been predicted to land 24 hours before. The potential uncertainty of hurricane specific forecasts could also make it difficult for consumers to learn about hurricane risk and how they should prepare.

2.3 Data

The National Hurricane Center (NHC) GIS Archive of Tropical Cyclone Forecasts contains information on hurricane location and properties as well as their forecast paths and weather advisories starting in 2008. The data contains every tropical disturbance in the Atlantic and East Pacific Basins, though I focus on the Atlantic. For each storm, I observe the current location, the projected path, and relevant weather advisors every six hours. Following the methods of Beatty et al. (2019), I generate an indicator variable which is equal to one if a county was hit by a hurricane as follows: for each hurricane I find the point where the center of the hurricane transitions from over water to over land. Once the hurricane is over land, I draw a circle around the center with a radius of 100 nautical miles. Although the average hurricane has three times this radius, the hurricane-force winds and the majority of any damage tend to be more centralized and rarely surpass this smaller radius. Counties that fall within the 100 nautical mile radius are considered hit by the hurricane's landfall. Occasionally, the eye of a hurricane can pass between ocean and land multiple times [3]. Each separate motion from over water to over land by the eye of the hurricane is recorded as a separate landfall.

Table 1 shows the count of tropical cyclones that formed in the Atlantic Basin from 2008 – 2019. There are counts for all disturbances formed regardless of wind speed. The column 'Hurricane' gives the count of all disturbances that reached a minimum sustained wind speed of 74 mph and thus reached the NOAA classification (i.e. Saffir-Simpson Scale) of category 1 hurricane or higher. 'Major Hurricane' indicates the number of storms that reached a minimum sustained wind speed of 111 mph and were thus classified as a category 3 storm or higher. The number of hurricanes and major hurricanes varies significantly from year to year with the highest count of both occurring in 2010 and the lowest in 2013.

The third column of table 1 shows the count of storms which were forecast to make landfall within the United States at any point. The final column has the count of storms that actually made landfall in the United States as defined above. The discrepancy between the two columns shows that it is not uncommon for cyclones with predicted landfalls to change course and go back out to the Atlantic.

Figure 2 shows the total number of tropical disturbances of any classification that made landfall as described above. The counties which where most impacted by any type of storm during this time were those in North Florida and South Georgia and those on the North and South Carolina border. There is also a lot of

[3] In 2005 Hurricane Katrina made three separate landfalls in the United States. The first landfall was in Hollywood, Florida after which it continued into the Gulf of Mexico. The second landfall recorded was four days later when the eye passed onto land just south of New Orleans, Louisiana. The eye then passed back over water before making final landfall at the Louisiana-Mississippi border.

Table 1: Hurricane Season Characteristics

Year	Total Cyclones	Cyclone Category		Cyclone Path	
		Hurricane	Major Hurricane	Threatened	Made Landfall
2008	17	10	5	9	6
2009	11	4	2	5	2
2010	21	14	6	10	3
2011	19	10	4	8	3
2012	19	11	1	7	4
2013	14	3	0	5	1
2014	9	6	2	3	1
2015	12	6	2	5	2
2016	16	8	3	6	4
2017	19	11	6	9	6
2018	16	9	3	5	4
2019	20	8	3	9	3
Total	193	100	37	81	39
Percent	100%	51.81%	19.17%	41.97%	20.21%

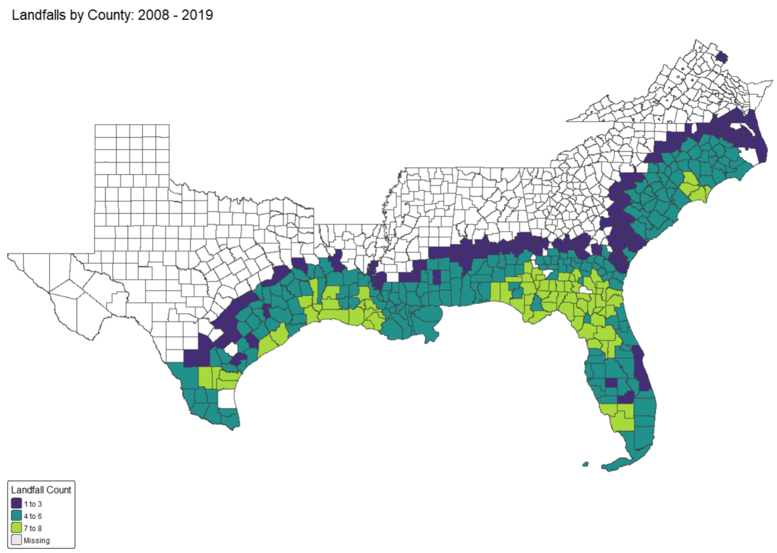
Note: This table gives the total counts of different types of tropical cyclones in the Atlantic Basin from 2008 - 2019. Total Cyclones is the number of individual cyclones on record. The columns "Hurricane" and "Major Hurricane" gives the count of tropical cyclone that reached wind speed high enough to receive the respective classification by the National Hurricane Center. The column "Threatened" gives the count of cyclones that had their forecast paths overlap any part of the United States. The column "Made Landfall" is the count of hurricanes that made landfall as defined in this paper.

activity along the entire Gulf Shore and South Florida. There are only two storms that made landfall north of Virginia during this time, one of them being Hurricane Sandy.

In addition to the GIS Archive, I also use NOAA's HURDAT2 (a.k.a. "Best Track") data from NOAA to establish historical patterns across counties. This database contains information on where each tropical disturbance was at 6-hour increments since it was first reported. Each update contains information on the date, if the storm made landfall, what classification it was, and its location. I collect this data for all storms starting in 1983 (25 years before the beginning of the scanner data). To capture patterns of county level learning, I create "experience" variables defined as the total amount of landfalls of different storm types (all storms, only hurricanes, and only major hurricanes) that a county was exposed to before 2008. I took each landfall in the HURDAT2 data in the 25 years before 2008 and drew a circle with a 100 nautical mile radius around it. Any county that laid within the circle was considered hit by this storm. The total hits for each county during this 25-year period are the values they entered the panel with. Once in the panel, as a county was hit by a new storm, the hit was added to the total landfalls in an appropriate manner.

I also construct "recency" variables that track the number of years that have passed since the last storm of a given classification made landfall in a given county. The breakup of storm classifications is the same

Figure 2: Total Landfalls by County



Note: This map shows the total count of landfall that each county had from 2008 to 2019. Landfall includes any storm of any classification that was tracked by NOAA, not just hurricanes. Counties in white do not appear in the NielsenIQ data from 2008 to 2019.

as the total landfall variable. I begin by finding the most recent storm to the beginning of the scanner data and then calculating the years between the dates. I choose to round this variable at six months so that storms that fall within the next hurricane season but not 52 weeks later are still shown as being a year later. I then update this calculation each week, while checking to see if a new storm has hit the county. For the new storm to reset the count, it must be of the classification in the variable definition. For example, suppose I was calculating the years since the last hurricane made landfall for Chatham County, Georgia (Savannah). The most recent hurricane to the start of the data was in 2004, so the data begins with 3. The next 8 years consists of 7 tropical storms, which would reset the years since any storm count, but do not reset the years since a hurricane count. The years since the last hurricane count are not reset until hurricane Michael in 2016.

2.3.1 Scanner Data

To see how consumption patterns change with the experience and timing of hurricanes, I use NielsenIQ Retail Scanner Data for states on the Eastern Seaboard and the Gulf Coast[4]. With this data, I see quantities, prices, and volume of purchases of goods across a comprehensive set of retail stores in the Unites States at

[4]The included states are Alabama, Connecticut, Delaware, Florida, Georgia, Louisiana, Maine, Maryland, Massachusetts, Mississippi, New Hampshire, New Jersey, New York, North Carolina, Pennsylvania, Rhode Island, South Carolina, Texas, Vermont, and Virginia

Table 2: Summary Statistics of Emergency Preparedness Supplies

	Revenue (USD)		Volume (See Note)	
	Mean	SD	Mean	SD
Bottled Water	3,792	9,087	2,442	6,192
Batteries	1,143	2,641	1,343	3,185
Flashlights	112	299	21	54
Observations				293,921
Counties				500
Weeks				626

Note: These statistics are for the weekly sales of emergency preparedness supplies in the counties hit by any hurricane from 2008-2019. Revenue is the total revenue in USD from sales of that item in a county-week. Total Volume for water is by gallons sold in a county-week. Batteries and flashlights are reported in terms of individual items, not packages of the item.

the item-week level. I filter the data for goods that are recommended to have in a hurricane kit, specifically focusing on bottled water, flashlights, and batteries. I chose to limit my analysis to these items for a few reasons. First, they are more homogeneous and less prone to individual tastes than emergency supplies like food. Second, they are goods that can be found at a wide variety of stores including mass merchandisers and grocery stores.

I calculate the total revenue and total volume for each item-week. I then aggregate the data to the county-week level by summing the volume and revenue and averaging the prices across items within the categories of bottled water, flashlights, and batteries. Table 2 reports summary statistics on the chosen emergency supplies for the counties that are treated by a landfall.

2.3.2 Climate Data

To control for local climate, I use data from NOAA's Global Historical Climatology Network. Data on precipitation, mean temperature, maximum temperature, and minimum temperature are recorded at the daily level at hundreds of weather stations across each state. To match the scanner data, I aggregate the weather data to the weekly level. The final variables are total precipitation for the week, the highest recorded temperature, the lowest recorded temperature, and the average temperature for the week. If a weather station is missing data for any day during a week, that station-week observation is dropped.

To assign values to a given county-week I identify which weather station is closest to each county's population centroid and assign its data to the county. If the nearest weather station is missing an observation for a given week, I use the next nearest weather station that has data for the week. Because the data is already being aggregated to the weekly level, the daily variation is lost; however, the data that is left helps control for trends, seasonality, and overall climate of the area.

2.4 Methodology and Results

2.4.1 Event Study Results

I begin the analysis by implementing an event study methodology similar to that of Beatty et al. (2019) using the following regression.

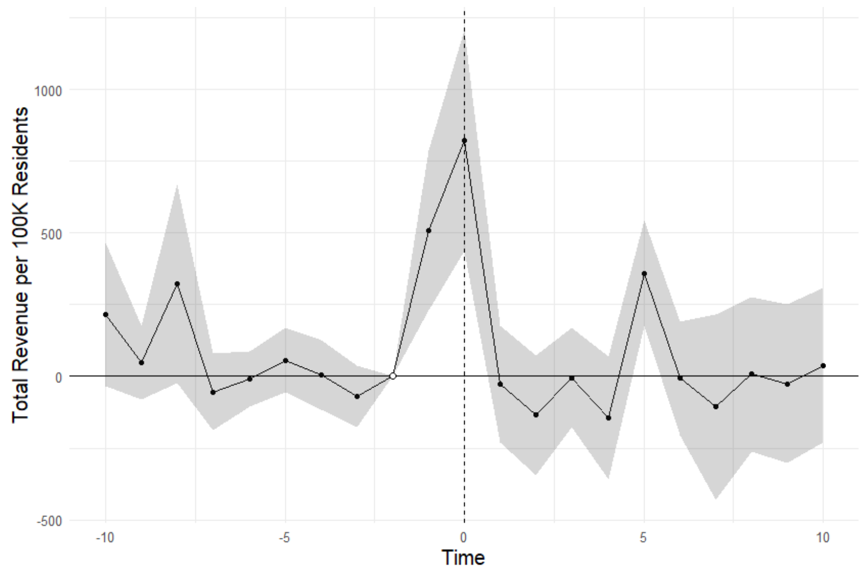
$$Sales_{c,t} = \sum_{\tau=-10,\tau\neq-2}^{10} \beta_{\tau=t} L_{c,\tau=0} + \alpha_c + \alpha_m + \alpha_y + \gamma X'_{c,t} + \varepsilon_{c,t} \tag{1}$$

$Sales_{ct}$ represents the total revenue per 100 thousand residents from sales of a given emergency supply for a given county-week. The variable $L_{c,\tau=0}$ is an indicator variable that is equal to one if a tropical disturbance makes landfall in a county during the event week $\tau = 0$. I use week $\tau = -2$ as the reference period for the event study to avoid spillover from the forecast in week $\tau = -1$. Because the scanner data is reported at a weekly level, if a storm were to make landfall early in the week (i.e. Sunday or Monday), much of the purchases in advance would be done in the sales week before the storm lands. The parameters of interest are $\beta_{\tau=-1}$, $\beta_{\tau=0}$, and $\beta_{\tau=1}$. Positive coefficients on $\tau = -1$ or 0 would indicate that individuals are waiting for a storm to purchase emergency supplies. A null result on these weeks would indicate that most individuals keep a sufficient stock of supplies in case of such an emergency. I control for trends in the temperature and precipitation with X'_{ct}. County, month, and year fixed effects are represented as α_c, α_m, and α_y respectively. I allow for clustering of the standard errors at the county level.

The results from the event study are shown in Figure 3. Panel (a) shows the results for bottled water, (b) for batteries, and (c) for flashlights. Revenue in weeks -10 to -3 and weeks 2 to 10 compared to week -2 is statistically insignificant. There are significant increases in sales of all three goods in the weeks immediately surrounding landfall. For the average county in the event study sample with 196,162 residents, this translates to a \$702.78 increase in bottled water the week before and a \$1,087 increase the week a storm makes landfall. For a larger county like Harris County, Texas (Houston) which in 2010 had 4.1 million residents, this increase translates to an expected increase in bottled water sales of \$14,678 and \$22,591 in the week before and during the storm's landfall respectively.

It is reasonable that two counties which are seemingly similar may respond to tropical disturbances differently if they have had different historical exposures to these disturbances. To understand how historical exposure to tropical disturbances may affect the average county level response, I rerun the event study analysis on different subsets of the data. The first group of subsets aims to understand the effect of total county-level exposure to tropical disturbances. I assume that if a county has been more exposed to a particular type of risk, then the average resident of that county will have higher knowledge of that risk than the average resident in a county with lower levels of exposure. The first subset of data is based on all tropical disturbances to make landfall in a county from 1983-2007 and are 0 to 5, 6 to 10 and 11 to 25 landfalls. The second subset is based on past hurricane landfalls in the county and are 0 to 3, 4 to 6, and 7 to 15. The third

Figure 3: Aggregate Event Study Results of Battery Sales



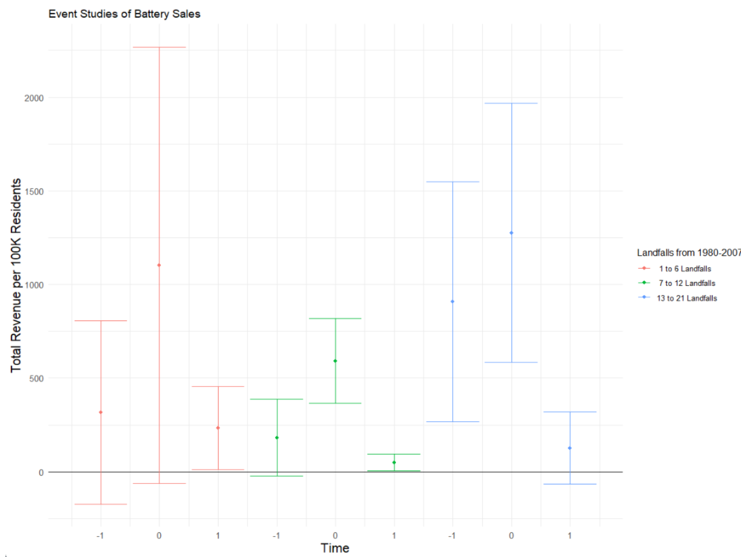
Note: Results from event studies following equation 10. The vertical axis represents total revenue per 100 thousand residents in USD. The horizontal axis represents weeks. The reference period is week -2. The vertical dashed line at week 0 represents the week when a storm made landfall. The band around the estimates represents the 95% confidence interval.

subset is based on past major hurricane landfalls (category 3 hurricane and above) and are 0 to 1, 2 to 3, 4 to 5, and 6 to 7. I then run the event study as described in equation 10 for each good.

Figure 4 shows the effect of a current tropical cyclone of any category on sales of batteries given a county's past exposure to different classifications of tropical disturbances. I find that the average sales of batteries per 100,000 residents in counties that have had low exposure to any type of tropical storm purchase significantly increase in the week before and during a storm compared to counties with more exposure. Counties that have had the most exposure to any type of tropical disturbance purchase marginally more emergency batteries than counties in the medium exposure group. The results from the event studies subset by hurricane exposure show that the counties with the least exposure have the largest increase in sales in the week before landfall. In the week of landfall, the largest increase in sales is seen by the counties with the most exposure to past hurricanes. Counties that are in the least exposed group or in the two highest exposed groups to major hurricanes have significantly higher sales in the week before a storm. In the week of a storm all groups see an increase in sales that are significantly indifferent from one another, but the sales in the historically more exposed counties do appear to be higher than in those less exposed.

I repeat the event study for bottled water and flashlight sales and find similar results presented in Figure A1 and Figure A2. The results for flashlights are nearly identical to those of batteries presented above. The results for water are similar until I subset on past major hurricane exposure. Rather than the most exposed

Figure 4: Event Studies of Historical Exposure on Battery Sales



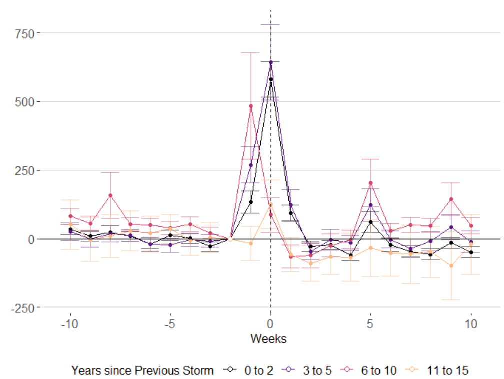
Note: Results from event study with subsets based on historical exposure of the county to hurricanes. The vertical axis represents total revenue per 100 thousand residents in USD. The horizontal axis represents weeks. Week 0 is the week that a tropical disturbance made landfall in a county. The bars represent the 10% confidence interval around the point estimate.

counties having marginally more sales than less exposed counties, they have sales that are near zero. Since the sales of the other emergency supplies are still significantly positive it is unlikely that this is an evacuation effect. Rather the pattern of all three goods indicates that the average agent in the county is learning about the risk of different levels of tropical disturbances as they experience more of them. It is likely that in the counties most exposed to major hurricanes, individuals choose to keep bottled water on hand at all times, mitigating a need to purchase it in the presence of a storm.

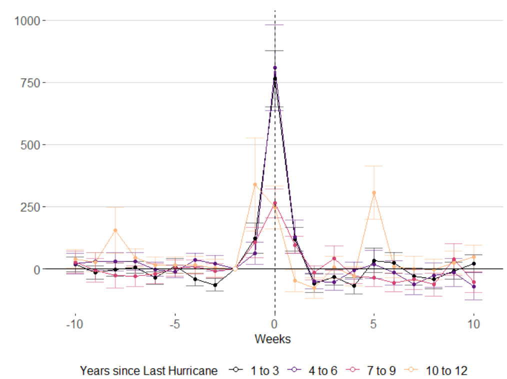
Because counties with historically more exposure to tropical disturbances would on average see storms more often, it is possible that the effect is not learning, but rather salience. Consumers simply do not have enough time to forget what happened, and if enough time passed, they would revert to the patterns of the lesser exposed counties. To for any patterns that might indicate purchasing behavior dependent on salience, I repeat the event studies on different subsets of the data. This time I subset the data by the length of time that has passed since the last tropical disturbance, hurricane, or major hurricane made landfall in each county. If the storm is salient for individual purchases, then as the number of years since the last storm increases the purchases of emergency supplies should decline.

Figure 5 presents the results of the different event study subsets when the outcome variable is total revenue per 100 thousand residents from battery sales. The results for the years since any past storm appear in panel (a). In the week before landfall the average response in counties that have seen a disturbance within the last decade is significantly higher than counties that had not seen a storm for over a decade. In the

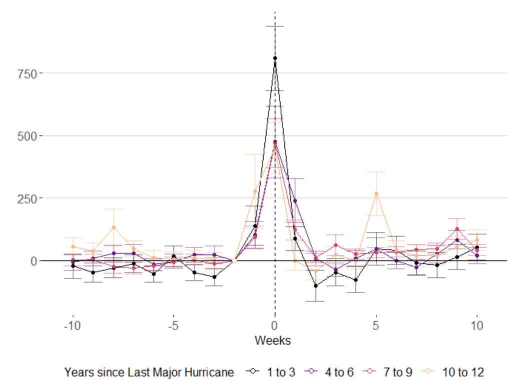
Figure 5: Event Studies of Storm Salience on Battery Sales



(a) All Disturbances



(b) Hurricanes



(c) Major Hurricanes

Note: Results from event study with subsets based on the years that have passed since that last storm made landfall in a county. The vertical axis represents total revenue per 100 thousand residents in USD. The horizontal axis represents weeks. Week 0 is the week that a tropical disturbance made landfall in a county. The bars represent the 10% confidence interval around the point estimate.

week that the storm makes landfall, counties that had experienced a prior disturbance in the last 6 years see significantly increased sales compared to the other counties in the sample. This difference between sales in counties that have experienced a hurricane in the last 6 years and those that had not is even stronger when only looking at hurricanes in panel (b). When focusing on the amount of time since the last major hurricane in panel (c), only the counties that had experienced a major hurricane in the last 3 years respond differently than the others. The increase in sales for the counties that had had more time pass is highest for major hurricanes indicating that as the storm becomes more damaging, the response afterwards does not fade to the extent it did with hurricanes or all disturbances.

When running the event studies for flashlights and bottled water, I find similar results to batteries. Flashlights again have a near identical pattern, and the results are displayed in Figure A4. Counties that have been hit by either a hurricane or any tropical disturbance in the last 6 years see significantly higher sales per 100 thousand residents than counties than in other counties. When looking at the years since the last major hurricane, the sales in each county became quite similar with those that had been hit within the last 3 years seeing sales that were only slightly higher than other counties and insignificantly so. The results for sales of bottled water are presented in Figure A3. The results for water are noisier, and only counties that have had 4 to 6 years pass since the last tropical disturbance of hurricane see significantly more sales than the other counties. Counties that have had a major hurricane in the last 3 years or it has been over 10 years see the largest increases in sales when the next storm arrives, but again none of these increases are significantly different from one another.

2.4.2 Regression Results

While the event studies above show the impact of having relatively more or less exposure or having relatively more recent exposure to tropical disturbances of different classifications, they do not tell us the effect of a single additional disturbance on sales of emergency supplies in a county. To estimate the effect of an additional historic landfall or an additional year in between subsequent landfalls, I use interacted regression models. I begin by running a model similar to that presented in Beatty et al. (2019) as a baseline. The regression used is as follows

$$lnSales_{c,t} = \beta_1 Threatened_{c,t} + \beta_2 Struck_{c,t} + \beta_3 After_{c,t} + \alpha_c + \alpha_m + \alpha_y + \gamma X'_{c,t} + \varepsilon_{c,t} \quad (2)$$

The outcome of interest is log total revenue from sales of emergency supplies for a given county-week, $lnSales_{c,t}$. $Threatened_{c,t}$ indicates if a county was in the projected path of a storm any day during a given week t. This variable was generated following Beatty et al. (2019): the county must be within the projected path of a storm and the storm is expected to make landfall within the next 72 hours. $Struck_{c,t}$ indicates if the eye of the storm landed within 100 nautical miles of the county. $After_{c,t}$ indicates if a county was struck by a storm in the past 72 hours. This picks up any lagged effect on purchases. The vector of controls, $X_{c,t}$ includes minimum, maximum, and mean temperature for the week and total rainfall in inches. I also include county, month, and year fixed effects and cluster the standard errors two-ways, at the county and year levels.

The results for the regression in equation 2 are presented in Table 3. I find that when a county is threatened by a storm, bottled water sales increase by 9.7%, and by 15.4% when a county is hit. Battery sales increase by 15.5% and 60.48%, and flashlight sales increase by 41.2% and 160% respectively. These increases in sales follow those seen in the aggregate event study for the same goods. Because the temperature controls are highly correlated with one another, and precipitation is highly correlated with the presence of a storm, I also run the regression omitting all weather controls expect mean temperature. The effect of removing the additional weather controls are minimal and presented in Table A2. I only use mean temperature as

Table 3: Aggregate Results

Dependent Variable:	lnSales		
	Bottled Water	Batteries	Flashlights
Model:	(1)	(2)	(3)
Variables			
Threatened	0.0930^{**}	0.1446^{**}	0.3453^{***}
	(0.0320)	(0.0523)	(0.0911)
Struck	0.1433^{**}	0.4730^{***}	0.9566^{***}
	(0.0584)	(0.0742)	(0.1332)
After	0.0330	0.0538^{*}	0.0683
	(0.0228)	(0.0279)	(0.0697)
Fit statistics			
Observations	644,152	654,114	427,663
R^2	0.84741	0.89753	0.72393

Results from the regression in equation (2). Two-way clustered (county & year) standard-errors in parentheses. lnSales is the log total revenue in U.S. dollars at the county-week level. ***: 0.01, **: 0.05, *: 0.1

a control variable in regressions for the remainder of the analysis.

To understand the effect of additional tropical disturbance landfall or an additional year since the last landfall, I interact the historical county level characteristics in the following manner.

$$\begin{aligned} lnSales_{c,t} =& \beta_1 Threatened_{c,t} + \beta_2 Struck_{c,t} + \beta_3 After_{c,t} + \beta_4 H_{c,t} \\ &+ \beta_5 Threatened \times H_{c,t} + \beta_6 Struck \times H_{c,t} + \alpha_c + \alpha_m + \alpha_y + \gamma X'_{c,t} + \varepsilon_{c,t} \end{aligned} \tag{3}$$

The variable $H_{c,t}$ captures the historical tropical disturbance characteristic of interest for that regression, historical count or years between landfalls. The historical count variable is created using HURDAT2 data in the following manner. The first week of 2008 is the total amount of storms to hit the county from 1980-2007. Afterwards the value is updated each time the county faces a new storm landfall of the classification of interest. The years between storms are created by determining the date of the last storm of a certain classification to make landfall before week 1 of 2008 for each county and calculating the time since the landfall in years. The value is then updated each week for that county. When the next storm of that classification makes landfall in the county, the date of the most recent storm is updated to reflect the new landfall in the subsequent weeks.

The results in table 4 show the effect of additional hurricane landfalls on sales of emergency supplies in a county. Columns (1) and (2) show that the effect of additional hurricanes making landfall in a county has no significant effect on their sales of bottled water. The response still strongly follows that of the base regression

Table 4: Regression of Total Hurricane Landfalls on Log Total Revenue

Dependent Variable:	lnSales					
	Bottled Water		Batteries		Flashlights	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Threatened	0.0846**	0.1094**	0.1524**	0.1508**	0.3672***	0.3424**
	(0.0316)	(0.0409)	(0.0520)	(0.0606)	(0.0894)	(0.1119)
Struck	0.1206*	0.0270	0.4940***	0.3496***	1.038***	0.7197***
	(0.0640)	(0.0859)	(0.0707)	(0.0683)	(0.1314)	(0.1586)
After	0.0328	0.0331	0.0665**	0.0712**	0.0790	0.0930
	(0.0241)	(0.0243)	(0.0298)	(0.0301)	(0.0681)	(0.0680)
Historical Count	-0.0706	-0.0725	-0.0175	-0.0177	0.0954***	0.0963***
	(0.0473)	(0.0475)	(0.0234)	(0.0238)	(0.0305)	(0.0291)
Threatened × Historical Count		-0.0108		0.0011		0.0112
		(0.0062)		(0.0099)		(0.0163)
Struck × Historical Count		0.0189		0.0267**		0.0537**
		(0.0169)		(0.0115)		(0.0243)
Fit statistics						
Observations	644,152	644,152	630,527	630,527	419,859	419,859
R^2	0.84741	0.84742	0.89904	0.89905	0.72128	0.72136

Results from the regression in equation (3) for the historical count of hurricanes to hit a county since 1983. lnSales is log total revenue for a county-week in U.S dollars. Standard errors in parentheses are clustered two-ways, at county and year. ***: 0.01, **: 0.05, *: 0.1

and is driven by the presence of a hurricane threat. Batteries and flashlights sales respond differently to increased hurricane activity as seen in columns (3) through (6). As counties experience more hurricanes, the average sales of flashlights in these counties increases. Additionally, in the week that a hurricane makes landfall in a county, there are increased sales of both batteries and flashlights as the number of hurricanes that have previously made landfall increases. This indicates that the residents of these counties are learning that they need to have these supplies during a tropical disturbance. Because the sales in these counties are increasing as exposure to hurricanes increases, it is also possible that the need to purchase these supplies is not transparent enough in counties that have not had much historical exposure to hurricanes.

The results for the heterogeneous effects of additional years since the last hurricane are presented in Table 5. I find that for each additional year since the last hurricane, average sales in a county increase by approximately 1.3% for bottled water and 0.7% for batteries. Sales from bottled water also increases in the week that a tropical disturbance threatens a county conditional on the years since the last hurricane. Additionally, the term $Threatened$ in column (2) has lost all significance. It appears that the number of years since the last hurricane is driving sales of bottled water in counties in the week before a hurricane landfall. These increases likely indicate that individuals have some leftover goods after the storm and are replenishing as time passes. Sales of water during the week before a storm is also consistent with people in a county having less water at home and needed to replenish more as they move farther away in time from the previous hurricane.

Flashlights have a different change in sales from additional years between storms than water and batteries, likely due to their durable nature. As the years since the previous landfall increases, the sales of flashlights actually decline by approximately 1.7% per year. Because flashlights last a long time, individuals do not need to repeat purchases frequently. The increase in sales of 2.68% on the interaction of $YearsBetween$ and $Threatened$ also follows with the durability of the good. The longer it has been since the last hurricane, the more likely a flashlight is to have been broken or misplaced leading to purchases increasing.

The effects of historical count of hurricanes and years between hurricanes when using independent regressions impact different goods at different points in the hurricane preparation process. To see if the results are independent of one another, I run a regression that includes all county hurricane history terms and interactions. The results from this regression are shown in Table 6 and reflect those shown in the prior tables. Sales of bottled water in a county that is threatened by a storm see significant increases directly related to the length of time that has passed since the last hurricane made landfall. The increases in battery sales in the presence of a storm are primarily driven by the historical exposure of the county to hurricanes. The increases in flashlight sales in the presence of a storm are largely driven by historical exposure of a county to hurricanes and partially by the length of time that has passed since the last hurricane.

2.4.3 Robustness

It is possible that the reason for the null response of historical exposure to hurricanes on bottled water sales and the weak response of years between on batteries and flashlights is driven partially by a shift in

Table 5: Effects of Years since last Hurricane on Sales

Dependent Variable:	lnSales					
	Bottled Water		Batteries		Flashlights	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Threatened	0.0981***	-0.0035	0.2067***	0.0964***	0.4514***	0.2325***
	(0.0109)	(0.0182)	(0.0093)	(0.0143)	(0.0181)	(0.0284)
Struck	0.0839**	0.0894**	0.4542***	0.4566***	1.010***	1.111***
	(0.0328)	(0.0422)	(0.0245)	(0.0355)	(0.0452)	(0.0619)
After	0.0563**	0.0524**	0.0900***	0.0851***	0.0704**	0.0630*
	(0.0222)	(0.0222)	(0.0183)	(0.0182)	(0.0323)	(0.0321)
Years Between	0.0126**	0.0129**	0.0071**	0.0074***	-0.0175***	-0.0168***
	(0.0062)	(0.0062)	(0.0029)	(0.0029)	(0.0039)	(0.0039)
Threatened × Years Between		0.0134***		0.0145		0.0268*
		(0.0040)		(0.0089)		(0.0139)
Struck × Years Between		0.0011		0.0015		-0.0100
		(0.0040)		(0.0116)		(0.0136)
Fit statistics						
Observations	310,293	310,293	304,664	304,664	217,947	217,947
R^2	0.88411	0.88415	0.92048	0.92054	0.75550	0.75581

Results from the regression in equation (3) for the years that have passed since the last hurricane hit the county. lnSales is log total revenue for a county-week in U.S dollars. Standard errors in parentheses are clustered two-ways, at county and year. ***: 0.01, **: 0.05, *: 0.1

Table 6: Dynamic Effects of Hurricane on Sales

Dependent Variable:	lnSales		
	Bottled Water	Batteries	Flashlights
Model:	(1)	(2)	(3)
Variables			
Threatened	-0.0315	0.0333	0.0993
	(0.0583)	(0.0663)	(0.1106)
Struck	-0.0522	0.2130	0.5541
	(0.1537)	(0.2076)	(0.3513)
After	0.0541**	0.0898**	0.0752
	(0.0245)	(0.0374)	(0.0811)
Historical Count	-0.0708	0.0368	0.0953
	(0.1071)	(0.0376)	(0.0546)
Threatened × Historical Count	0.0043	0.0109*	0.0228**
	(0.0062)	(0.0055)	(0.0076)
Struck × Historical Count	0.0213	0.0325*	0.0676*
	(0.0236)	(0.0180)	(0.0348)
Years Between	0.0041	0.0118*	-0.0051
	(0.0182)	(0.0059)	(0.0098)
Threatened × Years Between	0.0148***	0.0174*	0.0328**
	(0.0045)	(0.0091)	(0.0145)
Struck × Years Between	0.0061	0.0089	0.0080
	(0.0084)	(0.0141)	(0.0175)
Fit statistics			
Observations	310,293	304,664	217,947
R^2	0.88417	0.92058	0.75610

Results from the fully interacted heterogeneous regression using both historical characteristic variables: historical count and years between. lnSales is log total revenue for a county-week in U.S dollars. Standard errors in parentheses are clustered two-ways at the county and year levels. ***: 0.01, **: 0.05, *: 0.1

when people in those counties choose to purchase supplies. Rather than waiting for a hurricane to threaten a county, the average consumer may preemptively purchase emergency supplies at the start of hurricane season. To test for a change in sales at the start of hurricane season, I run a regression similar to the ones above, but with the start of hurricane season as the explanatory variable rather than a hurricane landfall. The official start of hurricane season is June 1 of each year as defined by NOAA. I create an indicator variable for if the week either contains June 1 or is a week immediately before or after June 1 to catch any overlap from the way the scanner data is constructed.

The results for the beginning of hurricane season are in Table A1 of the appendix. The coefficient on the start of season is significant and positive for batteries indicating that regardless of historical characteristics, sales in these counties see a significant increase at the start of summer. Bottled water and flashlights do not see these same increases. None of the coefficients on the interacted terms are significant indicating that the effect of past storms if fully felt by the average response to current storms that was found above.

2.5 Conclusion

As climate change continues, the intensity of natural disasters and extent of their destruction are expected to increase. Because this destruction also inhibits relief efforts, it is crucial that people know how to prepare for such disasters so that this delay is not harmful. I find that as counties are exposed to more hurricanes, the sales of emergency supplies actually increase in the presence of a storm. This indicates that people in these counties are learning how to prepare for disasters and adjusting. Additionally, the sales of emergency supplies decline in a way that follows the pattern of risk salience that is seen in other parts of the natural disaster literature when people are faced with a recurring disaster. The combination of needing experience and recent storms to purchase larger quantities of emergency supplies could leave areas with less experience or without a recent storm unprepared when faced with a hurricane. To help reduce the strain on relief efforts during future disasters, it may be useful to find ways to bridge these gaps in emergency purchases.

3 A Structural Model on Emergency Supply Sales

3.1 Introduction

There is significant evidence in the climate science literature that climate change is advancing (Gaffen and Ross, 1998; Kintisch, 2009; Peterson et al., 2013; Oswald and Rood, 2014). An expected consequence of this is increased natural disasters in both number and severity (Egan and Mullin, 2016; Witze, 2018). Natural disasters cost the United States' government an average of $62 billion each year through NOAA (2024). Additionally, they increase the unemployment rate, increase the rate of government payments through assistance programs, and slow international trade (Deryugina, 2017; Boustan et al., 2020; Sytsma, 2020). Disasters also impact the economic outcomes of individuals through increased insurance take-up, lost wages, and even loss of homes Gallagher (2014); Sheldon and Zhan (2019); Deryugina et al. (2018). The effects on these different economic outcomes are only expected to worsen with climate change (Tol, 2018).

Natural disasters also affect the budgets of individuals through the need for emergency supplies. While emergency supplies are available at stores throughout the year, there is a phenomenon where people wait until a disaster is imminent to purchase emergency supplies. This behavior is often called "panic buying" (Beatty et al., 2019). However, this is behavior is not ideal from a social standpoint as it leads to supply chain issues and market failures. In an attempt to reduce "panic buying" local news stations, grocery stores, weather stations, and the Federal Emergency Management Administration (FEMA) remind residents every year to not wait until a disaster is imminent but to plan ahead (Edinger, 2022; Garner, 2023; Fox 5 Digital Team, 2024). In Wood (2024) I find that the rate of "panic buying" is lower in counties that have historically been exposed to more hurricanes, but it never fully goes away. Therefore, there must be some mechanism that regardless of experience, education, and public reminders, people still find it optimal to wait to purchase emergency supplies.

The recommended emergency supplies to have on hand for a natural disaster are determined by the Department of Homeland Security (DHS) and can be found at "ready.gov" (Department of Homeland Security, 2022). Examples include bottled water, noon-perishable foods, batteries, flashlights, and first-aid kits. In addition to these goods being readily available for purchase, they are also durable goods that can be stored for a number of months. It is possible that individuals choose to keep some emergency supplies on hand and then purchase more once a disaster occurs. Boizot et al. (2001) find that when estimating effects of food purchases the timing since the last purchase influences the current decision. Because of this, I use a dynamic consumer choice model to structurally estimate the effects of natural disasters on sales of emergency supplies.

As "panic buying" occurs frequently with disasters that can be forecasts, I choose to focus my analysis on Atlantic hurricanes. Hurricanes affect large areas allowing for many different types of individuals to be impacted at the same time. They also have many different intensity levels indicated by the Saffir-Simpson scale which indicates the expected level of harm that will be caused upon landfall National Weather Service (2024). Hurricanes are tracked by the National Oceanic and Atmospheric Administration (NOAA) and the information is disseminated through the National Weather Service (NWS) allowing individuals to be well informed about the current and expected conditions and location of the hurricane. Finally, although NOAA predicts the best track of hurricanes, occasionally the final result changes and a hurricane that was expected to land does not, or one that was expected to go to sea make landfall. This provides significant variation in the model that helps to differentiate the effects of forecasts from landfalls.

For sales of emergency supplies I use NielsenIQ Consumer Panel Data which contains daily level expenditure data for households over 9 years, 2008 to 2016, in hurricane affected states. I combine this data with the NielsenIQ Retail Scanner Data which has store level sales data at the weekly level over the same time frame and for the same areas. The resulting data set is a snapshot of all available emergency supplies and their prices plus any purchases by each household for each day in the data. Using this data, I can observe not only when households buy emergency supplies, but what brand and how much they choose to purchase. I can also use the model itself to estimate the optimal consumption and current inventory level for a household at a given point in time based on the information from their last purchase.

When goods are storable, much of the industrial organization literature focuses on how price uncertainty drives consumer responses (Erdem et al., 2003; Hendel and Nevo, 2006; Erdem et al., 2008; Dubé et al., 2010). Hurricanes add an additional level of uncertainty to the consumer decision. Individuals face uncertainty on both where the forecast hurricane will land and how severe it will be upon landfall likely affecting the optimal quantity to purchase and consume. Additionally, individuals face inventory constraints and face opportunity costs of storing emergency supplies as they cannot fill the space in their home with other items unless the supplies are consumed. Depending on the magnitude of these costs, consumers could be incentivized to wait until emergency supplies are necessary to purchase them rather than keeping them on hand. I aim to understand how these factors influence the consumer's demand for emergency supplies and if they play a role in the "panic buying" behavior.

The model I use builds on the dynamic choice model proposed by Hendel and Nevo (2006) where consumers gain utility from consumption of emergency supplies while also facing costs of storage. The choice consumers make in each time period will be how much to consume and which brand and quantity to purchase. When no natural disasters are forecast, consumers will face the exact same problem as that of Hendel and Nevo (2006) and their choice will be conditional on the expectation of discounted prices tomorrow and there will be no uncertainty in future consumption. The problem that consumers face will change once there is an impending natural disaster. State governments set anti-price gouging laws into place meaning that consumers should not expect prices to deviate from their usual standard, while the expectation of increased demand implies that firms will likely not place emergency supplies on sale. Additionally, I run an event study on prices and find that hurricanes have no significant effects on prices. Thus, consumers can expect prices to follow closely to their normal process. The added uncertainty that consumers face now comes from expectations about the quantity of emergency supplies they will need to consume in the future based on the precision of the hurricane forecast.

To understand how hurricanes impact the consumer's choice problem and demand for emergency supplies, namely bottled water, I first estimate a model of storable goods similar to that proposed in Hendel and Nevo (2006), assuming that hurricanes do not impact the consumer's decision to purchase emergency supplies. Under this assumption I find that consumers are quite sensitive to changes in prices. The second thing I find is that because the average household purchased bottled water infrequently, the utility from consumption is extremely low. Additionally, the opportunity cost of storing the goods is initially low, but the marginal costs are increasing, leading to high total cost of storage very quickly. For a family of four to store bottled water for a natural disaster under federal guidelines (i.e. 12 gallons of water or 91, 16.9 oz single use bottles) the weekly opportunity cost is around \$28,000[5].

I then add hurricane forecasts and landfalls to the model and re-estimate the parameters. Under this new approach, the sensitivity of consumers to a change in prices during a week without a hurricane forecast is roughly the same as in the prior model. Interestingly, consumers become more price sensitive when there is a hurricane forecast. Presumably this follows because the quantity that consumers are purchasing is larger, so they substitute towards cheaper brands to help maintain their budgets. I also find the utility of consuming bottled water is drastically increased when a hurricane makes landfall. Additionally, the cost of storing goods decreases when a hurricane is forecast. The discrepancies in costs of storage and utility from consumption due to hurricanes and forecasts help to explain why people choose to "panic buy". With high costs and low utility during weeks without a hurricane or forecast, consumers have very little incentive to purchase emergency supplies ahead of time.

The current literature on dynamic consumer choices stems largely from two papers: Hendel and Nevo (2006) and Erdem et al. (2003). These papers focus on how random discounts in the price of differentiated products affect the consumer decision making process. In the literature following these works, the focus heavily remains on pricing as a signal, and as a source of uncertainty (Gowrisankaran and Rysman, 2012; Dubé et al., 2010; Erdem et al., 2008; Pires, 2016; Seiler, 2016). This literature relies on the assumption that consumers know the future rate of consumption for goods at the time of purchase. In many cases it is even assumed that people consume the same amount of product during each time period. I add to this literature by building on the model in Hendel and Nevo (2006) by incorporating observed state variables through hurricanes and forecasts into the model and then applying it to the consumer problem.

Second, this research will contribute to the literature on climate change and natural disasters. Much of this literature looks at how individuals and households respond after a natural disaster. Examples include migration, labor, sign up for government programs, and new insurance take-up (Deryugina, 2017; Deryugina et al., 2018; Groen and Polivka, 2008; Gallagher, 2014). Less research has been done on how individuals respond to the threat of a natural disaster. Beatty et al. (2019) show that consumers do a poor job of preparing for hurricanes in advance and tend to wait until the week of a storm to purchase the preparation goods recommended by the government. By utilizing details about hurricane locations relative to a consumer's, I am able to not only detect the "panic buying" behavior but also provide some insight into why it occurs.

The rest of the paper proceeds as follows. Section II discusses the data. The model is discussed in

[5]This cost is not necessarily monetary in nature. There could be other mental or more abstract costs affecting the parameters.

Section III, and the estimation is discussed in Section IV. Section V goes over the main results while Section VI concludes.

3.2 Data

Data on household purchases of bottled water come from the NielsenIQ Household Panel Data. This data consists of thousands of households each year who record each trip they take to any type of store. Once they return from a shopping trip, they scan the UPC code of each item purchased and enter which store they purchased the item from. If the store is a member of the NielsenIQ Retail Scanner Data stores then the price is automatically input, if not the participant manually inputs the prices. The dataset is also updated annually with information about the household's income, the type of residence they occupy, and how many members are in the household. The data also includes the participant's location at the zip-code level, age, and race.

I limit the analysis to states that are most often affected by the Atlantic Hurricane season: Alabama, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Texas, and Virginia. Data is available from 2008 to 2016 for all of the states of interest. Because households in the data can choose to leave after any year, I limit the data to only those households which appear in all nine years of data and make at least two purchases of bottled water per year leaving me with 402 households. Statistics for all households and their purchases can be found in Table 7. The variable *Size of Household* indicates how many individuals reside in the same home including adults and children with the average household in the sample consisting of 2 individuals. Income in the data is reported as a factor-variable for different ranges of income. As an indicator of poverty, I have created the variable *Income Less than 30 Thousand* that is equal to one if the total income of the household for the calendar year fell into any of the categories below $30,000 USD. 13% of the sample households fall into this category. *Single Family Home* indicates if the household owns or rents a single-family home rather than an apartment or multi-family complex.

Summary statistics of bottled water purchases can be found in the lower half of Table 7. Price represents the price paid for a singular item. The median price paid is $4.08. The size in fluid ounces is the size of a singular unit purchased by the household. For example, a one-gallon jug would be 128 while a 6 pack of 16.9 fluid ounce bottles would have a total size of 101.4. The median size purchased by households is 405.6 fluid ounces which is typically sold as 24-packs of 16.9oz bottles. Quantity indicates the number of individual units purchased in a singular shopping trip by the household with most purchasing one item at a time. The number of brands and stores visited by a household is based on all trips taken where a purchase of water was made over all nine years. On average households purchase bottled water from four different stores and equally as many brands.

Weekly-store level data is compiled using the NielsenIQ Retail Scanner Data. The data records the weekly quantity and average price each item in participating stores sold at. Using this data, I am able to see exactly which brands and sizes were available to each consumer at the store they shopped at during the same week. If a household purchased water at a store not in the scanner data, I use the county as a comparison

Table 7: Summary Statistics of Households Level Data

	Min	Max	Median	Mean	Std
Demographics					
Income Less than 30 Thousand	0.0	1.0	-	0.13	-
Size of Household	1	9	2	2.37	1.18
Single Family Home	0	1	-	0.85	-
Purchases of Bottled Water					
Price ($)	0.50	20.03	3.99	4.08	2.07
Size (oz.)	44.0	676.0	405.6	316.0	197.19
Quantity	1	20	1	1.91	1.56
Number of Brands Purchased	1	12	4	4.05	2.04
Number of Stores Visited	1	13	4	3.98	2.17

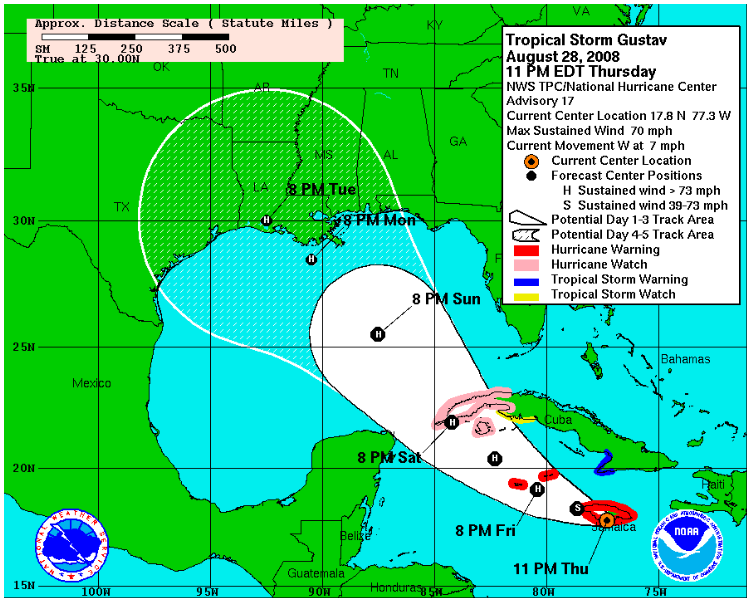
Note: Demographic variables are based on household level observations. Price, size and quantity are based on items purchased by the households in the data. Price is the price for a singular item purchased, this could be an individual bottle of water or a pack of multiple bottles. Size represents the total fluid ounces in the container purchased. Quantity is the number of separate items purchased in a single shopping trip. Number of brands purchased and stores visited are over the entire panel for the household.

since counties in the southeast are rather small. By combining the weekly store data with the daily household data, I am able to get a better look at which brands and sizes are most prevalent in the coastal southeast. I am also able to construct a full view of the store as each household saw it in the week they shopped. By having this complete panel of all available items to each household, I am able to learn about the consumer's decision from not only what they chose, but also what they left on the shelf. I also build out the panel for days where the consumer went shopping, but did not purchase any water at all.

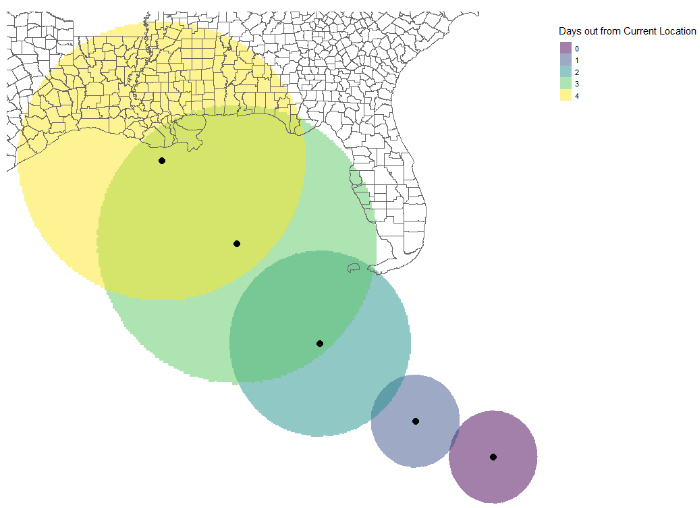
To determine when a household is affected by a hurricane, I use data from the National Oceanic and Atmospheric Administration (NOAA) on the Atlantic hurricane season. NOAA's GIS archive has data on the location and predicted path of each hurricane that has developed since 2008. The data for each hurricane is recorded in 6-hour increments since the hurricane's formation. The projection of a hurricane's future path is estimated at 12-hour increments. Following Beatty et al. (2019) I draw circles around each projected point that get marginally larger as the predicted point gets further away from the current location of the hurricane to resemble the "Cone of Uncertainty" that is shown on local news sources. If a county is within this range, then they are considered threatened by the hurricane. Households residing in a threatened county are themselves threatened. In addition to location, the data states what category the storm currently is and what category the storm is expected to be in the future indicating the level of risk that households face from the impending hurricane.

Figure 6 compares my mapping of the GIS archive data to the official forecast from the same date and time from NOAA (2008) for Hurricane Gustav. The tracks follow exactly because the points used are

Figure 6: Mapping of Forecast Paths



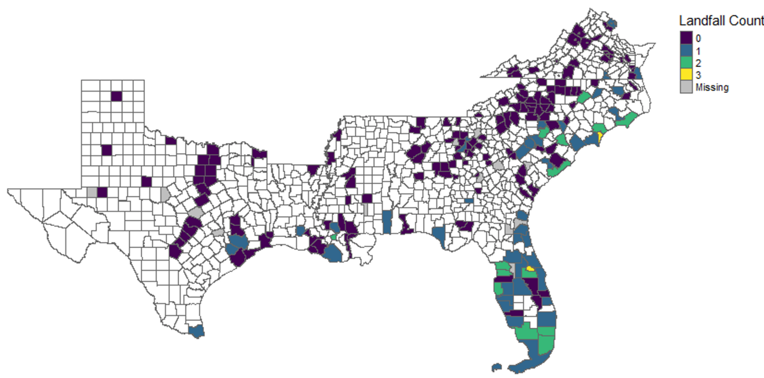
(a) Official Forecast



(b) Replicated Forecast

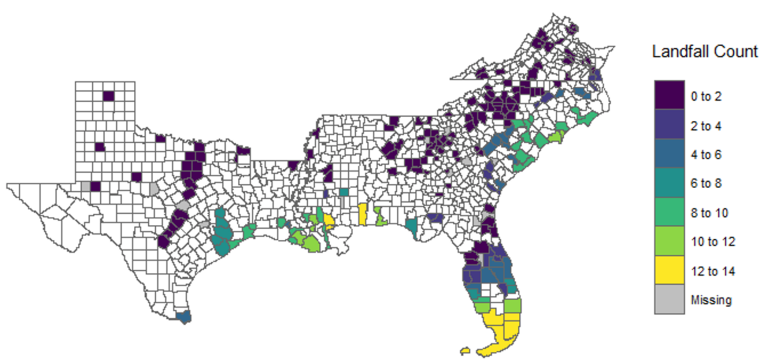
Note: Official and replicated forecasts for Hurricane Gustav on September 28, 2008. Circles around the points in the replicated paths are 100, 100, 200, 300, and 300 nautical miles. The point at the center of the "0 days out" circle represents the current location of the hurricane.

Figure 7: Total Landfalls from 2008 to 2016



Note: Map of all hurricane landfalls from 2008 to 2016. Counties are colored to represent how many times they were hit by a hurricane during this time. Counties not filled in are not represented by the final panel.

Figure 8: Total Landfalls from 1985 to 2007



Note: Map of all hurricane landfalls from 1985 to 2007. Counties are colored to represent how many times they were hit by a hurricane during this time. Counties not filled in are not represented by the final panel.

identical. The area representing the "cone" is slightly larger towards the end, but this is not a large concern, as this portion of the forecast also moves the most between consecutive advisories. In the map in panel (b) it is also clear that some of the areas overlap. Overlapping between points is not a concern. If a county is in both the three days out and four days out circle this simply means that the hurricane is expected to land sometime between 72 and 96 hours in the future. Additionally, hurricanes can sometimes move slowly resulting in areas being hit for more than one day.

Hurricane landfall information is recorded in HURDAT2 data by NOAA (2022b). This data contains

GPS coordinates of the center of landfall for all past hurricanes. It also includes the category of the hurricane and maximum sustained windspeed in knots at the time of landfall. To determine if a county was within the immediate area of landfall, I draw a circle of 100 nautical miles around each point in the data. Counties within this range are considered impacted by the landfall. Because of the shapes of some counties, it is possible to see counties farther inland "hit" by a hurricane and a county closer to the coast not. I repeat this exercise for hurricanes that landed from 1985 to 2007 to create a variable that is similar to relative experience, or knowledge, of hurricanes. I then divide the panel into four groups based on the expected prior experience. Those with no prior experience are the largest group. I divide the counties with a positive level of historical hurricane landfalls into terciles. The groupings are 1 to 4, 5 to 8, and 9 to 13 with 118, 124, and 115 households each.

The counties represented in the panel that are hit during the panel time frame can be seen in figure 7. Areas around coastal North Carolina and south Florida are hit the most during this time. The historical landfalls in figure 8 shows that these areas have also been hit quite often historically. However, the areas around Houston, Texas, and New Orleans Louisiana were also frequently hit historically, but are rather unaffected by hurricanes during the time of the panel, indicating significant variation over time.

Another potential weather variable that could influence the desire for bottled water is temperature. Higher temperatures could potentially lead to people needing to consumer more water than on cooler days. To control for this, I use data from NOAA's Global Historical Climatology Network. This network of weather stations provide daily temperatures throughout the United States. I match each county with its closest weather station and then assign the daily average temperature to each household.

3.3 Model

To understand how hurricanes impact the consumer decision to purchase emergency supplies, I choose to build my model on that presented by Hendel and Nevo (2006). Because emergency supplies are all durable goods by nature, I first looked to the literature on dynamic choice models. Because I expect hurricanes to change the amount of emergency supplies that a household would consume compared to a time without a hurricane, I needed a model that allowed for flexible consumption. I find that Hendel and Nevo (2006) is an ideal model to build on as it incorporates both of these as well as has the ability to expand for consumers to purchase additional quantities.

Let household h gain utility from consuming the good at time t. The utility received by the household from consuming quantity c of the good is

$$U(c_{ht}, \eta_{ht}, \nu_{ht}; \theta_h) + \alpha_h m_{ht},$$

and is affected by the current state of the world. The state of the world consists of unobserved shocks, ν_{ht}, that affect marginal utility. Hurricane landfalls and mean weekly temperature enter as observed stochastic parameters, η_{ht}, which allows the realized utility from consumption to vary. The vector of household specific parameters is represented by θ_h. Consumption of the outside good is m_{ht} and the marginal utility from its consumption is α_h. The product is offered in J different brands. The total consumption of all brands by the household at time t is $c_{ht} = \sum_j c_{jht}$. The stochastic shocks ν_{ht} and η_{ht} introduce randomness into the consumer's need for the products in various ways. Unobserved to the researcher are realizations of ν_{ht}. Higher realizations decrease the household's current need, decrease demand and make it more elastic. Following prior literature, I assume that this variable enters the utility function additively in consumption. The observed stochastic variable, η_{ht}, scales the utility that the consumer receives from using the product. Higher realizations increase the magnitude of the change in utility. This variable enters as a multiplicative scalar to the parameter on consumption so that the final form of the utility function is $U(c_{ht} + \nu_{ht}; \theta_h, \beta_{\eta_{ht}})$

Households gain goods to consume from two sources. They either enter the period with inventory not consumed in the prior period, i_{ht}, or they go to the store and purchase more. The decision to purchase consists of a brand j_{ht}, and the total amount of the good purchased, x_{ht}. Since the item of interest is bottled water, the total amount is in total fluid ounces throughout. As an expansion from the original model, I allow consumers to purchase multiple quantities of bottled water in addition to different sizes[6]. The final purchase decision for a household at time t is represented as $d_{hjxt} = 1$, and $x = 0$ stands for no purchase. For simplicity, I assume that $\sum_{j,x} d_{hjxt} = 1$, or simply households only purchase one particular brand-amount per time period. The price of purchasing a particular brand j of amount x at time t is denoted by p_{xjt}. The consumer's problems can be represented as

$$
\begin{aligned}
V(s_1) = \max_{c_h(s_t), d_{hjx}(s_t)} & \sum_{t=1}^{\infty} \delta^{t-1} E[U(c_{ht}, \eta_{ht}, \nu_{ht}; \theta_h) - C_h(i_{h,t+1}, \phi_{ht} : \theta_h) \\
& + \sum_j d_{hjxt}(\alpha_h p_{xjt} + \xi_{hjx} + \beta \phi_{ht} + \epsilon_{hjxt}) | s_1] \\
& s.t. \quad c_{ht} \geq 0, \quad i_{ht} \geq 0, \quad x_{ht} \geq 0; \\
& i_{h,t+1} = i_{ht} + x_{ht} - c_{ht}; \quad \sum_{jx} d_{hjxt} = 1
\end{aligned}
\tag{4}
$$

where s_t denotes the state at time t, $\delta > 0$ is the discount factor, and $C_h(i_{h,t+1}, \phi_{ht}; \theta_h)$ is the cost of storing unused inventory for the future. A second observed stochastic shock enters into the model through the variable ϕ_{ht}, which represents the forecast of a hurricane at time t. Hurricane forecasts potentially affect the consumers decision in two ways. First it enters the households cost function. Storing large quantities of emergency supplies come at an opportunity cost to consumers. The simplest version of this opportunity cost is though the household's limited storage space. Storing gallons of water in one's home takes up physical space that could be used for storing other, more preferred items, like beer or soda. A hurricane forecast may change the opportunity cost, and make households more willing to give up their preferred items to make room for bottled water. A hurricane forecast may also affect the household's price sensitivity,

[6]There are predominantly 4 sizes of bottled water purchased throughout the sample. Additionally, households rarely purchase more than 3 items at a time. When converted into total fluid ounces purchased, the result is twelve unique size options.

ultimately affecting their brand-amount decision. Household specific effects are picked up in ξ_{hjxt}, and product specific unobserved random shocks are captured in ϵ_{hjxt}. To simplify notation, I drop the subscript h for the remainder of the paper.

The state of the world at time t consists of current prices, beginning of period inventory (i_t), unobserved impacts to consumption, observed shocks through hurricane forecasts, landfalls, and temperature, and the vector of epsilons. Consumers face uncertainty through three avenues: future prices, unobserved shocks to consumption, and discrepancies in forecast accuracy. Over time, households could form beliefs about the relationships between the current state of ϕ_t and future states of η_t. To simplify the framework, I make the following assumption.

Assumption 1 *Households take hurricane forecasts as truth.*

This assumption could be relaxed to allow for household expectations of η_t to include a function of their past experiences with similar shocks which should be studied in future works.

Assumptions about the distributions and pricing process follow from Hendel and Nevo (2006).

Assumption 2 ν_{ht} *is independently distributed across time and consumers.*

This assumption can be relaxed to allow serial correlation, but at an increase in computational burden.

Assumption 3 *Prices follow an exogenous first-order Markov process.*

The assumption that prices follow a first order Markov process follows from how consumers perceive prices rather than how prices are set by the manufacturers. A higher order process would require consumers to not only make expectations about future prices but also remember the price of the good during the last time period. As most households in the panel do not purchase water frequently, it is not an unreasonable stretch to assume they do not know or remember the price of the good from the prior period.

Assumption 4 ϵ_{jxt} *is independently and identically distributed extreme value type 1.*

This assumption significantly reduces the computational burden. The purpose of this assumption is to force the product differentiation to take place at the time of purchase rather than the time of consumption. The household's decision to purchase a good gives information about the expected future utility they will receive from consuming that good.

3.4 Estimation

The estimation procedure follows the three-step procedure used in Hendel and Nevo (2006) which is based on the nested algorithm proposed by Rust (1987). Similarly I assume that there are unobserved shocks to the consumer's choice problem. I therefore assume a distribution for each of the unobserved variables and derive the likelihood of observing the entire sequence of choices made by each consumer. This computation of deriving the likelihood is then nested inside the search for the parameters that maximize the likelihood.

Table 8: Observed Shares of Bottled Water

Brands		Size	
Brand	Share	Ounces	Share
Store Brand	30.15	405.6	40.65
Zephyrhills	22.62	128.0	12.29
Nestle Pure Life	9.36	101.4	10.54
Deer Park	7.97	96.0	6.97
Ozarka	6.49	Other	29.56
Aquafina	6.09		
Dasani	5.53		
Other	11.79		

Note: The share of both brands and sizes is based on observed purchases by the households. Ounces represents the total fluid ounces in a package of bottled water including packages that have multiple bottles.

There were many challenges to using this procedure, some addressed by Hendel and Nevo (2006) and some new. First, is that inventory and consumption are not reported in the data. I follow Hendel and Nevo's approach to bypass this issue. I started by choosing a random initial value of inventory for each consumer. Using the model and the observed values for goods purchased, I solve for the value of consumption that maximizes the consumer's Value function. With consumption solved, inventory for the next period is simple arithmetic. I repeat this process a number of times until a distribution of inventory is generated. From this distribution I draw new starting inventories for each consumer and build a dataset of consumption choices from the model. From this procedure I can build the likelihood of observing the entire sequence of observed purchases for each household where the probability of an observed purchase for a household at time t conditional on the state is given by

$$Pr(d_{jx}|p_t, i_t, \eta_t, \phi_t, \nu_t) = \frac{exp(\alpha p_{jxt} + \xi_{jx} + \beta\phi_t + M(s_t, j, x))}{\sum_{k,y,r} exp(\alpha p_{kyt} + \xi_{ky} + \beta\phi_t + M(s_t, k, y))} \tag{5}$$

where $M(s_t, j, x) = Max_c U(c, \eta, \nu) - C(i_{t+1}, \phi_t) + \delta E(v(s_{t+1})|d_{jx}, c, s_t$ and $E(V)$ is the expected future V as a function of the choices and state today. The summation in the denominator is over all brands and sizes.

The second challenge came from the range of sizes and brands that bottled water specifically is sold in. Packs of water can have varying individual bottles of water in them and can vary by the fluid ounces in each bottle. For simplicity, I calculate the total fluid ounces in the pack that the households purchased [7]. This greatly reduced the number of options that each household faced. I then observed that the majority of sales

[7] i.e. a pack of water with 24 bottles each containing 16.9 fluid ounces is 405.6 total fluid ounces.

came from four options which can be seen in Table 8. Additionally, households rarely purchase more than 3 items at a time, so the sizes are limited to the four main sizes in options of 1, 2, or 3. To simplify the choice set I limit the options that households face to these 12 total amount options (size*quantity purchased) by binning the observed purchase into the choice that is closest numerically.

There are also roughly 85 brands of bottled water available to consumers across all the stores. Only 7 of these brands represent a significant portion of the total observed purchases. The market share of each brand can be seen in Table 8. All purchases of brands not listed are classified under the "other" category.

Even with the simplifications to the market and the choice set faced by consumers, the model is still computationally burdensome. Keeping track of every price for every time period for every bundle and every consumer is quite challenging. To handle this I use the three-step procedure used by Hendel and Nevo (2006). To start with, the problem can be simplified by solving for the parameters that do not vary over time: the *static parameters*. In this version of the model this includes solving for the effect of a change in price and forecast on the consumer's brand choice. These parameters are solved by finding the values that maximize the likelihood of the static discrete choice model of brand choice conditional the size purchased. The second step uses these parameters to build vectors of *inclusive values* for each size. From these vectors, the transition matrices for the indices can be calculated. This reduces the state space of prices from approximately 96 to 12. Finally, the simplified dynamic problem can be solved by estimating the values of the dynamic parameters that maximize the likelihood of the observed sequence of purchases for each household.

3.4.1 Three Step Procedure

Much of the three-step procedure follows directly from Hendel and Nevo (2006) with a few subtle changes. As they do, I begin by estimating the static parameters of the model using a fixed-effects logistics model. I omit the proofs shown in their paper and skip to the result that the probability of a household purchasing a specific brand j conditional on the amount purchased x and the state at time t can be written as

$$\begin{aligned} Pr(d_{jt}|x_t, i_t, p_t, \nu_t, \phi_t) &= \frac{exp(\alpha p_{jxt} + \xi_{jt} + \beta\phi_t)}{\sum_k exp(\alpha p_{kxt} + \xi_{kt} + \beta\phi_t)} \\ &= Pr(d_{jt}|x_t, p_t, \phi_t) \end{aligned} \tag{6}$$

where the summation is over other brands k available in the same size at the same time. Additionally, household options are limited to brands that they purchase at least one time during the panel, as the likelihood of them purchasing a brand outside of their chosen set is 0.

The second step of the procedure involves constructing a price index of inclusive values for each amount available to households. After solving for the static parameters, the price indices can be solved numerically. The adjusted price index formula for this model is

$$\omega_{xt} = log\{\sum_k exp(\alpha p_{kxt} + \xi_{jt} + \beta\phi_t)\} \tag{7}$$

and it follows the prior assumption that:

Assumption 5 $F(\omega_t|s_{t-1})$ *can be summarized by* $F(\omega_t|\omega_{t-1})$.

I begin my analysis by assuming households of all types face the same price process. Relaxing this to allow the process to vary by household would require solving the dynamic process by household which would be quite taxing.

The third step of the procedure is to estimate the parameters of the simplified model. In the simplified problem consumers choose a quantity to consume, c, and a total amount to purchase, x. The flow utility from purchasing an amount of the good is captured by the inclusive value ω_{xt} and ϵ_{xt}.

The bellman equation for the simplified model is

$$\begin{aligned} V(i_t, \omega_t, \nu_t, \epsilon_t, \eta_t, \phi_t) = \max_{c,x} \{ & U(c + \nu_t, \eta_t) - C(i_{t+1}, \phi_t) + \omega_{xt} + \epsilon_{xt} \\ & + \delta E[V(i_{t+1}, \omega_{t+1}, \nu_{t+1}, \epsilon_{t+1}, \eta_{t+1}, \phi_{t+1}, |i_t, \omega_t, \nu_t, \epsilon_t, \eta_t, \phi_t, c, x)]\}. \end{aligned} \tag{8}$$

The parameters for the utility and cost functions are estimated using the inclusive values from step 2, and the beliefs from assumption 1.

To solve for the dynamic parameters that remain, I estimate the model through parametric policy estimation. In the data I only observe the values for total amount purchased and do not observe consumption or inventory. To get around this I use a nested algorithm based on that in Rust (1987) and Hendel and Nevo (2006). Taking the parameters of the model as given, I parametrically solve the value function to obtain the expected value of the next period. Then I numerically solve for the values of c and therefore i_{t+1} that maximize the household's utility. I then calculate the log likelihood of the observed purchases given the information above. This process is repeated until the likelihood has been maximized. The likelihood of observing a household purchase some total amount in the data is given by:

$$Pr(x_t|\omega_t, i_t, \nu_t, \eta_t) = \frac{exp(\omega_{xt} + M(s_t, x))}{\sum_y exp(\omega_{yt} + M(s_t, y))} \tag{9}$$

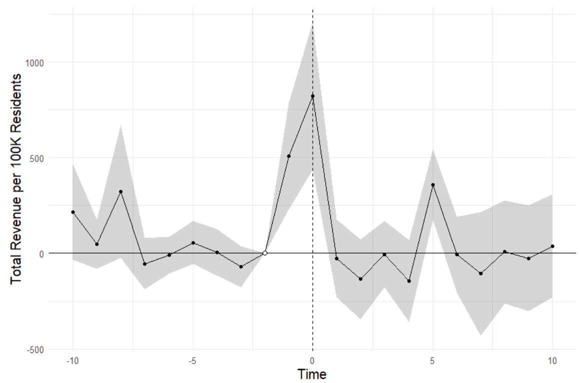
where $M(s_t, x)$ is the calculated value to the household after solving for the utility maximizing level of consumption given the current state and total amount purchased.

3.5 Results

3.5.1 Preliminary Analysis

I begin my analysis by studying the bottled water market as a whole using the NielsenIQ Retail Scanner Data. To see if the "panic buying" that is reported in the news can be seen in the data, I run an event study

Figure 9: Event Study Results of Bottled Water Sales



Note: Results from event studies following equation 10. The vertical axis represents the average sales per capita of water. The horizontal axis represents weeks. The reference period is week -2. The vertical dashed line at week 0 represents the week when a storm made landfall. The band around the estimates represents the 95% confidence interval.

using the following equation.

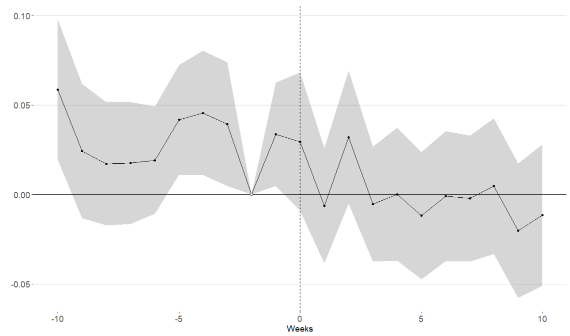
$$Sales_{c,t} = \sum_{\tau=-10,\tau\neq-2}^{10} \beta_{\tau=t} L_{c,\tau=0} + \alpha_c + \alpha_m + \alpha_y + \gamma X'_{c,t} + \varepsilon_{c,t} \tag{10}$$

For this analysis I condense the panel from a store-week level to a county-week level since all stores in the county will be hit by a hurricane at the same time, and consumers could choose to purchase at any of them. In the equation above $Sales_{ct}$ is the total revenue per hundred thousand residents for a given county-week. Total revenue is calculated by adding all the revenue from bottled water sold in each store in the entire county. I choose the reference period of -2 rather than -1 because the forecast of the hurricane could be in the sales week before the actual landfall in week 0 leading to spillover. I include county, month, and year fixed effects represented by α_c, α_m, and α_t respectively. Control variables are accounted for in $X_{c,t}$. Finally, I cluster the standard errors at the county level. If there is "panic buying" as reported in the news, then there should be a significant increase in sales in the week before a hurricane landfall or the week of a hurricane landfall.

The results of the event study can be seen in Figure 9. Before the hurricane forecast, sales are consistent. Once the hurricane is forecast there is a significant increase in sales for the weeks surrounding the hurricane landfall. This is evidence of the "panic buying" that is frequently reported on. It is also evident that the sales of bottled water quickly return to their pre-hurricane levels.

In addition to the event study on sales, I also run an event study where the dependent variable is average price rather than sales. If prices were to change by a large margin due to a hurricane, this would need to be accounted for in the model. If prices remain normal, then I can continue using the pricing process as

Figure 10: Event Study Results of Bottled Water Prices



Note: Results from event studies following equation 10. The vertical axis represents the average price of water. The horizontal axis represents weeks. The reference period is week -2. The vertical dashed line at week 0 represents the week when a storm made landfall. The band around the estimates represents the 95% confidence interval.

presented in Hendel and Nevo (2006). The results for this event study are seen in Figure 10. The results are extremely noisy and do not indicate that hurricanes cause any significant changes in price thus I continue with the model as previously detailed.

3.5.2 Model without Hurricanes

To begin my analysis, I first run the model following the specifications laid out in Hendel and Nevo (2006) and assume that hurricanes do not affect the consumer choice problem. This is the same as setting the variables for forecast and landfall to 0 for each time period. The only change from their model in this portion is that I allow for consumers to purchase multiple quantities, and I incorporate temperature as a potential impact to utility. For the utility function I use the specification $U(c+\nu_t, \eta_t) = (\gamma + \alpha temp_t) * log(c + \nu_t)$. $C(i_{t+1}) = \beta_1 i_{t+1} + \beta_2 i_{t+1}^2$. The unobserved ν_t is assumed to be distributed log normal.

The parameters for the static variables are presented in Table 9. The parameters are estimated using a fixed effects logistic model. Consumers only consider brands that are in the store where they shopped for that trip and that are the same size as the final purchase. The estimate in column (1) is the simplest form of the model and indicates that households are highly sensitive to changes in price. As the model is allowed to become more flexible and vary by brand size and households, the effect of price on final brand choice remains consistently significant and large. Columns (6) and (7) allow for household-brand fixed effects. The result remains consistent that consumers are highly significant to changes in the price of bottled water. Household demographics seem to play very little role in the sensitivity of consumers. As bottled water is a cheap item with many substitutes, it follows standard economic theory that its sales would vary significantly with changes in price. To calculate the price index for each size, I use the parameters from model (7) of the first stage.

Table 9: First Step: Results of Brand Choice Conditional on Size

Dependent Variable:	Brand Purchased?						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Price	-1.359***	-1.274***	-1.086***	-1.035***	-1.085***	-1.145***	-1.172***
	(0.272)	(0.131)	(0.270)	(0.387)	(0.258)	(0.111)	(0.126)
Price × Nonwhite			-0.056	0.067	-0.048	0.061	-0.052
			(0.077)	(0.087)	(0.073)	(0.074)	(0.060)
Price × Single Family Home			-0.041	0.018	-0.040	-0.026	-0.042
			(0.028)	(0.051)	(0.025)	(0.059)	(0.055)
Price × Large Family			-0.147	-0.281	-0.150	-0.106	-0.120
			(0.131)	(0.241)	(0.131)	(0.075)	(0.100)
Fixed-effects							
Size (oz.)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Brand		Yes	Yes	Yes			
Brand-Household						Yes	
Varying Slopes							
Nonwhite (Brand)				Yes			
Single Family Home (Brand)				Yes			
Large Family (Brand)				Yes			
Size (Brand)					Yes		
Size (Brand-Household)							Yes
Fit statistics							
Observations	10,576,293	7,387,896	7,387,896	7,387,896	10,576,293	7,096,170	10,576,293

Note: Results from a conditional logit model when the outcome of interest is if a household purchased a brand at the time they went shopping. Households only compare brands in the same store at the time of purchase that also care the same total fluid ounces. "Size" is the total fluid ounces of water in a single package. *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 10: Third Step: Dynamic Parameters for Base Model

Parameter	Value
Consumption	-9.52
	(3817)
Linear Inventory	-0.29
	(0.385)
Quadratic Inventory	12.22
	(0.305)
Log Likelihood	2393

Note: Results from parametrically solving the simplified bellman equation. Asymptotic standard errors are reported in parenthesis.

Using the results from logistic model and the corresponding price indices, I solve for the remaining dynamic parameters of the model. The resulting parameters can be found in Table 10. The resulting parameters on utility indicate that for household's to have positive utility, they must consume less ounce of bottle water per time period. Additionally, while the initial cost of storing water is negative, it very quickly increases to unreasonable costs for any household. Under these parameters the utility of a household consuming a gallon of water during an 80-degree week would be roughly -46 utils, and the cost of storing a gallon of water for one week would be around $196. These parameters do not follow traditional economic theory for common household and grocery items and makes one question why households would ever choose to purchase or consume bottled water, much less keep a large supply on hand at all times. Additionally, the standard errors are quite large in this model, thus it should likely not be used to explain purchases of bottled water.

3.5.3 Model with Hurricanes

Next, I allow utility and cost to vary with hurricanes and forecasts respectively. Because prior work and the event study above show that sales of emergency supplies and bottled water increase significantly during a hurricane and forecast, including them in the model will likely help explain much of the variation in sales and consumption. To re-estimate the model, I adjust the utility function so that it is $U(c + \nu_t, \eta_t) = (\gamma + \alpha_1 temp_t + \alpha_2 hurricane_t) * log(c + \nu_t)$. The new function forthe cost of storing inventory is $C(i_{t+1}) = (\beta_1 + \lambda_1 forecast_t) * i_{t+1} + (\beta_2 + \lambda_2 forecast_t) * i_{t+1}^2$. The distribution of ν_t is unchanged.

The results of the fixed effects logistic model including hurricane forecasts are presented in Table 11. Column (1) is the same as column (1) from Table 9, and column (2) shows the final parameter estimates from the model without hurricanes added (column (7) in Table 9). Hurricane forecasts are added to this portion as households must do their shopping before the potential hurricane landfall. The variables for a hurricane forecast are indicator variables for if a household was forecast to by hit by a hurricane at the time they went

Table 11: First Step: Results of Brand Choice Conditional on Size with Hurricanes

Dependent Variable:	Brand Purchased?			
Model:	(1)	(2)	(3)	(4)
Variables				
Price	-1.359***	-1.172***	-1.171***	-1.171***
	(0.272)	(0.126)	(0.126)	(0.126)
Price × Any Threat			-0.071***	
			(0.027)	
Price × Threat 1 Day Out				-0.142
				(0.106)
Price × Threat 2 Days Out				-0.054
				(0.073)
Price × Threat 3 Days Out				0.058
				(0.054)
Price × Threat 4 Days Out				0.019
				(0.045)
Price × Threat 5 Days Out				-0.074*
				(0.042)
Fixed-effects				
Size (oz.)	Yes	Yes	Yes	Yes
Varying Slopes				
Size (Brand-Household)		Yes	Yes	Yes
Fit statistics				
Observations	10,576,293	10,576,293	10,565,022	10,565,022

Note: Results from a conditional logit model when the outcome of interest is if a household purchased a brand at the time they went shopping. Households only compare brands in the same store at the time of purchase that also care the same total fluid ounces. Household demographic controls not shown in the table. "Size" is the total fluid ounces of water in a single package. *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 12: Third Step: Dynamic Parameters with Hurricanes

Model:	(1)	(2)
Variables		
Consumption	-9.52	-19.20
	(3817)	(1633)
Temperature	-0.158	1.03
	(5073)	(8088)
Landfall		14.02
		(2.04×10^{19})
Linear Inventory	-0.29	0.18
	(0.385)	(0.256)
Linear Forecast		-23.92
		(3.47×10^{20})
Quadratic Inventory	12.22	0.00
	(0.305)	(0.123)
Quadratic Forecast		-25.65
		(2.79×10^{19})
Log Likelihood	2393	2385

Note: Results from parametrically solving the simplified bellman equation. Asymptotic standard errors are reported in parenthesis.

shopping. I interact this variable with price to determine how a forecast changes the price sensitivity of consumers. Columns (3) and (4) show the result under different versions of the forecast variables. Column (3) shows the effect of households being threatened by a hurricane landfall at any point within the next 5 days. The parameter on price is unchanged by this additional variable. The realization of a hurricane forecast increases the average household's price sensitivity by 7%. This is likely because although households want to purchase larger quantities, their budget constraints do not suddenly increase when a hurricane is forecast. To balance this desire for larger purchases with limited budgets, it is likely that households seek cheaper brands.

I also break out forecasts by how many days are left before the expected landfall. The results for this breakdown of the forecast are in column (4) of Table 11. The forecast of a hurricane still significantly reduces price sensitivity 5 days out, similarly to the aggregate effect. There is not enough power to determine the effects of the other days individually. Because of this I choose to use the results from column (3) to construct the price indices used to solve for the dynamic parameters.

The results for dynamic parameters in both models can be found in Table 12. Column (1) presents the results from the original model from the prior section. Column (2) presents the results from the model that has been modified to include hurricanes and their forecasts. Hurricanes and forecasts have their own effect on utility from consumption and the cost of storing inventory for the future. Additionally, the addition of hurricanes and forecasts shifts the parameters from the original model indicating that their absence causes some level of bias. Under these now parameters the utility from consuming bottled water is highest during hot weeks and weeks when hurricanes make landfall. Additionally, the opportunity cost of storing water is much lower for the average week than the prior model predicts, but still costly. Once there is a hurricane forecast, the cost of storing water actually become negative for any amount they choose to store. This jump from positive costs to negative costs of storage shows clear incentives for households to wait until there is a forecast before purchasing any large amount of bottled water, thus it is value maximizing for households to "panic buy".

While the parameters of the model help explain the behavior of "panic buying" as an optimal strategy for households, further work needs to be done before any policy measures are enacted. Currently the standard errors are quite large, indicating a lack of precision in these results. Further work should look at a longer time frame in order to better capture the effect of hurricanes and their forecasts. Additionally fine tuning of the sample household's may be necessary as well. The current set of households range drastically in their count of purchases with most households purchasing only a few times a year while a select few purchase multiple times per week. It is possible that the households purchasing an excessive amount have a different behavioral pattern than those who purchase more infrequently leading to the model having difficulty declaring one parameter for all household and thus leading to large standard errors.

Further work should also focus on making the household belief process of how hurricane forecasts predict landfall more flexible. As not all hurricane forecasts are accurate, it is unlikely that household beliefs are as rigid as those used by the current model. Allowing for a more flexible belief structure would also allow the model to be broken out by geographical areas based on how accurate forecasts have been in the past. This geographic breakup would help us to fully understand the household decision and how it varies across different states in the southeast.

3.6 Conclusion

Before hurricanes make landfall, many news stations report on masses of people going to the store at the same time to purchase emergency supplies. This behavior has been given the name "panic buying" and increases burdens on supply chains and leads to welfare inefficiencies. Many of these locations are along the Gulf Coast and are frequently hit by hurricanes. Since these areas have frequent opportunities to learn and update their beliefs on hurricanes and forecasts, there must be something in their choice model that makes this behavior optimal.

Building on the structural model on Hendel and Nevo (2006) I am able to estimate the household dynamic choice problem for emergency preparation supplies, namely bottled water. Using purchasing and hurricane data, I find that when there is a hurricane forecast the likelihood of consumers purchasing bottled water significantly increases. I also find that the consumer's price sensitivity significantly increases when there is a hurricane forecast. Both of these results are consistent with the behavior of “panic buying”.

I also am able to begin to understand the underlying mechanisms that leads to this behavior. During a normal week the utility from consuming bottled water is very low, but a hurricane landfall increases this utility. Additionally, the storing bottled water is costly for households during non-hurricane weeks. The forecast of a hurricane drastically reduces the cost of storing water and potentially even gives the household benefit from having stored quantities. These results show that the average consumer has very little incentive to purchase water ahead of time, and that they are actually maximizing their expected future value by “panic buying”.

4 The Effects of Recency Bias on Natural Disaster Preparation

4.1 Introduction

Natural disasters require individuals to determine the amount of risk they both believe they will accept and are willing to accept. Disasters that can be forecast, like hurricanes, allow individuals to gather additional information to determine how much risk they believe they will face and time to prepare for this perceived risk. There is an extensive literature on risk and its perception in many facets of the economy from financial markets, (Rigotti and Shannon, 2005; Gokhale et al., 2015; Rabbani et al., 2020) to climate and disasters, (Gallagher, 2014; Bakkensen et al., 2019; Burke et al., 2022) to gambling (Ladouceur et al., 1995; Studer et al., 2015; Durand et al., 2021). In all branches that focus on risk, there is discussion of various fallacies and biases that people fall victim to. Given these biases show up in so many aspects of decision making, it is natural that they may also occur when facing the risk of natural disaster forecasts.

Two prominent biases in decision making are the recency bias and the hot-hand bias. Both biases occur when individuals place undue weight on prior results rather than the individual probabilities. Recency bias occurs whenever individuals place high weight on a specific outcome occurring, simply because it occurred recently, regardless of the actual probability (Gallagher, 2014; Rabbani et al., 2020; Metz and Jog, 2023; Huseynov et al., 2025). With hurricanes, individuals may be less inclined to believe that a current hurricane forecast for the area will affect them if the last forecast ended with no landfall. Such behavior would be undesirable on a large scale. People less inclined to believe a forecast may not prepare sufficiently, or may wait until the last minute to do so. Both outcomes could further increase the already high costs of disaster recovery (Norris et al., 1999; Sattler et al., 2000; Baker, 2011; Deryugina, 2017; Beatty et al., 2019).

The hot-hand fallacy occurs whenever people believe that a certain independent outcome will occur with high probability because there is currently a streak of the specific outcome, (Croson and Sundali, 2005; Stöckl et al., 2015; Studer et al., 2015; Miller and Sanjurjo, 2024). In hurricane forecasting, there are few streaks of accurate forecasts, all relatively short. Inaccurate forecasts occur more often and streaks last for longer. Current literature shows that as streaks lengthen, individuals tend to overweight them; however, if a streak gets too long people begin to underweight them(Rabin and Vayanos, 2010). Overreacting to a forecast does not impose any inherent danger to individuals, but is not efficient because people will over-purchase. Underreacting or not reacting at all, on the other hand, could be potentially hazardous and leave people without enough food, water, or other emergency supplies.

I utilize historic hurricane forecast data from the National Oceanic and Atmospheric Administration (NOAA) along with NielsenIQ Retail Scanner Data on sales of bottled water to test for both recency bias and the hot-hand fallacy. I find that there is strong evidence of recency bias. If the prior hurricane forecast was inaccurate, sales of bottled water are 16 percentage points higher than if the prior forecast was accurate. This effect holds with various definitions of a current hurricane forecast. Using various definitions of a streak, I also find significant evidence of recency bias. As a streak of accurate forecasts increases, there is a significant reduction in sales of bottled water, indicating a reduction in panic buying. However, as streaks of inaccurate forecasts get longer, sales of bottled water begin by increasing, with the increase slowing around 15 inaccurate forecasts in a row and then decreasing once the streak hits 30.

The effects of recency bias and the hot-hand fallacy would both be reduced under more consistently accurate forecasts. To show the impacts of increased forecasting technology, I estimate the change in sales of bottled water that would occur from an improved forecast history. By comparing the expected sales from a hurricane under the current and improved forecast records, it is clear that the hot-hand behavior would be reduced. Counties which currently have streaks of 15 or more inaccurate forecasts would increase their purchases of bottled water by up to $4,700 per 100 thousand residents. Counties with current streaks less than 15 inaccuracies would see reduced sales of bottled water of up to $8,250 per 100 thousand residents. Thus improved forecasting technology would likely lead to more consistent preparation and reduced panic buying for the majority of coastal counties.

Much work has been done in the natural disaster literature on the market effects after a disaster occurrence (Groen and Polivka, 2008; Semenza et al., 2011; Deryugina, 2017; Deryugina et al., 2018; Sytsma, 2020). Many have also shown that panic buying of natural disasters occurs frequently before natural disasters even though this is an undesirable effect(Norris et al., 1999; Baker, 2011; Beatty et al., 2019). There is still little understood about what effects panic buying behavior. Because hurricane landfalls are massively destructive events (NOAA, 2024) with significant variance in their forecasts, the general population faces large amounts of uncertainty during hurricane forecasts. I utilize past forecast tracks and results to test for signs of bias from the results of past experiences. I find significant evidence that the majority of panic buying is based on past forecast accuracy rather than the current forecasts.

Recency bias in the climate change literature has primarily focused on larger purchases immediately following a disaster (Hallstrom and Smith, 2005; Gallagher, 2014; Bakkensen et al., 2019) or on surveys between events (Kelly et al., 2012; Meyer et al., 2014). By using sales data across many years, I am able to follow patterns before and after many different events. This gives me the ability to determine that not only does the population respond differently to past forecasts based on whether or not they were correct. The general population is far more likely to panic buy supplies when the last forecast resulted in no hurricane landfall. The implications of this behavior could further help businesses and the government to determine which areas will be most affected by panic buying in the future.

Literature on the hot-hand fallacy has primarily focused on gambling, sports, and financial markets (Croson and Sundali, 2005; Rigotti and Shannon, 2005; Rabin and Vayanos, 2010; Stöckl et al., 2015; Studer et al., 2015). There has been little work outside on these specific areas. By testing for the hot-hand in natural disaster prep, I show that the hot-hand fallacy extrapolates to nontraditional risk environments. Additionally, hot-hand studies have primarily focused on streaks in one-direction (i.e. bets on a team with a win streak (Durand et al., 2021)). Hurricane forecasts over the last decade have had both streaks of accurate forecasts and inaccurate forecasts. I take advantage of this unique scenario to show the novel result that the hot-hand fallacy holds not only for streaks of positive outcomes, but also for streaks of negative outcomes.

The remainder of the paper proceeds as follows. Section II discusses the data and variable creation.

Section III discusses the methodology while section IV reports the results. I conclude with section V.

4.2 Data

4.2.1 Sales Data

To measure responses to hurricane forecasts, I analyze sales of emergency supplies using NielsenIQ Retail Scanner Data. The data records sales from various stores throughout the country and has coverage in almost every southeastern county. These sales figures include the average weekly price for each product, how many were sold in a given week, and which county the store is located in. By combining the stores in a county, I calculate the weekly total revenue for each product.

There are a variety of items recommended by the Department of Homeland Security to keep on hand when living in a Natural Disaster prone location. Some items are quite durable and rarely purchased, such as flashlights or hand radios leading to little variation in sales over time. Others have broad definitions that lead to strong taste preferences, such as non-perishable ready-to-eat foods, resulting in potentially large variation in the preferred supplies from one geographical location to another. This makes it difficult to extrapolate any potential results. I choose to focus on sales of bottled water as a way to measure reactions. Bottled water is a consumable good that is accessible at a variety of stores, cheap enough for nearly any household to purchase, and relies less on tastes and preferences, making it an ideal product for analysis.

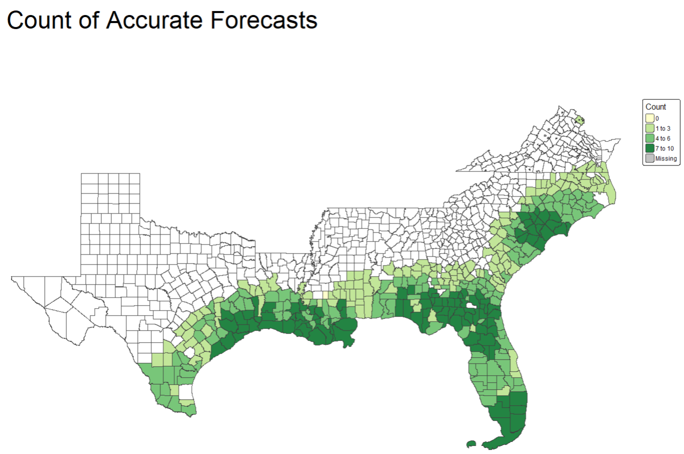
4.2.2 Hurricane Forecast Data

NOAA records past hurricane forecasts since 2008 in their GIS Archive (NOAA). Each tropical cyclone on record since 2008 is recorded along with every advisory update since a storm's inception. Each advisory includes the storms current location, the center of its projected path for the next five day, the projected cone of uncertainty, as well as current and projected windspeed. Using this data, I can see exactly how the hurricane forecast was presented to the general public at different points in time.

Since tropical advisories are updated every six hours, there are four advisories in a single day. To see if a county is under threat of a hurricane, I test if any portion of a county overlapped the "cone of uncertainty" during each advisory. If a county is overlapped by the cone during at least one advisory on that day, it is considered threatened. This accounts for movement of the hurricane parallel to the coast. Additionally, counties may fall into different timing of a potential threat. As the hurricane moves closer to shore, the number of days until landfall for counties may also change. Because hurricanes may land at any point, it is quite feasible for a county to start a day with a hurricane expected in four days and end the day with the hurricane expected in three days. To reflect this, I allow counties to fall under multiple day-out threat levels during a single calendar day.

To align with the sales data, I aggregate the daily forecasts to a weekly level. Because a hurricane may land during any day of the week, and forecasts are at most five days prior, it is possible for the landfall and forecasts to all fall during the same week, or for all forecasts to be during the week prior to landfall. To

Figure 11: Accurate Forecasts from 2008-2019



Note: Map of all forecasts resulting in a hurricane landfall from 2008 to 2019. Darker counties had more accurate forecasts than lighter counties. Only counties with at least one landfall are colored.

avoid any loss of information, I create variables to indicate if a county was under a specific timing of threat (i.e. three days until expected landfall) from one day to five days. Then I create the aggregate variable to indicate if the county was under a threat of any type by summing the daily threat variables.

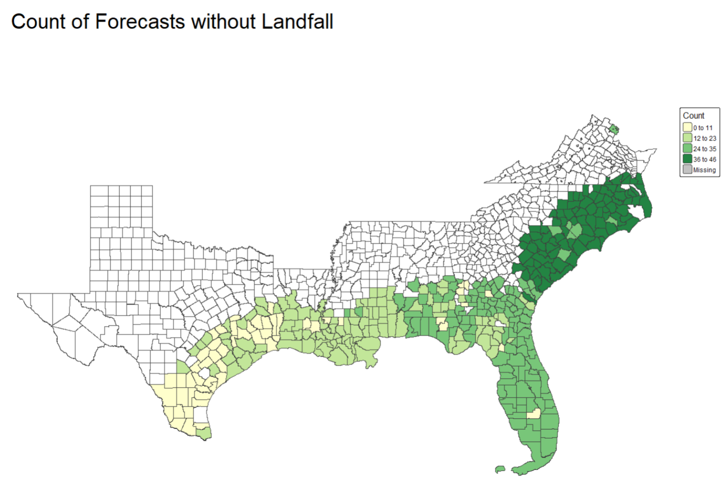
To study the impact of the most recent hurricane forecast, I must determine which forecasts where accurate or not. I build three definitions for final forecast type: hurricane forecast resulting in a landfall, hurricane forecast with no landfall, and landfall without any prior forecast. The third class of forecast is exceptionally rare with only one significant occurrence from 2008 to 2019. Due to this, I focus on the first two definitions which will respectively be called hit and miss for simplicity.

To estimate the effects of any recency bias, I need the results of the most recent prior hurricane forecast. Simply put, once a county has their first hurricane forecast in the data, the result gives their most recent forecast result, hit or miss, from the next week onward. Once a new hurricane has been forecast and the result defined, the most recent forecast data is replaced with the new result.

Figure 11 shows the total count of forecasts in each county that resulted in a hurricane landfall. It is clear from this map that there are meteorological factors that lead to certain areas being more prone to landfalls. Similarly, figure 12 shows the total count of forecasts that did not result in a landfall for each county. While the map has a consistent grade on accuracy the more west one goes, the maps are not inverses of one another indicating there is still some variation when only looking at the effect of the most recent forecast result.

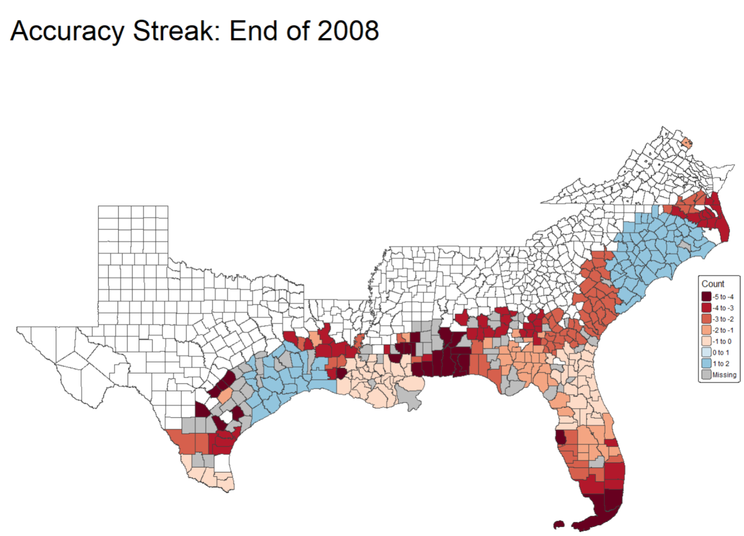
To determine if the hot-hand fallacy is at play, I create variables to indicate the streaks of the hit and miss forecasts. I build three versions of this variable for robustness. One is a pure hot-hand variable which increases by one for each hit forecast, but resets to zero whenever a miss occurs. The second definition is

Figure 12: Inaccurate Forecasts from 2008-2019



Note: Map of all forecasts which did not result in a hurricane landfall from 2008 to 2019. Darker counties had more inaccurate forecasts than lighter counties. Only counties with at least one landfall are colored.

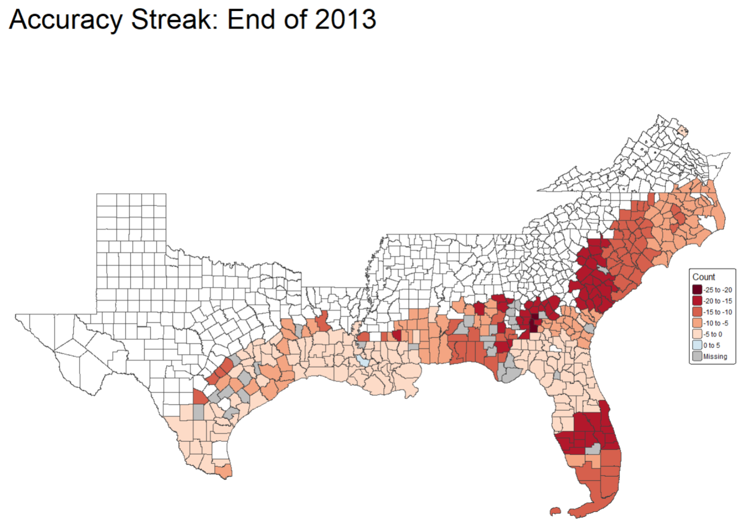
Figure 13: Streak of Forecast Accuracy, December 2008



Note: Counties are colored by their accuracy streak at the end of December 2008. Counties in blue have had a streak of accurate forecasts and those in red have had streaks of inaccurate forecasts

for a string of misses which increases by one for each miss and resets to zero when there is a hit. The third definition combines the previous two as an overall indicator of accuracy. At a first hit the streak is set to 1

Figure 14: Streak of Forecast Accuracy, December 2013



Note: Counties are colored by their accuracy streak at the end of December 2013. Counties in blue have had a streak of accurate forecasts and those in red have had streaks of inaccurate forecasts

and increases by 1 for each subsequent hit. At a first miss the variable is set to -1 and decreases by 1 for each subsequent miss.

Figure 13 shows the accuracy streak for each county at the end of 2008, and the streak in 2013 is shown in figure 14. While the maps of total hits and misses in figures 11 and 12 show that certain areas are more or less prone to certain forecast results. Figures 12 and 13 show the streaks of the same result can vary drastically within a few years.

4.2.3 Control Data

In addition to the scanner and forecast data above, I also utilize population and weather data. I use county level population reports from the U.S. Census's 2010 National Census. I utilize this data to scale the total revenue by each counties population. This keeps the larger coastal towns, like Miami and Houston, from driving the results. Because there may also be a tendency for people to purchase more bottled water in the warmer month when spending more time outdoors, I control for the mean temperature for each county-week observation. This data comes from NOAA's Global Historical Daily Climatology Network. This data is aggregated to the weekly level by taking the mean of all reported daily mean temperatures for the given county-week.

4.3 Methodology

4.3.1 Recency Bias

To determine if there is any recency bias, I estimate the effect of the last forecast and result for each county. I use a difference in differences model of the following specifications to obtain my results.

$$
\begin{aligned}
Sales_{ct} = &\beta_1 Forecast_{ct} + \beta_2 Landfall_{ct} + \\
&\beta_3 Forecast \times PriorHit_{ct} + \beta_4 Landfall \times PriorHit_{ct} + \\
&\beta_5 Forecast \times PriorMiss_{ct} + \beta_6 Landfall \times PriorMiss_{ct} + \\
&\alpha_c + \alpha_m + \alpha_y + \gamma X_{ct} + \varepsilon_{ct}
\end{aligned} \tag{11}
$$

In the model $Sales_{ct}$ is the log total revenue per 100 thousand residents for a county-week observation where the revenue comes from the NielsenIQ scanner data and the county population comes from the 2010 census. $Forecast$ indicates if a county boundary overlapped with a hurricane forecast during the week, and $Landfall$ indicates if the county was within the hurricanes radius upon landfall. $PriorHit$ indicates if the last forecast the county saw resulted in a landfall; whereas, $PriorMiss$ indicates those last forecasts that did not result in a landfall. County, month, and year fixed effects are represented by α_c, α_m, and α_y respectively. X is the control for mean temperature and $\varepsilon_c t$ is the errors.

The primary coefficients of interest in the model are β_3, β_4, β_5, and β_6. Any significance on the coefficient indicate that on average people learn from their most recent experiences. If $\beta_3 = \beta_5$ and $\beta_4 = \beta_6$ then the model implies that people learn from the exposure of hurricanes in general regardless of the outcome. If these results are not equal, then the model implies that people respond differently depending on how accurate forecasts are. In an ideal environment, the coefficient would be statistically the same, or even insignificant altogether. During hurricane season, sources such as the National Weather Service provide many services to help people learn about hurricanes and how to prepare for disasters. If people fully follow this information, then the outcome of the current storm should not change the way people prepare in the future.

4.3.2 Hot-Hand Fallacy

If there are signs of recency bias, it is also possible that strings of inaccurate forecasts could further amplify such biases. In the gambling literature the hot-hand fallacy occurs whenever individuals believe that a streak of outcomes indicates a series even if the draws are independent from one another. In a similar but reverse manner, each hurricane forecast is independent, and is based on many current weather conditions surrounding the hurricane. It is possible that people still fall into a “hot”-hand fallacy of sorts when there is a streak of forecasts that result in no hurricane landfall leading people to believe that the next forecast must also be wrong. To test for this I use the following model.

$$
\begin{aligned}
Sales_{ct} =& \beta_1 Forecast_{ct} + \beta_2 Landfall_{ct} + \\
& \beta_3 Forecast \times Streak_{ct} + \beta_4 Landfall \times Streak_{ct} + \\
& \beta_5 Forecast \times Streak_{ct}^2 + \beta_6 Landfall \times Streak_{ct}^2 + \\
& \alpha_c + \alpha_m + \alpha_y + \gamma X_{ct} + \varepsilon_{ct}
\end{aligned} \tag{12}
$$

Similar to equation(11) $Sales_{ct}$ represents log total revenue per 100 thousand residents, $Forecast$ indicates overlap with a hurricane forecast, and $Landfall$ indicates overlap with a hurricane landfall. County, month, and year fixed effects are represented by α_c, α_m, and α_y respectively. X controls for mean weekly temperatures, and ε_{ct} and errors. The variable $Streak_{ct}$ represents the current streak length of accurate or inaccurate forecasts. If individuals are falling into the how hand fallacy, longer streaks should further cement their beliefs and likewise affect their pattern of emergency supply purchases. Thus, $Streak$ enters into the equation quadratically.

Parameter estimates β_5 and β_6 are the key parameters of interest for the hot-hand fallacy. While β_3 and β_4 help to reaffirm any findings for recency bias. A fallacy in beliefs occurs in the population when there is an over inference of the effect a streak has on potential outcomes. Thus, if either β_5 or β_6 is negative, then there is evidence of fallacy beliefs.

4.4 Results

4.4.1 Preliminary Results

I begin my analysis by estimating the effects of a current hurricane forecast and landfall on sales with a simplified version of the previous models:

$$
\begin{aligned}
Sales_{ct} =& \beta_1 Forecast_{ct} + \beta_2 Landfall_{ct} + \\
& \alpha_c + \alpha_m + \alpha_y + \gamma X_{ct} + \varepsilon_{ct}
\end{aligned} \tag{13}
$$

The variables are defined the same as in equations (11) and (12). Because hurricanes are forecast up to five days out, I test multiple definition of the $Forecast$ variable. First I use the definition from above, if at any point a county overlaps with the forecast path of the hurricane. I then break this definition up by days until landfall. When a county if in the path of a future hurricane they can be 4 or 5 days from potential landfall which is called and *Early Forecast*. If the county is 3 days from a potential landfall then they are in the *Middle Forecast*. Counties which are 1 to 2 days from a potential landfall have a *Late Forecast*. During a given hurricane counties can be in any combination of the different forecast categories.

Table 13: Effect of Current Forecast on Sales

Dependent Variable:			Sales		
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Any Forecast	0.0436***				
	(0.0067)				
Early Forecast		0.0377***			0.0378***
		(0.0073)			(0.0090)
Middle Forecast			0.0301***		0.0228*
			(0.0092)		(0.0124)
Late Forecast				-0.0005	-0.0394***
				(0.0107)	(0.0131)
Landfall	0.1162***	0.1357***	0.1334***	0.1531***	0.1563***
	(0.0271)	(0.0266)	(0.0273)	(0.0283)	(0.0282)
Fit statistics					
Observations	495,301	495,301	495,301	495,301	495,301
R^2	0.59370	0.59369	0.59368	0.59367	0.59370

Results from the regression in equation (13). Clustered (county) standard-errors are in parentheses. Sales is the log total revenue per 100 thousand residents in U.S. dollars at the county-week level. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Results of equation (13) and the different definitions of a forecast can be found in table 13. Column (1) shows that for any hurricane forecast, county level sales of bottled water increase by just over 4%, whereas a landfall increases sales by just over 12%. The early and middle forecasts also see significant increases in sale. The late forecast does not show significant increases in sales; however, the estimate on landfall has increased to absorb the increase. Since there is less time until landfall in the late category, there are more observances of the late forecast and landfall weeks overlapping perfectly explaining this change in estimates. Similar results are found in column (5) when the three timing forecast variables are included at once. Due to the potential strong collinearity with the late forecast variable, I elect to focus on the inclusive variable, any forecast, for the remainder of the analysis. Results for the other definitions of forecast are included in the appendix.

4.4.2 Recency Bias Results

Tests for recency bias follow the model from equation (11) and can be found in table 14. Column (1) repeats the main findings from the simplified regression results in table 13. Once variables for prior forecast results are added to the model, the sign on forecast flips, with the prior outcomes determining the magnitude of purchases. The effect of a hurricane landfall is still positive and significantly larger, with the prior result

Table 14: Effect of Most Recent Forecast on Sales

Dependent Variable:	Sales			
Model:	(1)	(2)	(3)	(4)
Variables				
Forecast	0.0436***	0.0571***	0.0234	-0.3570***
	(0.0067)	(0.0069)	(0.0243)	(0.1370)
Landfall	0.1162***	0.1958***	0.0568	0.8473**
	(0.0271)	(0.0354)	(0.0456)	(0.3604)
Forecast × Prior Hit		-0.0152		0.3989***
		(0.0256)		(0.1397)
Landfall × Prior Hit		-0.1624***		-0.8139**
		(0.0607)		(0.3621)
Forecast × Prior Miss			0.0349	0.4153***
			(0.0250)	(0.1372)
Landfall × Prior Miss			0.1357**	-0.6547*
			(0.0616)	(0.3664)
Fit statistics				
Observations	495,301	464,519	464,519	464,519
R^2	0.59370	0.59194	0.59194	0.59195

Results from the regression in equation (11). Clustered (county) standard-errors are in parentheses. Sales is the log total revenue per 100 thousand residents in U.S. dollars at the county-week level. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

determining the final magnitude of sales. Using the results from column (4) the estimated increase in sales from a current hurricane forecast is roughly 4.3% when the last hurricane hit and 6.0% when the last hurricane missed. Similarly, the estimated increase in sales from a current landfall is 3.4% when the last hurricane hit and 21.2% when the last hurricane missed.

While the estimates in table 14 are significant, they do not show evidence of recency bias unless they are also statistically different from one another. Specifically, the following hypothesis test must be rejected:

$$H_0 : \beta_3 = \beta_5 and \beta_4 = \beta_6$$
$$H_1 : \beta_3 \neq \beta_5 or \beta_4 \neq \beta_6$$

Table 15: Test for Recency Bias

	(1)	(2)	(3)
Test Criteria:	$\beta_3 = \beta_5$	$\beta_4 = \beta_6$	$\beta_3 = \beta_5 \& \beta_4 = \beta_6$
Test Statistic			
χ^2	0.413	6.805	9.811
	(0.520)	(0.009)	(0.007)

Result of F-test using the test criteria as the restricted model and equation (11) as the unrestricted model. p-values are reported parentheses. Sales is the log total revenue per 100 thousand residents in U.S. dollars at the county-week level. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

To test this hypothesis, I modify the model from equation (11) in the following manner:

$$\begin{aligned} Sales_{ct} = &\beta_1 Forecast_{ct} + \beta_2 Landfall_{ct} + \\ &\beta_3 \left(Forecast \times PriorHit_{ct} + Forecast \times PriorMiss_{ct} \right) + \\ &\beta_4 \left(Landfall \times PriorHit_{ct} + Landfall \times PriorMiss_{ct} \right) + \\ &\alpha_c + \alpha_m + \alpha_y + \gamma X_{ct} + \varepsilon_{ct} \end{aligned} \tag{14}$$

The results from this test are found in table 15. Column (1) shows the result of testing for differences in only the forecast variables. Under this weaker test, there is not enough evidence to determine recency bias in the population decision to purchase emergency supplies. Columns (2) and (3), which test for difference in the landfall variables and the combined test of forecast and landfall variables, have significantly low p-values. Overall, this suggests that there is strong evidence of recency bias, with the larger effect of the bias occurring later in the forecast cycle when a landfall is more assured.

As a robustness test, I rerun the prior regressions and F-test using the different definitions of forecast based on timing. This ensures that the bias is consistent across all points of the hurricane forecast, and not just based on the way the forecasts land in the weekly level data. Table B1 of the appendix shows the regression results for the different timing of the forecast. Under all definitions the effect of the most recent forecast is significant. The results of the F-tests are shown in table B2 of the appendix, which further demonstrates that recency bias is prevalent no matter how we cut the hurricane forecast.

4.4.3 Hot Hand Results

To test for evidence of the hot-hand fallacy, I use equation (12) along with different definitions of a streak. The results for all definitions can be found in table 16. A hot-hand in the traditional sense would come from

Table 16: Effect of Streaks of Forecast Outcomes

Dependent Variable:	Sales					
Streak Type	Hit		Miss		Accuracy	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Forecast	0.0566***	0.0572***	0.1254***	0.0724***	0.1234***	0.0748***
	(0.0069)	(0.0069)	(0.0126)	(0.0149)	(0.0123)	(0.0138)
Landfall	0.2191***	0.1984***	-0.0072	-0.0033	0.0020	0.0312
	(0.0338)	(0.0352)	(0.0330)	(0.0380)	(0.0314)	(0.0319)
Forecast × Streak	0.0006	-0.0404	-0.0066***	0.0068**	0.0064***	-0.0064**
	(0.0155)	(0.0389)	(0.0011)	(0.0029)	(0.0011)	(0.0027)
Landfall × Streak	-0.1942***	0.0167	0.0242***	0.0442***	-0.0244***	-0.0393***
	(0.0430)	(0.0891)	(0.0047)	(0.0127)	(0.0044)	(0.0106)
Forecast × Streak^2		0.0191		-0.0005***		-0.0004***
		(0.0169)		(0.0001)		(9.63×10^{-5})
Landfall × Streak^2		-0.1107***		-0.0014**		-0.0013**
		(0.0365)		(0.0006)		(0.0006)
Fit statistics						
Observations	464,513	464,513	464,513	464,513	464,513	464,513
R^2	0.59196	0.59196	0.59202	0.59206	0.59202	0.59207

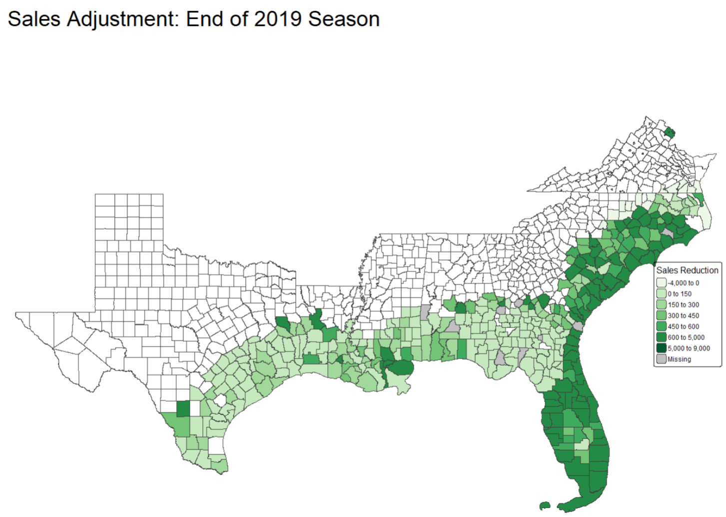
Results from the regression in equation (12). Clustered (county) standard-errors are in parentheses. Sales is the log total revenue per 100 thousand residents in U.S. dollars at the county-week level. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

a string of accurate weather forecasts leading the population to believe that the forecasts can never be wrong. The coefficients under this more traditional definition are found in column (2). While only the estimate of $Landfall \times Streak^2$ is significant, it still indicates some level of hot-hand beliefs. The estimates indicate that any amount of consecutive correct forecasts leads to significant reductions in panic buying of emergency supplies.

While streaks of current forecasts lead to some hot-hand behavior, streaks of incorrect forecasts happen much more frequently and tend to last longer. To test if the hot-hand fallacy holds for string of negative results, I look to column (4) of table 16. With significant negative estimates on both squared terms, there is strong evidence to suggest that the hot-hand fallacy can also hold for strings of negative outcomes. Specifically, these parameters imply that as streaks of incorrect forecasts lengthen, panic buying becomes increasingly worse once an accurate forecast is finally realized.

As a robustness check, I also use a definition that includes both streaks of hits and misses with hits being represented positively and misses negatively. The results from this definition can be found in columns (5) and (6). This definition returns parameters that are quite similar to those in columns (3) and (4). The

Figure 15: Estimated Reduction in Panic Buying



Note: Map of the estimated reduction in emergency supply sales the week of a hurricane landfall at the end of the 2019 hurricane season. Sales is total revenue per 100 thousand residents in USD. Darker counties benefit the most from reduced panic buying with more accurate forecasts. Only counties with at least one landfall from 2008-2019 are colored.

resulting interpretation is the same. Streaks of more accurate forecasts will result in less panic buying, and streaks of inaccurate forecasts will increase panic buying once a hurricane finally makes landfall.

4.4.4 Implication of Results

The increased panic buying coming from recency bias and the hot-hand fallacy impacts states with more misses than hits. Historically, the states most prone to inaccurate forecasts are those of the South Atlantic Coast, namely North Carolina, South Carolina, Georgia, and Florida. Thus, these states will likely benefit the most from improved forecasting methods and technology. The results in table 16 imply that panic buying will begin to decrease if the number of consecutive inaccurate forecasts remains less than 16. I use this metric to simulate a world with better forecasting technology. To build this data, I begin by calculating the streaks of misses and hits as in the data section. For this data, I set a hard rule that the 16th forecast must result in a landfall.

To determine the difference in sales of emergency supplies resulting from a hurricane forecast and landfall, I assume that a hurricane hits all counties on the last day of hurricane season in 2019 (November 30th). Using the results from column (6) of table 16 I estimate the total revenue per 100 thousand residents for each county under both the original data, and the simulated better forecast data. Figure 15 shows the predicted change in sales for all counties. The largest effect is on the Atlantic coast as predicted. Reductions in these four most effected states are on average over $75 per 100 thousand residents and as large as nearly $3,000 per 100 thousand residents. One thing to notice is that some counties show an increase in sales around a hurricane. These counties all have 30 or more misses in a row. The model suggests that the people in these counties have such strong beliefs that the hurricane will miss that they currently respond much less to forecasts than other counties. Such places beginning to see accurate forecasts would, at first, increase their panic buying before over time reducing it.

4.5 Conclusion

There is strong evidence that the population on average waits until the last minute to purchase emergency supplies for hurricanes. However, there is less know about the factors that affect the magnitude of these purchases. The decision of how much to prepare for an impending natural disaster could be thought of as the determination of anticipated risk from the disaster. Because of this I look to the risk and gambling literature for an explanation in variation in emergency supply sales from one disaster to the next.

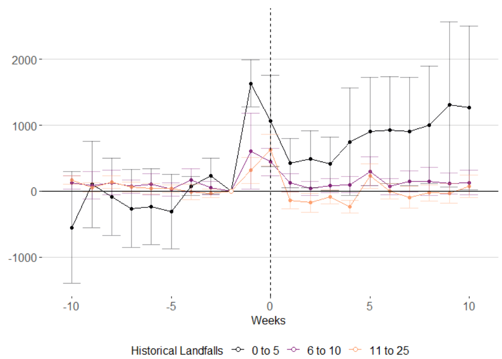
Using results from past hurricane forecasts and sales of bottled water, I test for both recency bias and hot-hand bias. I find significant evidence of recency bias with the last forecast resulting in no landfall leading to significantly higher sales than when the last forecast was accurate. Additionally, I find significant evidence of the hot-hand fallacy which follows results from experimental and gambling literature. Specifically, sales increase as forecasts become less and less accurate; however, once there are more than 15 inaccurate forecasts in a row the response begins to reduce. Through estimating a better forecast timeline I find that as technology for forecasts improves, panic buying will likely reduce significantly, and by over $4,000 per 100 thousand residents along some parts of the East Coast.

Appendix A

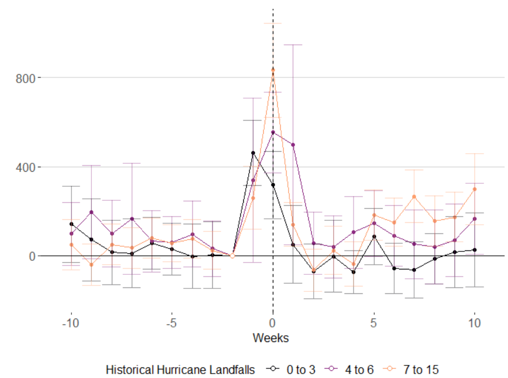
CHAPTER 2 APPENDIX

Figure A1: Event Studies of Historical Exposure on Water Sales

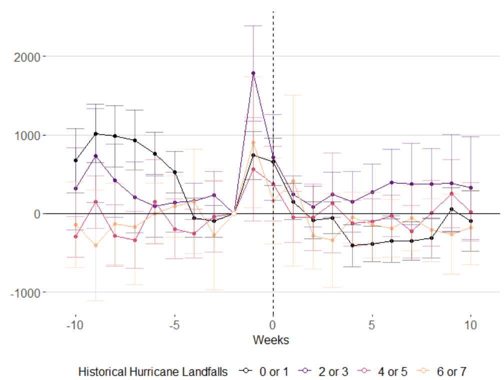
(a) All Disturbances



(b) Hurricanes



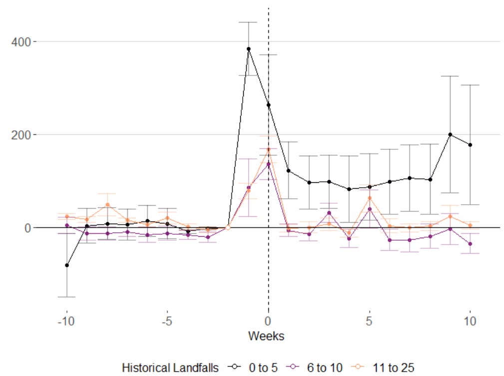
(c) Major Hurricanes



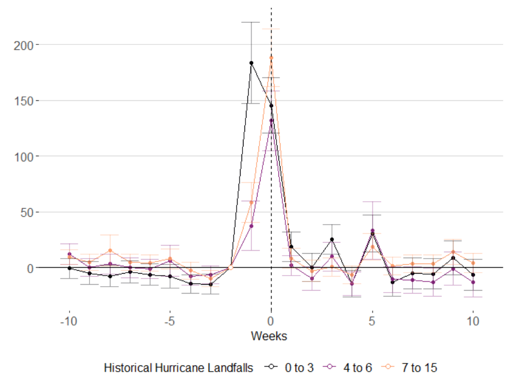
Note: Results from event study with subsets based on historical exposure of the county to hurricanes. The vertical axis represents total revenue per 100 thousand residents from sales of bottled water in USD. The horizontal axis represents weeks. Week 0 is the week that a tropical disturbance made landfall in a county. The bars represent the 10% confidence interval around the point estimate.

Figure A2: Event Studies of Historical Exposure on Flashlight Sales

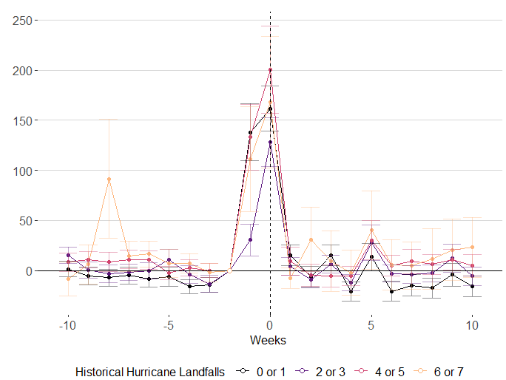
(a) All Disturbances



(b) Hurricanes



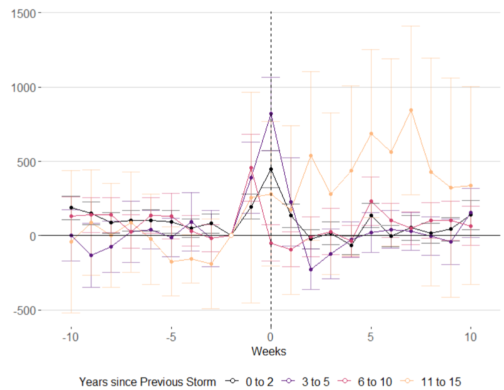
(c) Major Hurricanes



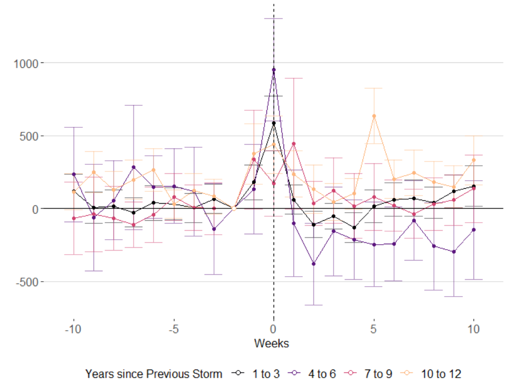
Note: Results from event study with subsets based on historical exposure of the county to hurricanes. The vertical axis represents total revenue per 100 thousand residents from sales of flashlights in USD. The horizontal axis represents weeks. Week 0 is the week that a tropical disturbance made landfall in a county. The bars represent the 10% confidence interval around the point estimate.

Figure A3: Event Studies of Storm Salience on Water Sales

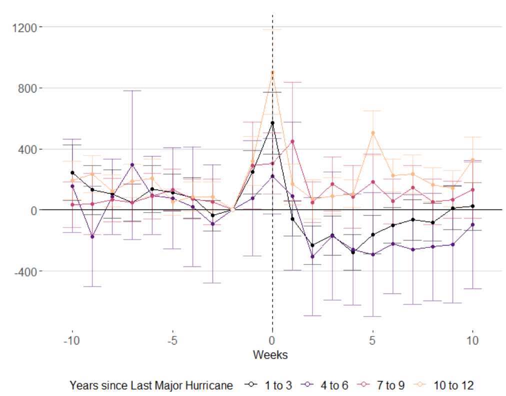
(a) All Disturbances



(b) Hurricanes



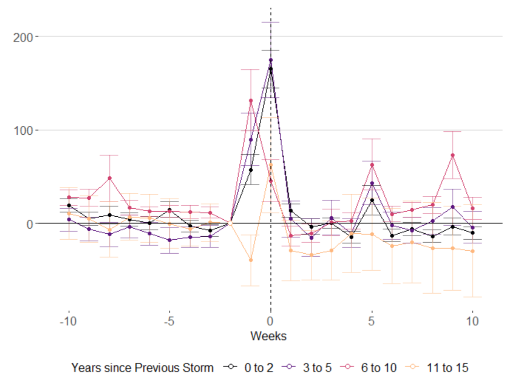
(c) Major Hurricanes



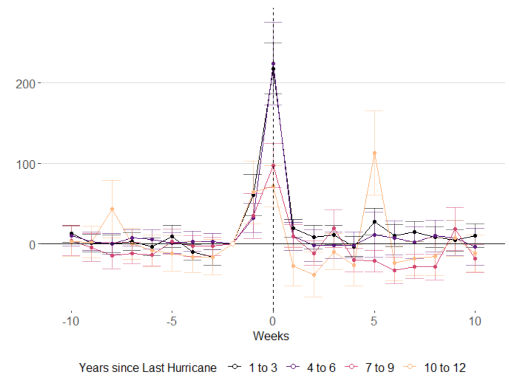
Note: Results from event study with subsets based on the years that have passed since that last storm made landfall in a county. The vertical axis represents total revenue per 100 thousand residents from sales of bottled water in USD. The horizontal axis represents weeks. Week 0 is the week that a tropical disturbance made landfall in a county. The bars represent the 10% confidence interval around the point estimate.

Figure A4: Event Studies of Storm Salience on Flashlight Sales

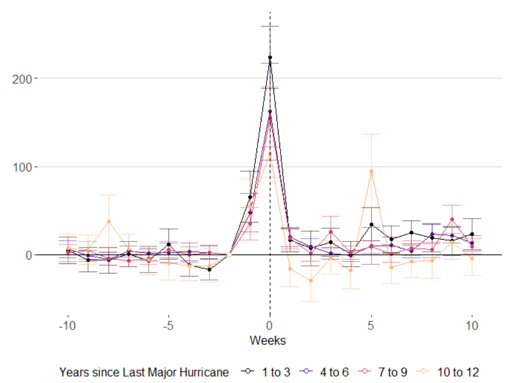
(a) All Disturbances



(b) Hurricanes



(c) Major Hurricanes



Note: Results from event study with subsets based on the years that have passed since that last storm made landfall in a county. The vertical axis represents total revenue per 100 thousand residents from sales of flashlights in USD. The horizontal axis represents weeks. Week 0 is the week that a tropical disturbance made landfall in a county. The bars represent the 10% confidence interval around the point estimate.

Table A1: Effect of Past Hurricane on Beginning of Season Sales

Dependent Variable:	log(total_rev)		
	Bottled Water	Batteries	Flashlights
Model:	(1)	(2)	(3)
Variables			
Season Start	0.0069	0.0397**	-0.0414
	(0.0257)	(0.0128)	(0.0337)
Historical Count	-0.0629	0.0590	0.1524**
	(0.1050)	(0.0434)	(0.0689)
Years Between	0.0050	0.0148**	0.0029
	(0.0180)	(0.0065)	(0.0114)
Season Start $\times$ Historical Count	0.0008	0.0012	0.0067
	(0.0015)	(0.0013)	(0.0039)
Season Start $\times$ Years Between	-0.0008	-0.0004	0.0007
	(0.0010)	(0.0007)	(0.0015)
Fit statistics			
Observations	310,293	304,664	217,947
R^2	0.88407	0.91983	0.75145

Results from the fully interacted heterogeneous regression with the beginning of hurricane season using both historical characteristic variables: historical count and years between. lnSales is log total revenue for a county-week in U.S dollars. Standard errors in parentheses are clustered two-ways at the county and year level. ***: 0.01, **: 0.05, *: 0.1

Table A2: Replication Results

Dependent Variable:	lnSales					
	Full Controls			Limited Controls		
	Bottled Water	Batteries	Flashlights	Bottled Water	Batteries	Flashlights
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Threatened	0.0930**	0.1446**	0.3453***	0.0871**	0.1505**	0.3645***
	(0.0320)	(0.0523)	(0.0911)	(0.0324)	(0.0513)	(0.0880)
Struck	0.1433**	0.4730***	0.9566***	0.1152*	0.4971***	1.034***
	(0.0584)	(0.0742)	(0.1332)	(0.0609)	(0.0719)	(0.1292)
After	0.0330	0.0538*	0.0683	0.0271	0.0594*	0.0847
	(0.0228)	(0.0279)	(0.0697)	(0.0239)	(0.0284)	(0.0691)
Mean Temperature	0.0012	-0.0008	0.0024**	0.0044***	-0.0021**	-0.0008
	(0.0016)	(0.0010)	(0.0010)	(0.0006)	(0.0007)	(0.0007)
Min Temperature	0.0011	-0.0006	-0.0017**			
	(0.0006)	(0.0006)	(0.0006)			
Max Temperature	0.0025*	-0.0008	-0.0016**			
	(0.0014)	(0.0005)	(0.0007)			
Total Precipitation	-0.0107***	0.0117***	0.0366***			
	(0.0021)	(0.0023)	(0.0033)			
Fit statistics						
Observations	644,152	654,114	427,663	644,152	654,114	427,663
R^2	0.84741	0.89753	0.72393	0.84736	0.89747	0.72320

Results from the regression in equation 2 with different versions of temperature controls. lnSales is log total revenue for a county-week in U.S dollars. Standard errors in parentheses are clustered two-way at the county and year level. ***: 0.01, **: 0.05, *: 0.1

Appendix B

CHAPTER 4 APPENDIX

Table B1: Effect of Most Recent Forecast on Sales by Treatment Timing

Dependent Variable:	Sales			
	(1)	(2)	(3)	(4)
Forecast Type:	Any	Early	Middle	Late
Variables				
Forecast	-0.3570***	-0.3710***	-0.5832***	-0.7229***
	(0.1370)	(0.1391)	(0.1702)	(0.1771)
Landfall	0.8473**	0.4897	0.9865**	1.209***
	(0.3604)	(0.3278)	(0.3936)	(0.3722)
Forecast × Prior Hit	0.3989***	0.4208***	0.6788***	0.7758***
	(0.1397)	(0.1433)	(0.1754)	(0.1835)
Landfall ×Prior Hit	-0.8139**	-0.4466	-0.9917**	-1.193***
	(0.3621)	(0.3315)	(0.3954)	(0.3740)
Forecast × Prior Miss	0.4153***	0.4240***	0.6246***	0.7328***
	(0.1372)	(0.1390)	(0.1704)	(0.1782)
Landfall × Prior Miss	-0.6547*	-0.2720	-0.7703*	-0.9766**
	(0.3664)	(0.3325)	(0.3990)	(0.3789)
Fit statistics				
Observations	464,519	464,519	464,519	464,519
R^2	0.59195	0.59193	0.59192	0.59190

Results from the regression in equation (11) during different points in the current forecast. Clustered (county) standard-errors are in parentheses. Sales is the log total revenue per 100 thousand residents in U.S. dollars at the county-week level. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table B2: Additional Tests for Recency Bias

	(1)	(2)	(3)	(4)
Forecast Type:	Any	Early	Middle	Late
Test Statistic				
χ^2	9.811	9.7919	13.29	11.04
	(0.007)	(0.007)	(0.001)	(0.004)

Result of F-test using the test criteria as the restricted model and equation (11) as the unrestricted model. p-values are reported parentheses. Sales is the log total revenue per 100 thousand residents in U.S. dollars at the county-week level. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table B3: Additional definitions of accuracy

Dependent Variable:	Sales			
Model:	(1)	(2)	(3)	(4)
Variables				
Forecast	0.1234***	0.0748***	0.1337***	0.0796***
	(0.0123)	(0.0138)	(0.0137)	(0.0173)
Landfall	0.0020	0.0312	0.1061**	-0.0163
	(0.0314)	(0.0319)	(0.0500)	(0.0795)
Forecast $\times$ Accuracy	0.0064***	-0.0064**		
	(0.0011)	(0.0027)		
Landfall $\times$ Accuracy	-0.0244***	-0.0393***		
	(0.0044)	(0.0106)		
Forecast $\times$ Accuracy^2		-0.0004***		
		(9.63×10^{-5})		
Landfall $\times$ Accuracy^2		-0.0013**		
		(0.0006)		
Forecast $\times$ Hits			-0.0412**	-0.0652
			(0.0171)	(0.0425)
Landfall $\times$ Hits			-0.1245**	0.2905**
			(0.0530)	(0.1285)
Forecast $\times$ Hits^2				0.0251
				(0.0175)
Landfall $\times$ Hits^2				-0.1817***
				(0.0436)
Forecast $\times$ Misses			-0.0070***	0.0058*
			(0.0012)	(0.0031)
Landfall $\times$ Misses			0.0136**	0.0465**
			(0.0057)	(0.0191)
Forecast $\times$ Misses^2				-0.0004***
				(0.0001)
Landfall $\times$ Misses^2				-0.0015*
				(0.0008)
Fit statistics				
Observations	464,513	464,513	464,513	464,513
R^2	0.59202	0.59207	0.59204	0.59208

Results from the regression in equation (12). Clustered (county) standard-errors are in parentheses. Sales is the log total revenue per 100 thousand residents in U.S. dollars at the county-week level. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table B4: Effect of Streaks of Forecast Outcomes by Timing

Dependent Variable:	Sales)							
Forecast Type:	Any		Early		Middle		Late	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Forecast	0.1234***	0.0748***	0.1207***	0.0885***	0.1122***	0.0901***	0.0902***	0.0390**
	(0.0123)	(0.0138)	(0.0128)	(0.0142)	(0.0139)	(0.0167)	(0.0158)	(0.0198)
Landfall	0.0020	0.0312	0.0519*	0.0529*	0.0359	0.0350	0.0269	0.0595*
	(0.0314)	(0.0319)	(0.0299)	(0.0305)	(0.0308)	(0.0319)	(0.0324)	(0.0338)
Forecast × Accuracy	0.0064***	-0.0064**	0.0067***	-0.0022	0.0066***	0.0004	0.0075***	-0.0062*
	(0.0011)	(0.0027)	(0.0011)	(0.0028)	(0.0011)	(0.0030)	(0.0013)	(0.0036)
Landfall × Accuracy	-0.0244***	-0.0393***	-0.0221***	-0.0445***	-0.0231***	-0.0465***	-0.0254***	-0.0398***
	(0.0044)	(0.0106)	(0.0043)	(0.0105)	(0.0043)	(0.0106)	(0.0044)	(0.0107)
Forecast × Accuracy^2		-0.0004***		-0.0003***		-0.0002**		-0.0005***
		(9.63×10^{-5})		(0.0001)		(0.0001)		(0.0001)
Landfall × Accuracy^2		-0.0013**		-0.0016***		-0.0016***		-0.0013**
		(0.0006)		(0.0006)		(0.0006)		(0.0006)
Fit statistics								
Observations	464,513	464,513	464,513	464,513	464,513	464,513	464,513	464,513
R^2	0.59202	0.59207	0.59200	0.59202	0.59195	0.59197	0.59193	0.59196

Results from the regression in equation (12). Clustered (county) standard-errors are in parentheses. Sales is the log total revenue per 100 thousand residents in U.S. dollars at the county-week level. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

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