

Product Availability, Consumer Stockpiling, and Hurricane Events: Empirical Evidence from Natural Experiments

Xiaodan Pan, Martin Dresner, Benny Mantin, and
Jun A. Zhang

For publication in
Production and Operations Management

Abstract:

The provision of essential supplies is a key service provided by retailers when demand spikes due to consumer stockpiling during environmental emergencies. Moreover, it is important for retailers to quickly recover from these events by replenishing the stock of essential supplies to meet the continuing needs of local residents. As exogenous events, hurricanes provide natural experiments to test retail operational performance in the face of environmental emergencies. We study consumer stockpiling behavior prior to the onset of hurricane landfalls, with a focus on the impact of this behavior on in-store product availability for various formats of retail store outlets. Specifically, we focus on the bottled water product category, an essential emergency category in hurricane preparedness. On average, consumers stock 60% more bottled water before hurricanes approach. This study combines an event study methodology with econometric models using archival retail scanner data from 60 U.S. retail chains located in 963 counties and real-time data from four recent U.S. continental hurricanes. We find that supply-side characteristics (retail network and product variety), demand-side characteristics (hurricane experience and household income), and disaster characteristics (hazard proximity and hazard intensity) significantly affect consumer stockpiling propensity as the hurricanes approach. The increased consumer stockpiling has immediate and lasting impacts on retail operations, namely, in-store product availability. Among various retail formats, drug stores are associated with the highest consumer stockpiling propensity before hurricanes, while dollar stores and discount stores are associated with the lowest in-store product availability following hurricanes. Our study points to the need for retailers and policymakers to carefully monitor factors affecting consumer stockpiling behavior that will allow for better allocation of critical supplies during the hurricane season.

Key words: product availability; consumer stockpiling; hurricane disasters; natural experiment

1. Introduction

Consumers flock to retailers before, during and after environmental emergencies, such as earthquakes, hurricanes and snowstorms, to obtain adequate quantities of essential supplies. Therefore, the provision of essential supplies is an important function of retailers during times of environmental emergencies (Morrice et al. 2016; Windle 2018). Target's "Green Team" describes its preparations in advance of a hurricane: *"In the days leading up to landfall, we identified the 1,500 products our guests need most, and loaded and shipped as many extra trailers of those products as possible to our stores before the storm hit...As guests stocked up, some of these items sold out, but we're working around the clock to restock them as quickly as possible."* (Target 2018) But ensuring the availability of supplies can be difficult for retailers, such as Target, given the unpredictability of these emergencies, compounded by the potential for supply chain disruptions and the tendency for consumers to stockpile or hoard emergency provisions. In addition, the performance of retailers in recovering to "normal" operations following an environmental emergency may vary considerably, depending on consumer demand, the retailer's supply chain and disaster characteristics.

From the perspective of consumer stockpiling behavior, we address an operational challenge faced by retailers seeking to position inventory ahead of a forecasted hurricane event to facilitate the availability of critical grocery supplies during and after the hurricane. In particular, we utilize hurricanes as "natural experiments" investigating: 1) the impact of supply-side, demand-side, and disaster characteristics on consumer stockpiling behavior prior to a hurricane event and 2) the impact of consumer stockpiling behavior on product availability during and after the hurricane passes. Specifically, we focus on the bottled water product category, a representative emergency category in hurricane preparedness. Given the predicted hurricane path, our study can help retailers identify consumer stockpiling propensity along the path based on supply-side, demand-side, and disaster characteristics. As such, our study primarily relates to inventory pre-positioning in the path of hurricanes (Davis et al. 2013, Lodree and

Taskin 2009, Lodree et al. 2012, Morrice et al. 2016, Rawls and Turnquist 2010, Taskin and Lodree 2010, 2011).¹

The behavior of consumers as they choose (or choose not) to stockpile supplies in anticipation of hurricanes deserves attention from retailers as they forecast consumer demand and plan their inventories. During the time lag between storm formation and storm landfall, some people will take preventive actions; however, others will disregard the potential for disastrous outcomes. Members of the former group may purchase adequate supplies or even surplus supplies as they prepare for the worst, while members of this latter group may choose not to purchase sufficient essential supplies. Thus, from the perspective of disaster operations, it is critical for retailers to identify factors that are associated with consumer stockpiling behavior.

We focus on four hurricanes with wide-ranging impacts on the Continental U.S. – Ike in 2008, Irene in 2011, Sandy in 2012, and Arthur in 2014. Specifically, we follow Gupta et al. (2016)’s guidance and carry out analysis using archival retail scanner data and real-time hurricane data. Data were collected from retail store outlets in the proximity of the hurricanes’ paths to obtain 38,418 store-event observations. Using event study methodology, we first define the INFLUENCE date as the day when the hurricane is at its nearest proximity to the store outlet observed. Thus, different store outlets may be associated with different INFLUENCE dates, depending on where they are situated relative to the hurricane’s path. Then, we categorize the course of a hurricane disaster into four event periods: EARLY and LATE, corresponding to the calendar week before and the calendar week after the INFLUENCE date of hurricanes, and PRE and POST, corresponding to a time period of four calendar weeks before the EARLY period and after the LATE period, respectively. We set the PRE-event period as the benchmark and then examine consumer stockpiling propensity during the EARLY event period and its relationship to in-store product availability following the hurricane events, namely the LATE and the POST event periods.

¹ Various administrative functions have been studied in the context of hurricane disaster management, such as decision-making processes, evacuation procedures, humanitarian logistics, emergency prevention/mitigation, emergency restoration/recovery, and casualty management (see Gupta et al. 2016, for review).

We first examine factors that are associated with consumer stockpiling at a retail outlet during the EARLY event period. From a supply-side perspective, we find that consumer stockpiling propensity is impacted by characteristics of the retailer, such as the retailer's intra-regional store network, its inter-regional store network, and the bottled water variety offered at a given outlet. From a demand-side perspective, we show that consumer stockpiling propensity is related to factors that affect a consumer's risk perception and purchasing power, such as recent hurricane experience and household income level. From a disaster perspective, we illustrate how consumer stockpiling propensity is linked to factors that impact risk magnitude and consumer response, such as distance of a retail outlet to points of hurricane landfall, the path of the hurricane, and the intensity of storm winds.

We then show how consumer stockpiling propensity during the EARLY event period is related to in-store availability of bottled water during the LATE and POST event periods. Given the time lag between hurricane formation and landfall, retailers can pre-position inventory in potentially-affected markets (Target 2018); however, consumer stockpiling propensity may have immediate and lasting impact on in-store availability over the course of hurricane events. For example, we find that consumer stockpiling during the EARLY event period is negatively associated with in-store product availability during the LATE and POST event periods, as the increased stockpiling depletes bottled water inventories and supply chains are slow to recover inventory availability.

Interestingly, consumer stockpiling propensity and in-store product availability vary significantly across retail formats over the course of a hurricane. For example, drug stores provide a combination of critical products for hurricane preparedness, such as emergency kits, prescription drugs, and bottled water. They are associated with the highest consumer stockpiling propensity during the EARLY event period. Moreover, we find that retail formats with quick restoration capabilities (as measured by their fast inventory turnover and short inventory processing periods) are likely to achieve superior performance in product availability over the course of hurricane events. For instance, grocery stores and warehouse clubs have consistently higher in-store product availability during the LATE and the POST event periods. In contrast, low-cost oriented retail chains, such as discount stores and dollar stores, are associated with

relatively lower in-store product availability during the LATE and the POST event periods. The results imply that store format may relate to a retailer's strategy in disaster preparedness, such as prepositioning inventory and investing in disaster management capabilities (Kunz et al. 2014).

Both retailers and local governments have to face challenges caused by consumer stockpiling when a hurricane hits. Therefore, it is critical they understand the impacts of supply-side, demand-side, and disaster characteristics on consumer stockpiling behavior. Policymakers may be able to influence both the supply and demand for critical supplies through public announcements and advisories, thereby altering stockpiling behavior and retail prepositioning behavior. Moreover, supply chain managers should focus on the disaster-related factors, as they will be key determinants of stockpiling propensity. Specifically, we propose that collaboration among hurricane meteorologists, local, state, and federal government officials, emergency-response organizations and retail managers can allow for better allocation of essential supplies in the preparation for and response to disasters.

Our research has several contributions: First, we contribute to the macro level "architectural blueprint" of disaster management research (Gupta et al. 2016), developing empirically-grounded work in emergency operations (Pedraza-Martinez and Van Wassenhove 2016). In particular, we investigate in-store product availability in light of consumer stockpiling behavior utilizing hurricane disasters as natural experiments. Second, we triangulate our research questions with multiple data sources and research methods (Gupta et al. 2016, Pedraza-Martinez and Van Wassenhove 2016). Specifically, we combine event study with an econometric model using archival retail scanner data from 60 U.S. retail chains located in 963 counties and with real-time data from four recent hurricanes. Third, we disentangle factors that impact consumer stockpiling propensity by exploring supply-side characteristics (retail network and product variety), demand-side characteristics (hurricane experience and household income), and disaster characteristics (hazard proximity and hazard intensity). Fourth, we show that consumer stockpiling propensity has immediate and persistent effects on retail operations, such as lower in-store product availability following hurricanes, with the effects varying across retail formats. Finally, our study shows the need for retailers and policymakers to carefully monitor factors affecting consumer stockpiling

behavior during the hurricane season to enhance coordination when prepositioning inventory and directing disaster-relief efforts.

2. Theoretical Foundations

This study investigates factors that affect consumer stockpiling behavior prior to hurricanes (step one), and the impact of stockpiling behavior on in-store product availability during and after hurricanes (step two). Figure 1 illustrates the theoretical model used to study these effects. To that end, we survey literature related to consumer stockpiling behavior and retail operations management in the context of environmental emergencies. We start by reviewing the theory of consumer stockpiling during natural disasters and the effects of disasters on in-store product availability (Section 2.1). We then examine factors affecting consumer stockpiling, such as supply-side, demand-side, and disaster-related characteristics (Section 2.2).

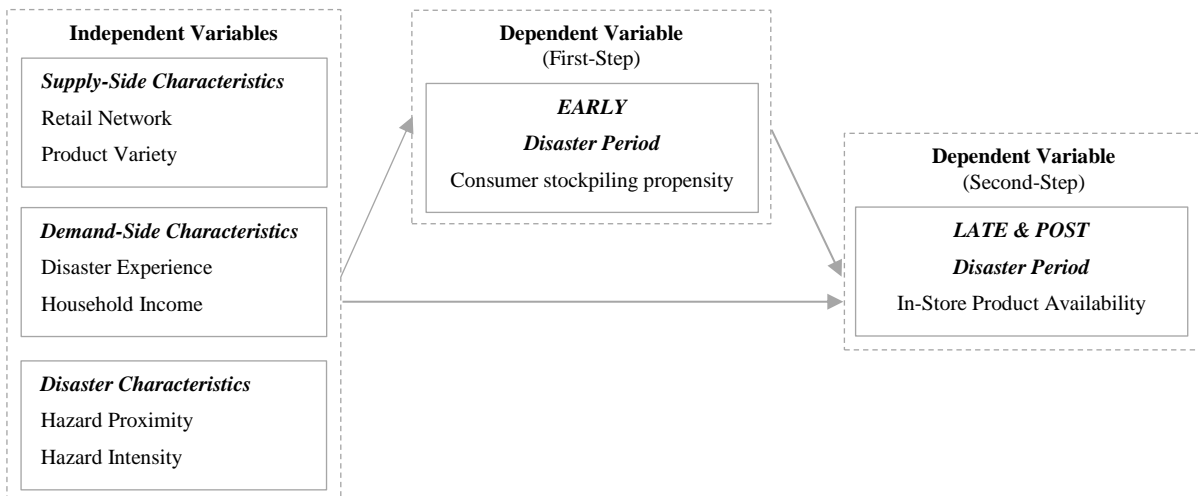


Figure 1: Theoretical Model: Product Availability, Consumer Stockpiling, and Hurricane Events

2.1. Effects of Consumer Stockpiling on In-Store Product Availability

Consumer stockpiling for natural disasters can be viewed as an unconventional inventory accumulation activity designed to minimize loss or a perceived threat of loss. McKinnon et al. (1985) distinguish inventory accumulation activities based on two sets of criteria: 1) whether the accumulation is for profit-seeking or loss-avoidance, and 2) whether the accumulation can be viewed as conventional or

unconventional. According to King and Devasagayam (2017), consumer stockpiling for natural disasters can be explained using commodity theory (Brock 1968) and prospect theory (Kahneman and Tversky 1979). Commodity theory deals with the psychological effects of scarcity (Lynn 1991), in that any commodity will increase in value due to scarcity (Brock 1968). During natural disasters, the potential scarcity of products is likely to affect consumer attitudes and behavior (Brock 1968, Lynn 1991), and thus stimulate stockpiling desirability. Prospect Theory (Kahneman and Tversky 1979) describes how people choose between alternatives that involve risk and uncertainty. The theory states that people make decisions based on the potential value of losses and gains. In the face of risk and uncertainty from pending natural disasters, consumers can be loss averse; thus, they may increase their stockpiling behavior.

Such consumer stockpiling behavior may have immediate and lasting effects on retail operations. First, retailers may increase product availability before a hurricane strikes in anticipation of stockpiling behavior. In practice, retailers can plan inventory based on hurricane information updates while setting expectations for operational costs and service level (Davis et al. 2013, Lodree and Taskin 2009, Lodree et al. 2012, Morrice et al. 2016, Rawls and Turnquist 2010, Taskin and Lodree 2010, Taskin and Lodree 2011). However, natural disasters are difficult to accurately forecast and are beyond the control of firms (Hendricks et al. 2017, Hu et al. 2013, Kleindorfer and Saad 2005). Thus, consumer stockpiling may result in lower in-store product availability following a disaster (Cavallo et al. 2014, Hu et al. 2013, Kleindorfer and Saad 2005). Depending on supply readiness, these effects may persist for several order cycles. For example, Cavallo et al. (2014) find that it took considerable time for retailers to recover from product supply disruptions following the 2010 earthquake in Chile and the 2011 earthquake in Japan, with a significant share of products remaining out of stock after six months.

2.2. Factors Associated with Consumer Stockpiling for Natural Disasters

We distinguish between three groups of characteristics associated with consumer stockpiling: supply-side, demand-side, and disaster characteristics.

2.2.1. Supply-Side Characteristics

During hurricane disasters, consumer stockpiling may be influenced by supply-side characteristics that influence store attractiveness. Intuitively, a broad store network is likely to attract consumers due to name recognition. Hence, this network association may enhance stockpiling at individual store outlets. However, according to inventory theory (Zipkin 2000), retailers with a dense intra-regional network may carry less inventory at individual store outlets due to inventory pooling effects, thus limiting an individual store's ability to respond to demand-side shocks as a hurricane approaches. In contrast, retailers with a dense inter-regional store network may carry more overall inventory across their store networks due to scale considerations (Cachon and Olivares 2010, Gaur et al. 2005, Rajagopalan, 2013); thus, they may respond to demand-side shocks by bringing in inventory from outside the affected region (Holmes 2011, Lim et al. 2017). However, transshipment costs, such as long-distance transportation tariffs, may limit a retailer's inclination to accommodate consumer stockpiling demand. Accordingly, we expect a retailer's intra-regional and inter-regional store networks to affect consumer stockpiling during hurricane disasters, although the impacts are difficult to predict *a priori*.

Another supply-side characteristic is the variety of products offered at an individual outlet. Product variety plays a major role in attracting consumers as can be explained by psychology-based (Kahn 1998, McAlister and Pessemier 1982, Ren et al. 2011), stockout-based (Chen and Plambeck 2008, Gilland and Heese 2013, Honhon and Seshadri 2013, Kraiselburd et al. 2004) and budget-based motivations (Huchzermeier et al. 2002). Increased product variety is also linked to an increase in total inventory (Zipkin 2000, Gaur et al. 2005, Rajagopalan 2013, Ton and Raman 2010), but this inventory increase is limited since retailers take substitutability of demand into consideration in stocking decisions (Gilland and Heese 2013). Therefore, we expect stockpiling to be positively associated with product variety but with a decreasing rate due to demand substitutability.

2.2.2. Demand-Side Characteristics

With natural disasters, consumer stockpiling propensity may be related to demand-side characteristics that influence risk perception and purchasing power. We focus on two key characteristics: disaster experience and household income. Prior experience is likely to affect stockpiling propensity in two somewhat opposite directions. Sattler et al. (2000) point out that experience predicts hurricane disaster preparedness, supporting both the resource stress model (Hobfoll 1989) and the warning and response model (Lindell and Perry 1992). Thus, individuals with more hurricane experience tend to have higher awareness of hurricane hazards (Trumbo et al. 2011), which may stimulate consumer stockpiling propensity due to higher perceived risk. However, prior experience may have a diminishing effect on consumer stockpiling prior to disasters. Consumers with significant hurricane experience may have already stockpiled due to seasonal preparedness instead of last-minute preparedness (Beatty et al. 2018). Moreover, significant experience may adversely affect a consumer's good judgment. The consumer may become blasé about risks, resulting in lower stockpiling propensity. Overall, these mixed effects indicate that prior hurricane experience may influence consumer stockpiling behavior in a complex relationship.

A handful of studies show that hurricane preparedness is related to household income (Baker 2011, Fothergill and Peek 2004). Individuals with higher income are more capable of purchasing emergency supplies in the face of natural disaster. For example, Baker (2011) finds that a household's hurricane preparedness in Florida is strongly related to home ownership, residence type, and household income. Fothergill and Peek (2004) conclude that the poor in the U.S. are vulnerable to natural disasters due to factors such as residence location, residence type, building construction, and social exclusion. However, individuals who belong to a higher socio-economic group with abundant resources may have a lower purchasing desirability before and during a natural disaster (Peacock et al. 2005). They are more capable of fleeing from the disaster-affected area, resulting in a discounting effect on consumer stockpiling behavior.

2.2.3. Disaster Characteristics

The proximity (i.e., distance to landfall points and distance to path of hurricane) and intensity (wind speed) of the approaching hurricane may play an important factor in consumer stockpiling propensity. Recent studies have shown that proximity to a hazard and the intensity of the hazard are associated with greater risk awareness (Moffatt et al. 2003, Peacock et al. 2005). According to Prospect Theory, people associate greater psychological discomfort with risks, and the value function is steeper for greater risk due to loss aversion. The theory predicts that people may not make rational decisions and stockpile more than needed based on the potential for a disaster. Notably, hazard proximity and hazard intensity also affect consumer response. For example, storm information and forecasts are normally issued based on hazard proximity and hazard intensity, such as hurricane and tropical storm watches, warnings, advisories, and outlooks. Overall, we expect that hazard proximity and intensity positively impact consumer stockpiling behavior.

3. Research Methodology

Using event study methodology, we study in-store product availability of bottled water in light of consumer stockpiling behavior during hurricane events. Below we outline the methodological steps involved.

3.1. Data Collection

We collect data from recent continental hurricanes making landfall in the U.S. between 2008 and 2014. To compare consumer stockpiling behavior across geographic markets, we focus on hurricane events with a wide range of impacts, including Ike in 2008, Irene in 2011, Sandy in 2012, and Arthur in 2014. Figure 2 shows the storm tracks of these four hurricanes. The tracks are from the National Oceanic and Atmospheric Administration's (NOAA's) National Hurricane Center Atlantic Basin Best Tracks HURDAT2 database (Landsea and Franklin 2013) and are also listed in NOAA's Tropical Cyclone Reports (Ike in Berg 2009, Irene in Avila and Cangialosi 2011, Sandy in Blake et al. 2013, and Arthur in

Berg 2015). For each hurricane, we gather key parameters including landfall date and location, storm path, wind speed, and area affected.

We estimate consumer stockpiling propensity and in-store product availability of individual store outlets by matching hurricane event data with retail-level data. We collect retail-level information from the Nielsen Retail Scanner Data, which captures grocery sales from major retail chains across U.S. markets.² The dataset consists of information on product category, sales volume, and store environment generated by point-of-sale systems from participating retail chains. Specifically, we collect data on the bottled water product category, an essential emergency category in hurricane preparedness, and we compare various formats of store outlets impacted by the four hurricanes.

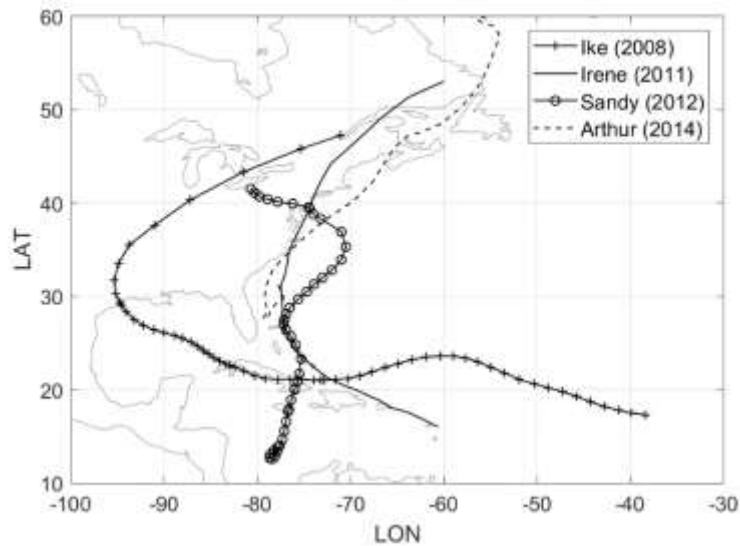


Figure 2: The storm tracks of Hurricanes Ike (2008), Irene (2011), Sandy (2012) and Arthur (2014)

3.2. Sample Description

We match each hurricane event with the affected states and keep all store outlets within the affected states as our initial sample, generating 60,146 store-event observations. Limiting our attention to observations

2

that are potentially affected by hurricane events, we refine our sample following cleaning approaches used in the literature, ultimately resulting in 38,418 store-event observations. The refinement steps are explained below.

Hurricane landfall. We first use distance to landfall to determine geographic areas affected by the sample hurricanes. Beatty et al. (2018) explored hurricane preparedness within 125 miles of landfall points, which corresponds to the “2/3 probability circle” for Atlantic Basin tropical cyclone forecasts for approximately 48 to 72 hours before expected landfall. The National Hurricane Center (NHC) issues a five-day ‘cone of uncertainty’ to indicate the probable track of the center of a tropical cyclone.³ The radii of the cone circles are set to enclose 2/3 of the historical track forecast probabilities; namely, “2/3 probability circles”. We note that the threshold used by Beatty et al. (2018) limits the study of consumer stockpiling behavior, as it does not account for potential wide-ranging impacts due to storm path uncertainty. In practice, potentially hazardous conditions may occur inside or outside of the cone; for example, a storm surge may stretch up to 1,000 miles wide causing flood damage across a large coastal area. Therefore, to study consumer stockpiling due to forecasted hurricanes, we extend Beatty et al.’s (2018) measure and study store outlets within 1,000 miles of the expected landfall points.

Hurricane size. We further refine the geographic area affected by the sample hurricanes based on the size of the hurricane. The size of the NHC’s annual “cone of uncertainty” is fixed for all storms and does not vary for forecasts during the hurricane season. Moreover, the cone only contains the probable path of the storm center but does not account for the size of a specific storm. The radius of the outermost closed isobar (ROCI) is a parameter that can be used to determine the size of a specific hurricane (or more formally, tropical cyclone) (Cangialosi and Landsea 2016, Carrasco et al. 2014, Demuth et al. 2006). It is measured as the average of the radii from the center of the storm to its outermost closed isobar. The values are determined every six hours in real time, and generally delimit the outermost extent of a

³ The National Hurricane Center defines the ‘cone of uncertainty’ as: “*The cone represents the probable track of the center of a tropical cyclone, and is formed by enclosing the area swept out by a set of circles (not shown) along the forecast track (at 12, 24, 36 hours, etc.). The size of each circle is set so that two-thirds of historical official forecast errors over a 5-year sample fall within the circle.*”

hurricanes' wind circulation.⁴ These hurricane data were collected from the Extended Best Tracks (EBT) dataset by Demuth et al. (2006). We refine the boundary of the hurricane-affected area utilizing the median of ROCI for each sample hurricane event (230 miles for Ike, 345 miles for Irene, 483 miles for Sandy, and 207 miles for Arthur).

Event clustering. We address potential concerns over event clustering in applying the event study method. Event clustering may impact the independence assumption of the variables of interest (Brown and Warner 1985). As two successive hurricane events may affect the same geographic areas within a short time window, such event clustering may contaminate the variables of interest (namely, consumer stockpiling propensity and in-store product availability). For example, Ike made landfall on September 13, 2008, while Gustav made landfall 12 days prior, on September 1, 2008. Among the fourteen states affected by Ike, four states (FL, LA, TX, and AR) were also affected by Gustav. Using data from stores in the overlapping area affected by the two hurricanes can bias the estimation with respect to individual hurricane events. Thus, for hurricane Ike, we do not incorporate the four states with event-clustering concerns. In this study, Gustav was not included in our samples due to its limited-ranging impact within the continental U.S.

3.3. Event Study

We utilize the event study approach to estimate the two variables of interest: consumer stockpiling propensity and in-store product availability. To match the retail-level data with the hurricane event data, we define four hurricane event periods for each store outlet as follows based on our weekly calendar (i.e., Sunday through Saturday) retail data availability.

A hurricane can be tracked for around two weeks from formation to dissipation. We split this event duration into two periods: an EARLY event week and a LATE event week. We identify the

⁴ Three parameters are usually chosen to define the size of a tropical cyclone: the radius of maximum wind (RMW), the average 34-knot radius (AR34), and the radius of the outermost closed isobar (ROCI) (Cangialosi and Landsea 2016, Carrasco et al. 2014, Demuth et al. 2006). From a retail operations perspective, consumers may show stockpiling propensity beyond the thresholds of RMW and AR34; therefore, we utilize the most relevant parameter, ROCI, to study consumer stockpiling propensity.

INFLUENCE date for each sample store outlet as the date when the hurricane track is in closest proximity to the store in the observation. The EARLY event week is a calendar week that contains at least four days before the INFLUENCE date (not including the INFLUENCE date). The LATE event week is the week after the EARLY event week. We then define a PRE event period as the four weeks preceding the EARLY event week and a POST event period as the four weeks following the LATE event week.⁵ Using the PRE event period as a benchmark, we estimate consumer stockpiling propensity during the EARLY event period and in-store product availability during the LATE and POST event periods.⁶

Table 1 illustrates the event periods surrounding the four sample hurricane events. Given the availability of the weekly calendar retail data, the estimation of consumer stockpiling propensity requires the EARLY event week to contain most of days during the week before the INFLUENCE date.⁷ To capture variation of the INFLUENCE date during the EARLY event week, we control for the number of sales days before the INFLUENCE date during the EARLY event week in our estimations.

Table 1: The Event Periods for the Four Hurricanes in the Sample

Name	LANDFALL Date	INFLUENCE Dates	INFLUENCE Date minus LANDFALL Date (Range)	# of Days in EARLY prior to INFLUENCE Date (Range)	PRE Period (4 Weeks)	EARLY Period (1 Week)	LATE Period (1 Week)	POST Period (4 Weeks)
Ike 2008	09/13 (Sat)	09/12 - 09/14 (Fri - Sun)	(-1, 1)	(5, 7)	08/10 - 09/06 (Sun - Sat)	09/07 - 09/13 (Sun - Sat)	09/14 - 09/20 (Sun - Sat)	09/21 - 10/18 (Sun - Sat)
Irene 2011	08/27 (Sat)	08/25 - 08/29 (Thu - Mon)	(-2, 2)	(4, 7)	07/24 - 08/20 (Sun - Sat)	08/21 - 08/27 (Sun - Sat)	08/28 - 09/03 (Sun - Sat)	09/04 - 10/01 (Sun - Sat)
Sandy 2012	10/29 (Mon)	10/26 - 10/31 (Fri - Wed)	(-3, 2)	(5, 7)	09/23 - 10/20 (Sun - Sat)	10/21 - 10/27 (Sun - Sat)	10/28 - 11/03 (Sun - Sat)	11/04 - 12/01 (Sun - Sat)
Arthur 2014	07/04 (Fri)	07/01 - 07/02 (Tue - Wed)	(-3, -2)	(7, 7)	05/25 - 06/21 (Sun - Sat)	06/22 - 06/28 (Sun - Sat)	06/29 - 07/05 (Sun - Sat)	07/06 - 08/02 (Sun - Sat)
		07/03 - 07/05 (Thu - Sat)	(-1, 1)	(4, 6)	06/01 - 06/28 (Sun - Sat)	06/29 - 07/05 (Sun - Sat)	07/06 - 07/12 (Sun - Sat)	07/13 - 08/09 (Sun - Sat)

Note that the INFLUENCE date may either happen before or after a hurricane actually makes landfall. Landfall is the intersection of the surface center of a tropical cyclone with a coastline. As the

⁵ For this study, we pre-define a four-week PRE event period and a four-week POST event period for all four hurricane events to keep a similar degree of demand subject to seasonality.

⁶ In the current analysis INFLUENCE date is defined as the date of the hurricane's nearest proximity. As an alternative, we test the results when INFLUENCE date is defined as the landfall date, giving rise to similar insights. We thank the anonymous referee for suggesting the current definition of INFLUENCE date.

⁷ For example, if the INFLUENCE date is on Thursday, Friday or Saturday, we use the week containing the INFLUENCE date as the EARLY event week, but if it is on Sunday, Monday, Tuesday, or Wednesday, we take the previous week as the EARLY event week.

strongest winds in a tropical cyclone are not located precisely at the center, it is possible for a cyclone's strongest winds to be experienced before landfall.⁸ To capture the interaction of LANDFALL date and INFLUENCE date on consumer stockpiling behavior, we control for the elapsed time between the LANDFALL and INFLUENCE dates.⁹

3.4. Estimation Model

We conduct our analysis in two steps. In estimating consumer stockpiling propensity during the EARLY event period, we utilize the supply-side, demand-side, and disaster characteristics as independent variables. In estimating in-store availability during the LATE and POST events periods, we treat stockpiling propensity during the EARLY event week as an endogenous variable. Accordingly, we employ two-stage least squares estimation (2SLS), thereby using the estimated values of stockpiling propensity instead of their actual values. To obtain the estimated values for consumer stockpiling propensity during the EARLY event periods, we utilize market geodemographic features as instrumental variables.

Equations (1) and (2) are the first and second stage regressions, respectively, where $STOCK_PROP_{ich}$ and $PRODUCT_AVAIL_{ich}$ are the dependent variables observed for individual store outlet i located in county c affected by hurricane event h ; $\delta_c (\theta_c)$ is the unobserved county-invariant individual effects; $\mu_{ich} (\varepsilon_{ich})$ is the error term. The variables are fully defined in 3.5.

⁸ The 2019 hurricane, Dorian, is an illustration of this phenomenon. The coastal area of Florida was influenced by the hurricane (September 2-4) prior to its landfall in North Carolina (September 6).

⁹ Some hurricanes may make multiple landfalls. For example, hurricane Irene in 2011 made landfalls in Cape Lookout, NC, at 12:00 on August 27, Brigantine Island, NJ, at 09:35 on August 28, and Coney Island, NY, at 13:00 on August 28. We use the first landfall date, while controlling for the elapsed time from the first landfall to when the hurricane track is in proximity to the store in the observation.

Step 1: Consumer Stockpiling Propensity

$$\begin{aligned}
\text{LN}(\text{STOCK_PROP}_{\text{ich}}) = & \beta_0 \\
& + \beta_1 \cdot \text{INTRA_NTW_COUNTY}_{\text{ich}} + \beta_2 \cdot (\text{INTRA_NTW_COUNTY}_{\text{ich}})^2 \\
& + \beta_3 \cdot \text{INTER_NTW_COUNTRY}_{\text{ich}} + \beta_4 \cdot (\text{INTER_NTW_COUNTRY}_{\text{ich}})^2 \\
& + \beta_5 \cdot \text{PROD_VAR_SKU}_{\text{ich}} + \beta_6 \cdot (\text{PROD_VAR_SKU}_{\text{ich}})^2 \\
& + \beta_7 \cdot \text{HUR_EXP_STATE}_{\text{ich}} + \beta_8 \cdot (\text{HUR_EXP_STATE}_{\text{ich}})^2 \\
& + \beta_9 \cdot \text{PER_CAPITA_INC}_{\text{ich}} + \beta_{10} \cdot (\text{PER_CAPITA_INC}_{\text{ich}})^2 \\
& + \beta_{11} \cdot \text{HUR_LANDFALL_DIST}_{\text{ich}} + \beta_{12} \cdot (\text{HUR_LANDFALL_DIST}_{\text{ich}})^2 \\
& + \beta_{13} \cdot \text{HUR_TRACK_DIST}_{\text{ich}} + \beta_{14} \cdot (\text{HUR_TRACK_DIST}_{\text{ich}})^2 \\
& + \beta_{15} \cdot \text{HUR_TRACK_WIND}_{\text{ich}} + \beta_{16} \cdot (\text{HUR_TRACK_WIND}_{\text{ich}})^2 \\
& + \beta_{17} \cdot \text{RETAIL_FORMAT}_{\text{ich}} + \beta_{18} \cdot \text{RETAIL_CHAIN}_{\text{ich}} \\
& + \beta_{19} \cdot \text{DAYS_BEF_INFLUENCE_EARLY}_{\text{ich}} + \beta_{20} \cdot \text{DAYS_INFLUENCE_AFT_LANDFALL}_{\text{ich}} \\
& + \beta_{21} \cdot \text{VOL_COUNTY}_{\text{ich}} + \beta_{22} \cdot \text{VOL_STATE}_{\text{ich}} + \beta_{23} \cdot \text{HHI_COUNTY}_{\text{ich}} + \beta_{24} \cdot \text{HHI_STATE}_{\text{ich}} \\
& + \beta_{25} \cdot \text{POP_DEN_COUNTY}_{\text{ich}} + \beta_{26} \cdot \text{LAND_AREA_COUNTY}_{\text{ich}} + \beta_{27} \cdot \text{WATER_AREA_COUNTY}_{\text{ich}} \\
& + \beta_{28} \cdot \text{POP_DEN_STATE}_{\text{ich}} + \beta_{29} \cdot \text{LAND_AREA_STATE}_{\text{ich}} + \beta_{30} \cdot \text{WATER_AREA_STATE}_{\text{ich}} \\
& + \delta_c + \mu_{\text{ich}}
\end{aligned} \tag{1}$$

Step 2: In-Store Product Availability

$$\begin{aligned}
\text{LN}(\text{PRODUCT_AVAIL}_{\text{ich}}) = & \gamma_0 + (\alpha \cdot \text{PREDICTED_STOCK_PROP}_{\text{ich}}) \\
& + \gamma_1 \cdot \text{INTRA_NTW_COUNTY}_{\text{ich}} + \gamma_2 \cdot (\text{INTRA_NTW_COUNTY}_{\text{ich}})^2 \\
& + \gamma_3 \cdot \text{INTER_NTW_COUNTRY}_{\text{ich}} + \gamma_4 \cdot (\text{INTER_NTW_COUNTRY}_{\text{ich}})^2 \\
& + \gamma_5 \cdot \text{PROD_VAR_SKU}_{\text{ich}} + \gamma_6 \cdot (\text{PROD_VAR_SKU}_{\text{ich}})^2 \\
& + \gamma_7 \cdot \text{HUR_EXP_STATE}_{\text{ich}} + \gamma_8 \cdot (\text{HUR_EXP_STATE}_{\text{ich}})^2 \\
& + \gamma_9 \cdot \text{PER_CAPITA_INC}_{\text{ich}} + \gamma_{10} \cdot (\text{PER_CAPITA_INC}_{\text{ich}})^2 \\
& + \gamma_{11} \cdot \text{HUR_LANDFALL_DIST}_{\text{ich}} + \gamma_{12} \cdot (\text{HUR_LANDFALL_DIST}_{\text{ich}})^2 \\
& + \gamma_{13} \cdot \text{HUR_TRACK_DIST}_{\text{ich}} + \gamma_{14} \cdot (\text{HUR_TRACK_DIST}_{\text{ich}})^2 \\
& + \gamma_{15} \cdot \text{HUR_TRACK_WIND}_{\text{ich}} + \gamma_{16} \cdot (\text{HUR_TRACK_WIND}_{\text{ich}})^2 \\
& + \gamma_{17} \cdot \text{RETAIL_FORMAT}_{\text{ich}} + \gamma_{18} \cdot \text{RETAIL_CHAIN}_{\text{ich}} \\
& + \gamma_{19} \cdot \text{DAYS_BEF_INFLUENCE_EARLY}_{\text{ich}} + \gamma_{20} \cdot \text{DAYS_INFLUENCE_AFT_LANDFALL}_{\text{ich}} \\
& + \gamma_{21} \cdot \text{VOL_COUNTY}_{\text{ich}} + \gamma_{22} \cdot \text{VOL_STATE}_{\text{ich}} + \gamma_{23} \cdot \text{HHI_COUNTY}_{\text{ich}} + \gamma_{24} \cdot \text{HHI_STATE}_{\text{ich}} \\
& + \gamma_{25} \cdot \text{CHANGE_VOL_LATE_POST}_{\text{ich}} \\
& + \theta_c + \mu_{\text{ich}}
\end{aligned} \tag{2}$$

3.5. Variable Definitions

Dependent Variables

Consumer stockpiling propensity (STOCK_PROP_EARLY) is estimated for the EARLY event week. For each sample store outlet observation, the variable represents the ratio of the sales volume of the bottled

water category during the EARLY event week to the average weekly sales volume during the four PRE event weeks.¹⁰ **In-store product availability** (PRODUCT_AVAIL_LATE_POST) is estimated for the LATE event week and for each of the POST event weeks. Ideally, the measure for in-store product availability would be an inventory count of the stock-keeping units of bottled water relative to the PRE period. However, inventory counts are not publicly available to the researchers. Thus, similar to Gallino et al. (2016), we estimate in-store product availability using retail sales data. A possible measurement bias is that the number of product SKUs sold may be related to the sales volume, which we address using two methods. First, we estimate in-store product availability using a ratio-based measurement, the ratio of the number of product SKUs sold during the LATE (or each of the POST) event week(s) relative to the weekly average of the four PRE event weeks.¹¹ Second, we control for sales volume changes in the estimation model, using a variable that measures the difference between the sales volume during the LATE (or each of the POST) event week(s) and the weekly average of the four PRE event weeks.¹²

Independent Variables

The independent variables include supply-side, demand-side, and disaster characteristics. We focus on two supply-side characteristics: retail network and product variety. **Retail network** is defined as the number of stores within a geographic market belonging to the same retail chain as the sample store outlet (Rajagopalan 2013). For each sample store outlet, we measure its intra-regional store network at the county level (INTRA_NTW_COUNTY) and inter-regional store network at the country-level (INTER_NTW_COUNTRY). **Product variety** (PROD_VAR_SKU) is defined as the number of product

¹⁰ For each store outlet, we let VOL_PRE_i be the sales volume for each of the four PRE event weeks and VOL_EARLY be the sales volume for the EARLY event week. Thus, consumer stockpiling propensity in EARLY event week is $STOCK_PROP_EARLY = VOL_EARLY / \frac{1}{4} \sum_{i=1}^4 VOL_PRE_i$.

¹¹ For each store outlet observation, we let SKU_PRE_i be the number of different SKUs sold during each of the four PRE event weeks, and let SKU_LATE denote the number of different SKUs sold during the LATE event week. Thus, in-store product availability for the LATE event week is given by $PRODUCT_AVAIL_LATE = SKU_LATE / \frac{1}{4} \sum_{i=1}^4 SKU_PRE_i$, with similar expressions for in-store product availability for the four POST event weeks.

¹² In Section 4.3., we conduct another robustness check by accounting for alternative methods for estimating in-store product availability, in particular, by setting the maximum weekly number of product SKUs sold during the four PRE event weeks as a benchmark. As noted therein, the results are consistent with our primary findings.

SKUs in the bottled water category sold by a sample store outlet over the entire calendar year of the corresponding hurricane event.

We employ two demand-side characteristics: disaster experience and household income. **Disaster experience** (HUR_EXP_STATE) counts the number of historical landfalls experienced by an affected state before a hurricane event in the past 20 years. The hurricane landfall history, recorded by NOAA, is based on the historical record of continental hurricanes making landfalls in the United States. **Household income** (PER_CAPITA_INC) is a measure of the average household income level of the county where a sample store outlet is located. We utilize the county's per-capita household income in the analysis, collected from the U.S. Census Bureau.

We concentrate on three disaster-related characteristics: landfall distance, track distance, and wind speed. **Landfall distance** (HUR_LANDFALL_DIST) indicates the minimum distance from the county where a store outlet is located to landfall points. The latitude and longitude of the counties and the latitude and longitude of hurricane landfall locations are from the U.S. Census Bureau and NOAA, respectively. **Track distance** (HUR_TRACK_DIST) measures the minimum distance from the county where the store outlet is located to the hurricane track. The latitude and longitude of the hurricane track are from NOAA, which tracks the hurricane every six hours from hurricane formation to dissipation. **Wind speed** (HUR_TRACK_WIND) measures the intensity of the storm wind when the hurricane is in close proximity to a sample store outlet. The wind speed information associated with each documented hurricane track location is from NOAA.

Control Variables

We first control for retail format and retail chain measures. **Retail format** is defined as a vector of dummy variables indicating the store format type: grocery (CHAIN_GROC), warehouse clubs (CHAIN_WHS), discount (CHAIN_DISC), dollar (CHAIN_DOLLAR), drug (CHAIN_DRUG), liquor (CHAIN_LIQ), and convenience (CHAIN_CONV). We utilize the convenience store format as the base case

in our analysis. **Retail chain** (RETAIL_CHAIN) is defined as a vector of dummy variables indicating the retail chain the store belongs to.

We also control for category volume and market competition in the bottled water category. **Category volume** is the annual sales volume of the bottled water category sold by all the stores belonging to the same chain as the sample store outlet in a geographic market—at the county level (VOL_COUNTY) and at the state level (VOL_STATE). We measure **category competition** using the Herfindahl-Hirschman index (HHI) at the county-level (HHI_COUNTY) and state-level (HHI_STATE). HHI is the summation of the squared market share (by sales volume) of individual stores competing in the market (Hendel and Nevo 2006).¹³

We further capture the effects of INFLUENCE date and LANDFALL date. Given our use of weekly retail-level data, we control for the number of sales days before the INFLUENCE date during the EARLY week (DAYS_BEF_INFL_EARLY), as well as for the number of days between LANDFALL and the INFLUENCE date (DAYS_INFL_AFT_LANDFALL) for each store outlet.

We also utilize **geodemographic features** of the county and the state where a store outlet is located as instrumental variables. Variables include population density (POP_DEN_COUNTY and POP_DEN_STATE), land area (LAND_AREA_COUNTY and LAND_AREA_STATE), and water area (WATER_AREA_COUNTY and WATER_AREA_STATE). Geodemographic data is obtained from the U.S. Gazetteer Files (U.S. Census Bureau 2010, 2012, 2014).¹⁴

Since inventory counts of the stock-keeping units are not publicly available to researchers, we estimate in-store product availability using retail sales data. We also control for changes in sales volume (CHANGE_VOL_LATE\POST) in the estimation model, which captures the difference between the sales volume during the LATE (or each of the POST) event week(s) and the weekly average of the four PRE event weeks.

¹³ HHI is a measure of competition intensity. It ranges between 0 and 1, where the former indicates the theoretical perfectly competitive environment and whereas the latter reflects a monopolistic setting. HHI is calculated by taking into account all individual stores competing in a market, including stores of the same chain.

¹⁴ For hurricane Ike in 2008 and Irene in 2011, since the 2008 and 2011 U.S. Gazetteer Files are not available online, we use data from 2010 U.S. Gazetteer Files as the closest approximation.

Table 2 illustrates the descriptive statistics. In the estimation models, we log transform the dependent variables; that is, $\text{LN}(\text{STOCK_PROP}) \times 1000$ and $\text{LN}(\text{PRODUCT_AVAIL}) \times 1000$. Table A1 in Appendix I presents the correlation matrix after data transformations.

Table 2: Data Description

Variable	Unit	Mean	Std. Dev.	Min	Max
<u>Dependent Variable</u>					
<u>Consumer Stockpiling Propensity</u>					
STOCK_PROP_EARLY	Ratio	1.585	0.914	0.188	5.728
<u>In-Store Product Availability</u>					
PRODUCT_AVAIL_LATE	Ratio	0.983	0.135	0.057	3.692
PRODUCT_AVAIL_POST_W1	Ratio	0.949	0.125	0.024	4.000
PRODUCT_AVAIL_POST_W2	Ratio	0.956	0.124	0.024	4.000
PRODUCT_AVAIL_POST_W3	Ratio	0.951	0.126	0.048	4.513
PRODUCT_AVAIL_POST_W4	Ratio	0.952	0.126	0.020	4.513
<u>Independent Variable</u>					
<u>Supply-Side Characteristics</u>					
INTRA_NTW_COUNTRY	100 Stores	0.192	0.321	0.010	2.660
INTER_NTW_COUNTRY	100 Stores	38.455	31.708	0.010	84.840
PROD_VAR_SKU	Number of Product SKUs	93.869	65.189	1.000	340.000
<u>Demand-Side Characteristics</u>					
HUR_EXP_STATE	Number of Recent Landfalls	3.503	5.299	0.000	14.000
PER_CAPITA_INC	10K Dollars	4.647	1.747	1.710	15.321
<u>Disaster Characteristics</u>					
HUR_LANDFALL_DIST	100 Miles	3.559	2.615	0.036	9.969
HUR_TRACK_DIST	100 Miles	1.709	1.006	0.029	4.820
HUR_TRACK_WIND	Miles Per Hour	61.497	14.171	30.000	90.000
<u>Control Variable</u>					
<u>Retail Format</u>					
CHAIN_GROC	Dummy Variable (Binary)	0.280	0.449	0.000	1.000
CHAIN_WHS	Dummy Variable (Binary)	0.013	0.113	0.000	1.000
CHAIN_DISC	Dummy Variable (Binary)	0.076	0.265	0.000	1.000
CHAIN_DOLLAR	Dummy Variable (Binary)	0.191	0.393	0.000	1.000
CHAIN_DRUG	Dummy Variable (Binary)	0.381	0.486	0.000	1.000
CHAIN_LIQ	Dummy Variable (Binary)	0.009	0.092	0.000	1.000
CHAIN_CONV	Dummy Variable (Binary)	0.050	0.219	0.000	1.000
<u>Retail Chain</u>					
RETAIL_CHAIN	60 Dummy Variables (Binary)				
<u>Hurricane Influence</u>					
DAYS_BEF_INFL_EARLY	Days	6.376	0.907	4.000	7.000
DAYS_INFL_AFT_LANDFALL	Days	0.337	1.284	-3.000	2.000
<u>Category Competition</u>					
VOL_COUNTY	100,000,000 OZ	0.923	1.773	0.000	17.744
VOL_STATE	100,000,000 OZ	9.565	12.329	0.001	52.037
HHI_COUNTY	Herfindahl-Hirschman Index	0.129	0.162	0.005	1.000
HHI_STATE	Herfindahl-Hirschman Index	0.006	0.010	0.001	0.085
<u>Geodemographic Feature</u>					
POP_DEN_COUNTY	100 People Per Square Miles	33.311	103.409	0.043	722.531
LAND_AREA_COUNTY	100 Square Miles	6.363	4.645	0.227	66.711
WATER_AREA_COUNTY	100 Square Miles	1.288	2.437	0.000	27.542
POP_DEN_STATE	100 People Per Square Miles	6.276	9.336	0.244	375.386
LAND_AREA_STATE	100 Square Miles	235.694	160.212	0.610	550.904
WATER_AREA_STATE	100 Square Miles	33.765	34.517	0.002	325.393
<u>Changes in Sales Volume</u>					
CHANGE_VOL_LATE	10,000 OZ	1.316	14.194	-352.753	163.935
CHANGE_VOL_POST_W1	10,000 OZ	-1.176	6.901	-154.377	207.076
CHANGE_VOL_POST_W2	10,000 OZ	-1.620	8.299	-432.665	93.727
CHANGE_VOL_POST_W3	10,000 OZ	-2.288	11.464	-517.063	234.140
CHANGE_VOL_POST_W4	10,000 OZ	-1.973	11.600	-525.439	553.752
Observations		38,418			

4. Empirical Results

We first describe the three categories of factors that influence stockpiling of bottled water – demand-side factors (related to the consumers), supply-side factors (related to the retail outlets) and hurricane characteristics. We then examine how stockpiling behavior, along with the demand, supply and hurricane characteristics, impact in-store availability of bottled water following the hurricane event.

4.1. Consumer Stockpiling Propensity

The first research question addressed is: How do supply-side, demand-side, and disaster characteristics affect consumer stockpiling propensity during the EARLY event period? In Table 3, we set consumer stockpiling propensity during the EARLY event week as the dependent variable. Model 1.1, Model 1.2, and Model 1.3, in turn, add the supply-side, demand-side, and disaster characteristics as the focal independent variables. We utilize Model 1.4, the complete model, to describe our results. Figures 3, 4, and 5 reflect the effects of changes in the independent variables on the dependent variable (unlogged).¹⁵ In the three subsections, we study the impacts of supply-side, demand-side, and disaster-related characteristics on consumer stockpiling propensity.

¹⁵ As we utilize semi log regression models, Figures 3, 4, and 5 reflect the effects of changes in the independent variables on dependent variable (unlogged). The interpretation of the estimated coefficient $\hat{\beta}$ is that a c-unit increase in the independent variable will produce an expected increase in dependent variable (unlogged) by a factor of $e^{\hat{\beta}}$ (multiplied by $e^{c\hat{\beta}}$).

Table 3: Estimation Results (Consumer Stockpiling Propensity)

Dependent Variable LN(STOCK_PROP) × 1000	Model 1.1 EARLY Week	Model 1.2 EARLY Week	Model 1.3 EARLY Week	Model 1.4 EARLY Week
<u>Supply-Side Characteristics</u>				
INTRA_NTW_COUNTRY	-360.907*** (24.538)			-240.142*** (22.048)
(INTRA_NTW_COUNTRY) ²	60.665*** (9.493)			54.690*** (8.454)
INTER_NTW_COUNTRY	5.208** (1.889)			30.489*** (1.680)
(INTER_NTW_COUNTRY) ²	-0.012 (0.015)			-0.264*** (0.014)
PROD_VAR_SKU	1.848*** (0.308)			1.009*** (0.271)
(PROD_VAR_SKU) ²	-0.007*** (0.001)			-0.004*** (0.001)
<u>Demand-Side Characteristics</u>				
HUR_EXP_STATE		85.294*** (3.412)		-0.503 (3.390)
(HUR_EXP_STATE) ²		-6.652*** (0.273)		0.654* (0.271)
PER_CAPITA_INC		215.120*** (7.654)		93.358*** (7.006)
(PER_CAPITA_INC) ²		-13.290*** (0.557)		-5.343*** (0.506)
<u>Disaster Characteristics</u>				
HUR_LANDFALL_DIST			-151.661*** (4.741)	-152.738*** (4.788)
(HUR_LANDFALL_DIST) ²			7.933*** (0.425)	7.816*** (0.431)
HUR_TRACK_DIST			-174.498*** (9.070)	-166.996*** (9.045)
(HUR_TRACK_DIST) ²			23.926*** (1.900)	21.949*** (1.898)
HUR_TRACK_WIND			22.597*** (1.259)	23.464*** (1.304)
(HUR_TRACK_WIND) ²			-0.191*** (0.010)	-0.205*** (0.011)
<u>Retail Format</u>				
CHAIN_GROC	-548.548*** (109.380)	-432.760*** (106.804)	-346.533*** (95.401)	-198.446* (95.916)
CHAIN_WHS	223.843*** (31.807)	253.918*** (30.770)	156.904*** (27.503)	170.458*** (27.911)
CHAIN_DISC	-79.243 (72.900)	-122.834* (71.924)	23.173 (64.257)	133.965* (63.928)
CHAIN_DOLLAR	282.193*** (63.479)	454.057*** (25.131)	401.030*** (22.324)	-228.637*** (56.393)
CHAIN_DRUG	478.347*** (39.332)	405.356*** (38.477)	345.657*** (34.383)	450.413*** (34.525)
CHAIN_LIQ	236.486*** (59.304)	68.901 (57.506)	111.381* (51.245)	208.720*** (52.014)
<u>Retail Chain</u>				
RETAIL_CHAIN	Included	Included	Included	Included
<u>Hurricane Influence</u>				
DAYS_BEF_INFL_EARLY	67.337*** (2.865)	67.131*** (2.815)	20.341*** (3.765)	9.789* (3.916)
DAYS_INFL_AFT_LANDFALL	25.426*** (2.774)	10.848*** (2.945)	-29.978*** (2.566)	-28.854*** (2.856)
<u>Category Competition</u>				
VOL_COUNTY	2.451 (2.383)	-26.438*** (1.997)	-8.129*** (1.796)	4.807* (2.093)
VOL_STATE	5.860*** (0.370)	4.988*** (0.367)	4.674*** (0.326)	4.117*** (0.327)
HHI_COUNTY	-180.135*** (15.927)	109.918*** (16.817)	-42.010** (13.495)	22.695 (15.357)
HHI_STATE	1,773.741*** (289.161)	2,236.301*** (286.575)	2,185.494*** (255.476)	2,206.930*** (254.474)
<u>Geodemographic Feature</u>				
POP_DEN_COUNTY	0.357*** (0.040)	0.506*** (0.053)	-0.426*** (0.034)	-0.052 (0.049)
LAND_AREA_COUNTY	-4.638*** (0.617)	-0.188 (0.632)	1.786** (0.552)	4.581*** (0.567)
WATER_AREA_COUNTY	1.541 (1.293)	-10.499*** (1.289)	-0.046 (1.134)	-0.534 (1.175)
POP_DEN_STATE	-0.969** (0.353)	-1.918*** (0.355)	-2.590*** (0.313)	-3.433*** (0.315)
LAND_AREA_STATE	-0.854*** (0.033)	-0.896*** (0.033)	-0.684*** (0.029)	-0.620*** (0.030)
WATER_AREA_STATE	0.564*** (0.136)	1.679*** (0.150)	1.117*** (0.118)	0.652*** (0.138)
CONSTANT	-439.324*** (33.618)	-1082.873*** (38.890)	-70.532 (53.625)	-496.974*** (60.041)
Observations	38,418	38,418	38,418	38,418
F	185.35***	204.16***	377.25***	349.87***

Note: Standard errors in parentheses. * p<0.1, ** p<0.01, *** p<0.001.

4.1.1. Supply-Side Characteristics

We first examine the linkage between intra-regional store network and consumer stockpiling propensity.

For an individual store, a broader intra-regional store network may relate to more stockpiling due to store desirability (e.g., brand name recognition) or to less stockpiling due to alternate store locations (see 2.2.1). In Model 1.4, the coefficient of INTRA_NTW_COUNTRY is significantly negative (-240.142, p<0.001) and the coefficient of (INTRA_NTW_COUNTRY)² is significantly positive (54.690, p<0.001). In

Figure 3(a), intra-regional chain store network generally relates to decreasing (convex) consumer stockpiling. The histogram indicates 75% of the sample store outlets are associated with an intra-regional chain network of fewer than 22 stores. The convex relationship indicates a 4% decrease in per-store consumer stockpiling propensity as the county-level store network increases from 4 stores (25th percentile) to 22 stores (75th percentile).

Next, we explore the linkage between inter-regional store network and consumer stockpiling propensity. For an individual store, a broader inter-regional store network may accommodate more stockpiling due to inventory availability at the network given transshipment possibilities from outside the hazard-affected area. In Model 1.4, at the country level, the coefficient of INTER_NTW_COUNTRY is significantly positive (30.489, $p < 0.001$) and the coefficient of (INTER_NTW_COUNTRY)² is significantly negative (-0.264, $p < 0.001$). In Figure 3(b), inter-regional chain store network generally relates to increasing (concave) consumer stockpiling. The histogram demonstrates three groups of retail chains based on the size of the inter-regional store network, 1-2000 stores, 3000-4500 stores, and 6000-8000 stores. Among the 60 retail chains in our sample, those with an inter-regional store network of 6000-8000 stores are associated with high consumer stockpiling propensity. For example, as the country-level store network increases from 592 stores (25th percentile) to 7,308 stores (75th percentile), consumer stockpiling propensity increases by 108%.

Next, we investigate the linkage between product SKU variety and consumer stockpiling propensity. For an individual store outlet, product variety is positively associated with inventory availability but with a diminishing effect due, perhaps, to the substitutability of demand. In Model 1.4, the coefficient of PROD_VAR_SKU is significantly positive (1.009, $p < 0.001$) and the coefficient (PROD_VAR_SKU)² is significantly negative (-0.004, $p < 0.001$). Figure 3(c) implies a concave relationship, with stockpiling propensity reaching a maximum at 126 SKUs. For example, as the number of product SKUs carried by a store outlet increases from 44 SKUs (25th percentile) to 140 SKUs (75th percentile), consumer stockpiling propensity increases by 3%.

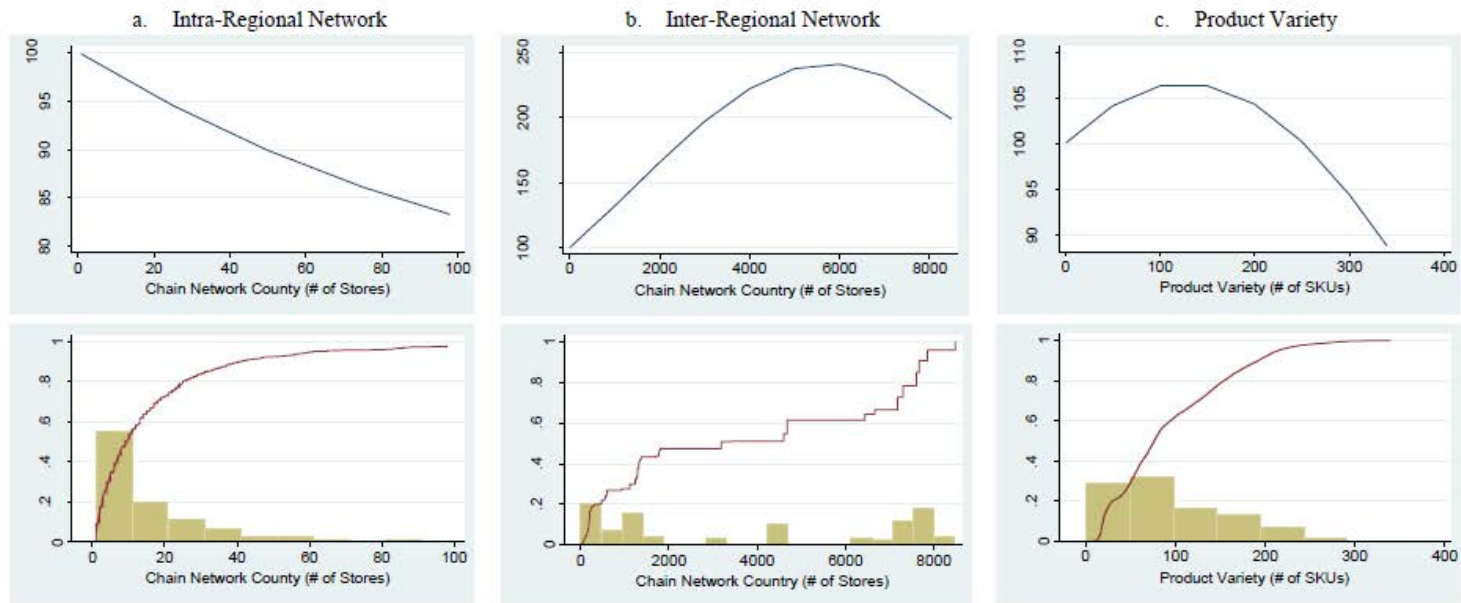


Figure 3: Supply-Side Characteristics and Consumer Stockpiling Propensity¹⁶

¹⁶ For illustration purposes, we truncate Figure 3(a) at 98 stores as this contains 97.5% of the observations. The full intra-regional network ranges to 266 stores revealing minimum stockpiling propensity at 200 stores.

4.1.2. Demand-Side Characteristics

We first explore the relationship between recent hurricane experience and consumer stockpiling propensity. Individuals with more hurricane experience may stockpile greater amounts due to higher perceived risk, or stockpile less due to seasonal preparedness or psychological inoculation. In Model 1.4, the coefficient of HUR_EXP_STATE is negative and insignificant (-0.503, $p > 0.1$) and the coefficient of (HUR_EXP_STATE)² is positive and significant (0.654, $p < 0.1$). In Figure 4(a), the results demonstrate an increasing convex relationship, with stockpiling reaching a maximum at 14 landfalls. We note that among the 25 sample states, Florida and North Carolina are the only two states that experienced over 10 landfalls during the past 20 years, while the remaining states experienced only up to 2 landfalls. Consumer stockpiling propensity at an experience level of 10 landfalls (75th percentile) is 6% higher than stockpiling propensity at 0 landfalls (25th percentile). Overall, high-risk perception due to recent hurricane experience appears to guide consumers in increasing their stockpiling behaviors.

Next, we investigate the relationship between household income levels and consumer stockpiling propensity. Consumers with a high-income level may stockpile more due to high purchasing power or stockpile less due to greater ability to vacate the hurricane zone. In Model 1.4, the coefficient of PER_CAPITA_INC is positive and significant (93.358, $p < 0.001$) and the coefficient of (PER_CAPITA_INC)² is negative and significant (-5.343, $p < 0.001$). As shown in Figure 4(b), the results imply a concave relationship reaching a maximum stockpiling propensity at a PER_CAPITA_INC value of \$87,365, with only four jurisdictions of the 963 counties (or separately incorporated cities) lying to the right of this point (i.e., having a per capita income over \$87,365). Thus, our analysis reveals a predominantly increasing concave relationship between household income and stockpiling propensity, with consumer stockpiling propensity increasing by 9% as household income increases from \$36,400 (25th percentile) to \$50,500 (75th percentile). Generally, purchasing power plays a positive role in affecting consumer stockpiling propensity, but with a diminishing impact.

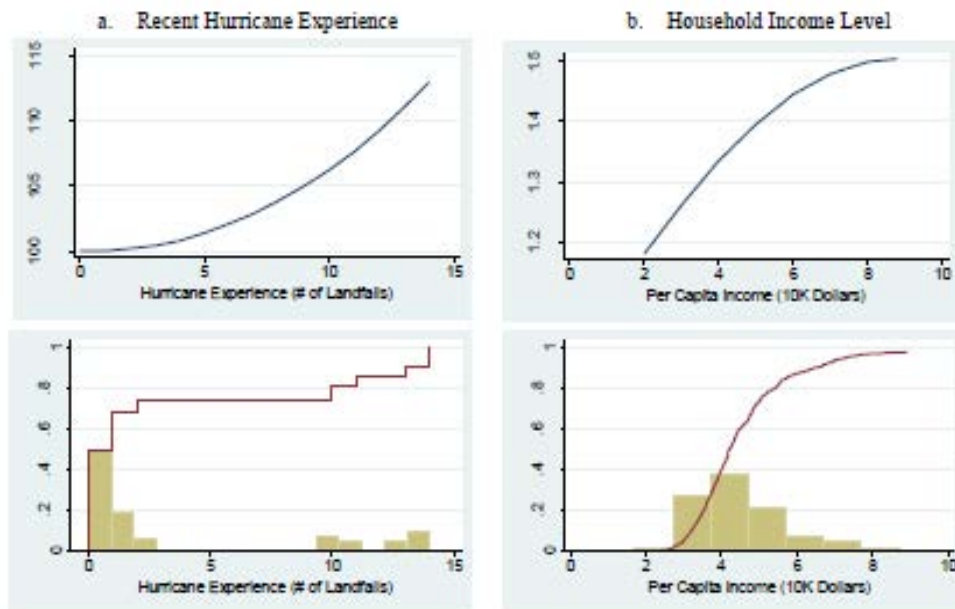


Figure 4: Demand-Side Characteristics and Consumer Stockpiling Propensity^{17,18}

4.1.3. Disaster Characteristics

We first examine the relationship between hazard proximity and consumer stockpiling propensity. In Model 1.4, the coefficient of HUR_LANDFALL_DIST is negative and significant (-152.738, $p < 0.001$) and the coefficient of $(\text{HUR_LANDFALL_DIST})^2$ is positive and significant (7.816, $p < 0.001$). In Figure 5(a), the results indicate a convex relationship, with stockpiling propensity reaching the lowest value at about 1000 miles.¹⁹ Thus, when the distance to landfall points increases from 151 miles (25th percentile) to 508 miles (75th percentile), consumer stockpiling propensity decreases by 25%. Moreover, the coefficient of HUR_TRACK_DIST is negative and significant (-166.996, $p < 0.001$) and the coefficient of $(\text{HUR_TRACK_DIST})^2$ is positive and significant (21.949, $p < 0.001$). In Figure 5(b), the results

¹⁷ For illustration purposes, we truncate Figure 4(b) at 87,800 dollars, reflecting 97.5% of the observations. The full per-capita income ranges increases to \$153,210 revealing a maximum stockpiling propensity at \$87,365.

¹⁸ In Figure 4 (a), th

¹⁹ Note that maximum distance from the county where a store outlet is located to landfall points is 996.9 miles. This value roughly coincides with our upper limit of the distance, 1000 miles. This indicates that this minimum is simply an outcome of the sample selection. Generally, one would expect the impact to further decrease with distance, so that the relationship does not achieve an absolute minimum.

demonstrate a convex relationship, with stockpiling reaching a minimum at 482 miles. Our results show that as the distance to hurricane track increases from 92 miles (25th) to 233 miles (75th), consumer stockpiling propensity decreases by 11%.

Next, we investigate the relationship between hazard intensity and consumer stockpiling propensity. The wind associated with hurricanes is one of the main causes of damage and loss of life. As the current or projected wind increases above a threshold, individuals may feel it unwise to venture out, even to purchase necessities. The coefficient of HUR_TRACK_WIND is positive and significant (23.464, $p < 0.001$) and the coefficient of $(\text{HUR_TRACK_WIND})^2$ is negative and significant (-0.205, $p < 0.001$). In Figure 5(c), the results indicate a concave relationship, with stockpiling reaching a maximum at 57 miles per hour winds and then declining as winds approach 90 miles per hour or higher. Therefore, from the perspective of hurricane development, the results imply that greater stockpiling behavior is tied to moderate wind-speed storms.

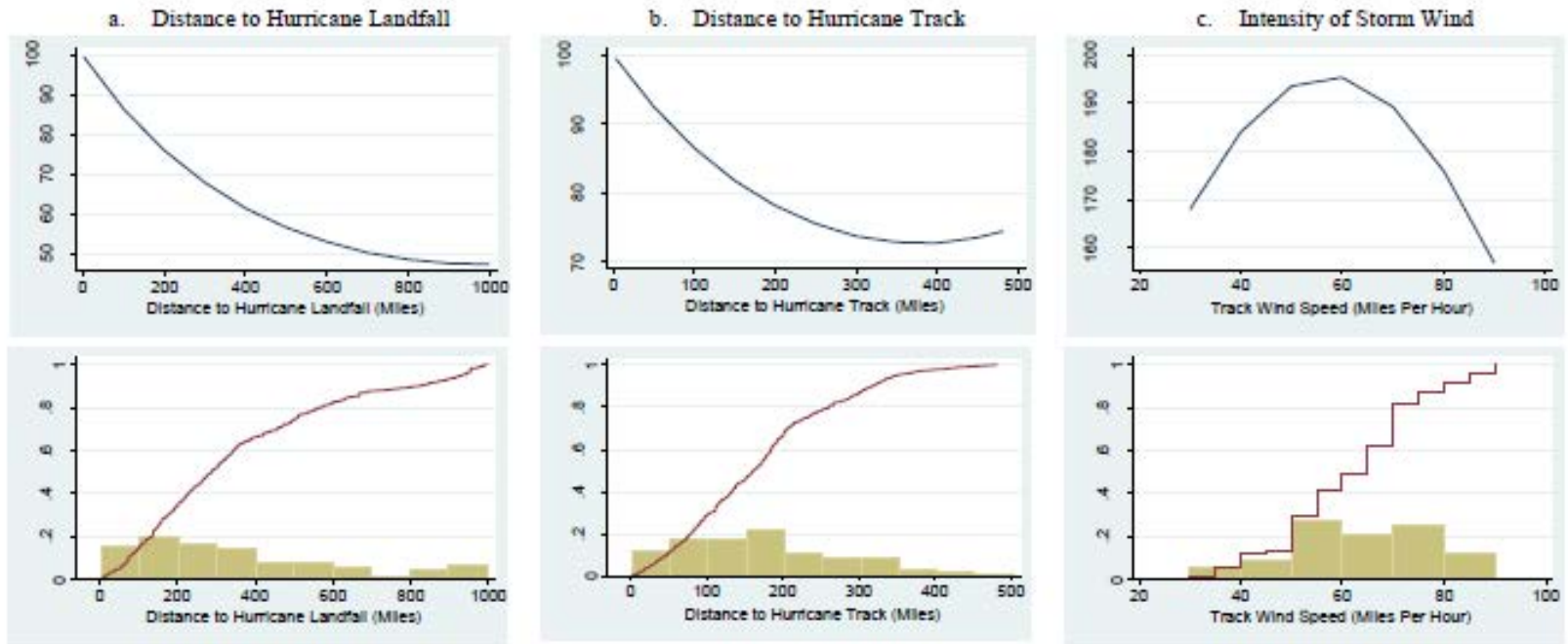


Figure 5: Disaster Characteristics and Consumer Stockpiling Propensity

4.2. In-Store Product Availability

From a managerial perspective, we have the following research question: How does consumer stockpiling propensity during the EARLY event period influence product availability during the LATE and the POST event periods? Recall both consumer stockpiling propensity and in-store product availability are measured at the store level. In Table 4, we set product availability during the LATE and POST event periods as dependent variables, while incorporating the estimated consumer stockpiling propensity during the EARLY event period estimated from the first-stage regression analysis.

We seek to explain how the effects of consumer stockpiling propensity persist during the LATE and the POST event periods. In Table 4, we find that consumer stockpiling propensity during the EARLY event period is negatively and significantly related to product availability during the LATE event week (-0.239, $p < 0.001$) and the first (-0.091, $p < 0.001$), second (-0.034, $p < 0.001$), and third POST week (-0.067, $p < 0.001$), but not fourth POST event week (-0.020, $p > 0.1$). Figure 6 illustrates the coefficients of PREDICTED_STOCK_PROP of Models 2.1-2.5, representing dynamic changes in the effects of stockpiling propensity on product availability over the LATE and POST event periods.

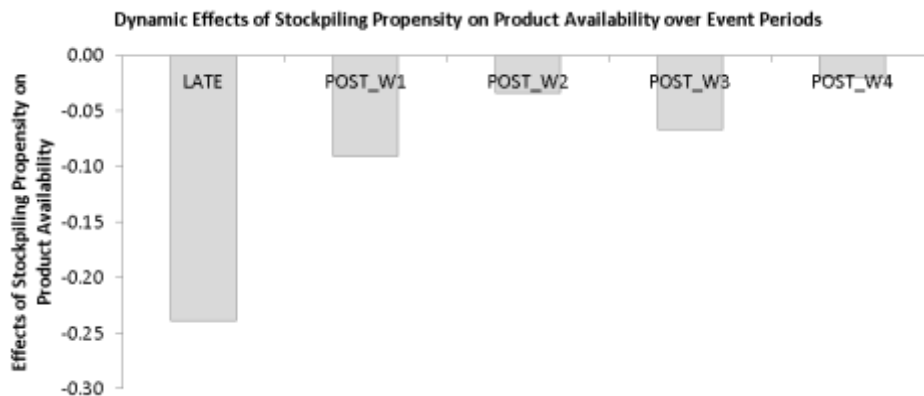


Figure 6: Stockpiling Propensity and Product Availability over Event Periods

The results demonstrate that consumer stockpiling propensity has immediate and longer-term effects on managerial stocking decisions and in-store product availability over hurricane event periods. Compared with unpredictable disasters, such as an earthquake, hurricane landfalls are largely determined

by weather patterns in place as a hurricane approaches. During the time lag between hurricane formation and landfall, retailers can use weather forecasting information to plan inventory needs and accelerate inventory supply (Target 2018). However, increased consumer stockpiling propensity may lead to lower product availability following hurricanes, specifically, during the weeks defined as the LATE event week and the POST event period in this study. These effects gradually dissipate over time. Indeed, as can be observed from Table 4, the absolute values of the coefficients of the estimated stockpiling propensity decreases as the elapsed time since the hurricane landfall increases. Further discussion of the results and relation to store formats is provided in Section 5.

Table 4: Estimation Results (In-Store Product Availability)

Dependent Variable	Model 2.1	Model 2.2	Model 2.3	Model 2.4	Model 2.5
LN(PRODUCT_AVAIL) × 1000	LATE Week	POST Week 1	POST Week 2	POST Week 3	POST Week 4
PREDICTED_STOCK_PROP	-0.239*** (0.016)	-0.091*** (0.015)	-0.034* (0.015)	-0.067*** (0.016)	-0.020 (0.016)
<u>Supply-Side Characteristics</u>					
INTRA_NTW_COUNTRY	-26.996** (9.527)	29.648** (9.111)	46.401*** (9.165)	12.383 (9.430)	8.508 (9.431)
(INTRA_NTW_COUNTRY) ²	4.691 (3.379)	-8.492** (3.232)	-13.523*** (3.251)	-0.482 (3.345)	3.653 (3.345)
INTER_NTW_COUNTRY	18.978*** (0.796)	10.123*** (0.761)	8.742*** (0.766)	3.796*** (0.788)	5.811*** (0.788)
(INTER_NTW_COUNTRY) ²	-0.135*** (0.007)	-0.087*** (0.006)	-0.076*** (0.006)	-0.037*** (0.006)	-0.043*** (0.007)
PROD_VAR_SKU	-0.108 (0.105)	0.479*** (0.101)	0.286** (0.101)	0.571*** (0.104)	0.043 (0.104)
(PROD_VAR_SKU) ²	-0.000 (0.000)	-0.001*** (0.000)	-0.001* (0.000)	-0.001*** (0.000)	0.000 (0.000)
<u>Demand-Side Characteristics</u>					
HUR_EXP_STATE	-8.852*** (1.256)	10.110*** (1.199)	2.357* (1.206)	-1.953 (1.241)	1.151 (1.241)
(HUR_EXP_STATE) ²	0.621*** (0.098)	-0.772*** (0.094)	-0.133 (0.094)	0.225* (0.097)	0.017 (0.097)
PER_CAPITA_INC	17.011*** (2.799)	8.878*** (2.676)	6.195* (2.692)	13.831*** (2.770)	11.176*** (2.771)
(PER_CAPITA_INC) ²	-1.094*** (0.179)	-0.505** (0.171)	-0.214 (0.172)	-0.657*** (0.177)	-0.461** (0.177)
<u>Disaster Characteristics</u>					
HUR_LANDFALL_DIST	-14.570*** (2.909)	-0.518 (2.782)	12.692*** (2.798)	2.695 (2.881)	5.433* (2.880)
(HUR_LANDFALL_DIST) ²	-0.193 (0.200)	-0.020 (0.192)	-1.391*** (0.193)	-0.696*** (0.198)	-1.051*** (0.198)
HUR_TRACK_DIST	-8.841* (4.398)	-10.222* (4.207)	-2.830 (4.234)	-26.254*** (4.353)	-8.870* (4.354)
(HUR_TRACK_DIST) ²	-1.702* (0.804)	1.097 (0.769)	-1.573* (0.774)	3.689*** (0.796)	1.149 (0.796)
HUR_TRACK_WIND	3.794*** (0.629)	-1.025* (0.602)	1.280* (0.606)	0.793 (0.623)	0.658 (0.623)
(HUR_TRACK_WIND) ²	-0.038*** (0.005)	0.003 (0.005)	-0.015** (0.005)	-0.010* (0.005)	-0.012* (0.005)
<u>Retail Format</u>					
CHAIN_GROC	100.702** (37.403)	27.943 (35.770)	73.632* (35.982)	26.213 (36.992)	60.416 (37.005)
CHAIN_WHS	126.327*** (11.375)	87.126*** (11.055)	56.641*** (10.967)	77.368*** (11.295)	43.902*** (11.134)
CHAIN_DISC	-23.709 (24.927)	-43.924* (23.838)	-149.839*** (23.979)	-104.881*** (24.673)	-168.821*** (24.677)
CHAIN_DOLLAR	-527.416*** (22.448)	-229.853*** (21.455)	-216.858*** (21.593)	-71.149** (22.206)	-210.309*** (22.209)
CHAIN_DRUG	130.740*** (14.857)	53.511*** (14.209)	-0.894 (14.293)	-12.869 (14.706)	-71.580*** (14.709)
CHAIN_LIQ	77.936*** (20.276)	54.747** (19.391)	-37.408* (19.506)	-18.871 (20.071)	-82.894*** (20.074)
<u>Retail Chain</u>					
RETAIL_CHAIN	Included	Included	Included	Included	Included
<u>Hurricane Influence</u>					
DAYS_BEF_INFL_EARLY	-6.561*** (1.541)	-14.584*** (1.469)	-20.868*** (1.476)	-10.894*** (1.519)	-17.570*** (1.519)
DAYS_INFL_AFT_LANDFALL	-5.414*** (1.194)	-9.799*** (1.141)	-4.548*** (1.148)	-5.664*** (1.181)	-6.314*** (1.181)
<u>Category Competition</u>					
VOL_COUNTRY	1.955* (0.818)	-0.986 (0.782)	-0.969 (0.786)	-0.540 (0.809)	0.884 (0.808)
VOL_STATE	0.469*** (0.117)	0.176 (0.112)	0.044 (0.113)	0.470*** (0.116)	0.120 (0.116)
HHI_COUNTRY	6.772 (5.838)	-15.423** (5.582)	-15.812** (5.614)	-8.835 (5.777)	-24.739*** (5.778)
HHI_STATE	499.453*** (104.259)	247.135* (99.709)	154.372 (100.299)	224.270* (103.201)	227.430* (103.218)
CHANGE_VOL_LATE_POST_W1, 2, 3, 4	Included	Included	Included	Included	Included
CONSTANT	-93.539*** (24.801)	52.651* (23.696)	21.946 (23.845)	-13.698 (24.519)	57.552* (24.522)
Observations	38,418	38,418	38,418	38,418	38,418
F	49.69***	52.16***	38.22***	32.98***	34.14***

Note: Standard errors in parentheses. * p<0.1, ** p<0.01, *** p<0.001.

4.3. Robustness Checks

As a robustness check, we apply the quantile regression technique. There is a rapidly expanding empirical quantile regression literature in economics (Koenker and Hallock 2001). Quantile regressions aim at estimating conditional median or other quantiles of the response variable as functions of observed covariates (Koenker and Bassett 1978, Koenker and Hallock 2001). Since this study involves a total of 38,418 store-event observations, we utilize simultaneous-quantile regressions for multiple classic quantiles (0.25, 0.50, and 0.75), which produce bootstrap standard errors. We illustrate the results in Table A2 in the Appendix. Qualitatively, the results are consistent with the findings reported in Table 3. However, some variations emerge; for example, we note that product variety bears no significance in predicting stockpiling propensity at the higher quantiles.

As a second robustness check, we estimate in-store product availability by considering the max of the weekly number of product SKUs sold during the four PRE event weeks as the benchmark. Since we estimate in-store product availability on a weekly basis (the LATE and each of the POST event weeks), the max value does not exist for these periods; thus, we treat in-store product availability as right-censored data estimated with a Tobit model. As illustrated in Table A3 in the Appendix, consumer stockpiling propensity during the EARLY event week is significantly negatively related to product availability during the LATE event period and first three weeks of the POST event period. The results are consistent with the primary findings in Table 4.

5. Discussion: The Role of Store Formats

Growing heterogeneity in consumer demand has led to the diversification of store formats (González-Benito et al. 2005). Consumers are influenced by store features, such as (1) product assortment, (2) pricing strategy, (3) transactional convenience, and (4) shopping experience (Messinger and Narasimhan 1997, Bustos-Reyes and Gonzalez-Benito 2008). From a demand-side perspective, the diversity of formats allows retailers to satisfy the needs of various consumer segments in different shopping situations (González-Benito et al. 2005). From a supply-side perspective, the diversity of retail formats represents a

mix of operations and distribution functions to support business strategies. Therefore, store format may relate to a retailer's disaster preparedness strategy, such as prepositioning inventory and investing in disaster management capability (Kunz et al. 2014), thus impacting consumer stockpiling propensity and in-store product availability during an environmental emergency.

During hurricane events, we expect consumer stockpiling propensity to vary among retail formats. Ranking the impacts of store formats on stockpiling propensity (utilizing Model 1.4 and setting convenience stores as the base case) we have: drug store (450.413, $p < 0.001$), liquor store (208.720, $p < 0.001$), warehouse club (170.458, $p < 0.001$), discount store (133.965, $p < 0.1$), convenience store (0, base case), grocery store (-198.446, $p < 0.1$), dollar store (-228.637, $p > 0.001$).²⁰ Among the various store formats, drug store channel is related to the highest stockpiling propensity. This implies that drug stores may play a critical role in disaster preparedness.

Moreover, following hurricane events, we also expect that operational performance, measured by in-store product availability, to vary across retail formats. To compare product availability across the various store formats over the course of hurricane events, we transform the coefficients of store formats into z-scores for each event week (Models 2.1-2.5) to represent the degree of product availability for each store format relative to the market average. Figure 7 illustrates the effects of retail formats on in-store product availability during the LATE week and the four POST event weeks. We find that grocery stores, warehouse clubs, and drug stores are associated with superior performance in in-store product availability during the LATE and the POST event period. In contrast, low-price-oriented retail channels, such as discount stores and dollar stores, are related to inferior performance in in-store product availability over the LATE and the POST event period.

²⁰ Since we use semi-log regression and the dependent variable is $\text{LN}(\text{STOCKPILING_PROP}) \times 1000$, the coefficient of the retail formats indicate the percentage change in stockpiling propensity relative to convenience stores (the base case retail format). For example, the coefficient for drug store is 450.413 implying consumer stockpiling propensity for drug stores is 45% higher than for convenience stores.

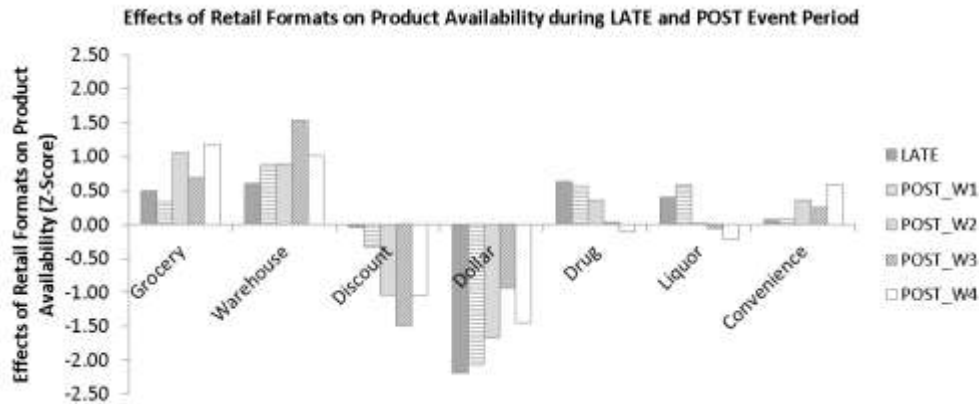


Figure 7: Retail Formats and Product Availability during LATE and POST Event Periods

Retail formats represent a mix of operations and distribution functions to support their business strategies; for example, inventory strategy varies across retail formats. Statistics by CSIMarket show that in the third quarter of 2012, the inventory turnover ratio and average inventory processing period were around 14 and 25 days, respectively, for grocery stores, such as Kroger, 12 and 32 days respectively for warehouse clubs, such as Costco, 9 and 39 days respectively for drug store channels, such as CVS, 6 and 61 days respectively for discount stores, such as Target, and 4 and 103 days respectively for dollar stores, such as Dollar Tree (CSIMarket 2012).²¹ The inventory turnover ratio and inventory planning cycle reflect, among other things, a retail chain's restoration capability, which could partially explain why low-price-oriented channels, such as discount stores and dollar stores, show the lowest in-store product availability during the LATE and the POST event period. In general, we expect high in-store product availability following hurricanes to take place at retailers with quick recovery capability.

6. Management and Policy Insights

Both retailers and governments need to understand the impacts of supply-side, demand-side, and disaster characteristics on consumer stockpiling behavior, as well as their potential compound effects. Table 5 illustrates the compound effects of supply-side, demand-side, and disaster characteristics on consumer stockpiling propensity. Note that individual factors (i.e., landfall distance and wind speed) may affect consumer stockpiling in different directions. To investigate the extent of compound effects, we use a two-

²¹ CSIMarket is an independent digital financial media company and provider of integrated financial information and analytical applications to the global investment community (<https://csimarket.com>).

step approach. First, for each category of factors (e.g., disaster-related), we estimate the impact of the individual factors (i.e., landfall distance, track distance, and wind speed) when they take values at the 25th percentile, 50th percentile, and 75th percentile. Second, we sort the impact of individual factors in increasing order and estimate compound effects when individual factors simultaneously have lower, middle, higher impact.

Table 5: Compound Impact of Supply-Side, Demand-Side, and Disaster Characteristics²²

		Impact on Consumer Stockpiling Propensity		
Supply-Side Characteristics				
INTRA_NTW_COUNTY	Stores (Percentile)	22 (75th)	9 (50th)	4 (25th)
	Impact	95.11%	97.91%	99.05%
INTER_NTW_COUNTRY	Stores (Percentile)	592 (25th)	3,187 (50th)	7,308 (75th)
	Impact	118.68%	202.09%	226.64%
PROD_VAR_SKU	SKUs (Percentile)	44 (25th)	76 (50th)	140 (75th)
	Impact	103.73%	105.50%	106.49%
	<i>Compound Impact</i>	<i>117.09%</i>	<i>208.75%</i>	<i>239.06%</i>
Demand-Side Characteristics				
HUR_EXP_STATE	Landfalls (Percentile)	0 (25th)	1 (50th)	10 (75th)
	Impact	100.00%	100.02%	106.22%
PER_CAPITA_INC	10K Dollars (Percentile)	3.64 (25th)	4.21 (50th)	5.05 (75th)
	Impact	130.87%	134.76%	139.82%
	<i>Compound Impact</i>	<i>130.87%</i>	<i>134.78%</i>	<i>148.52%</i>
Disaster Characteristics				
HUR_LANDFALL_DIST	Miles (Percentile)	508 (75th)	288 (50th)	151 (25th)
	Impact	56.32%	68.73%	80.83%
HUR_TRACK_DIST	Miles (Percentile)	233 (75th)	162 (50th)	92 (25th)
	Impact	76.34%	80.82%	87.37%
HUR_TRACK_WIND	Miles Per Hours (Percentile)	70 (75th)	65 (50th)	50 (25th)
	Impact	189.27%	193.29%	193.61%
	<i>Compound Impact</i>	<i>81.38%</i>	<i>107.37%</i>	<i>136.73 %</i>

On the supply side, consumer stockpiling propensity is related to characteristics that affect a retailer’s desirability, such as the retailer’s intra-regional store network, inter-regional store network, and product variety offered at a given outlet. As shown in Table 5, with intra-country stores at the 25th

²²As we utilize semi log regression models, the calculation of the “compound impact” in Table 5 is based on the estimated coefficient $\hat{\beta}_i$ in Model 1.4 in Table 3. For individual impacts, a c_i unit increase in independent variable i multiplies the expected dependent (unlogged) variable by $e^{\sum c_i \hat{\beta}_i}$.

percentile, and an inter-regional store network and product variety at the 75th percentile, stockpiling propensity approximately doubles compared to what would be experienced with an inter-county network at the 75th percentile and an inter-regional network and product variety at the 25th percentile. This result is largely driven by the inter-regional store network, implying that individuals generally head to the large national chain stores to stock bottled water in advance of hurricanes.

Evidently, as indicated in Table 5, the compound impact of the demand-side characteristics is not as large as for the supply-side characteristics. When the values of the two demand-side factors change from the 25th percentile to the 75th percentile—i.e., from 0 landfalls and 36,400 dollars to 10 landfalls and 50,500 dollars—consumer stockpiling propensity increases by 18 percentage points, as compared with an increase of 118 percentage point for a similar increase (from the 25th percentile to the 75th percentile) in the supply-side characteristics.

On the disaster side, consumer stockpiling propensity is associated with varying factors that impact risk magnitude and consumer response, such as distance to hurricane landfall, distance to the hurricane's path, and the intensity of storm winds. As illustrated in Table 5, when the three disaster factors—distance from landfall, distance from track and wind strength—change from 508 miles, 233 miles, and 70 miles per hour, respectively, to 151 miles, 92 miles, and 50 miles per hour, there is a 55 percentage point increase in consumer stockpiling propensity. This result is primarily driven by the impacts of the two hazard-proximity factors.

From a managerial perspective, retailers can plan inventory based on the effect of the supply-side, demand-side, and disaster characteristics on consumers stockpiling propensity. On the supply side, retailers should pay attention to the size of their inter-regional (i.e., national) store network, as consumers have a higher propensity to shop at national retailers, perhaps due to their expected disaster preparedness capability. For example, relative to store outlets with an inter-regional store network of fewer than 600 stores, consumer stockpiling propensity nearly doubled for retailers with an inter-regional store network of above 3,000 stores. On the demand side, retailers could categorize their markets by recent hurricane

experience and household income level. For instance, consumers in Florida and North Carolina (over 10 landfalls) show relatively higher stockpiling propensity than those in states with less hurricane experience (0-2 landfalls). Moreover, retailers should be cognizant of the effects of household income level. Consumer stockpiling propensity for store outlets located in communities with per-capita-incomes about \$50,500 are 9% higher than in those communities with per-capita incomes of about \$36,400. On the disaster side, all three factors must be carefully considered when pre-positioning inventory. Although retailers are likely to pay close attention to storm track, the intensity of the winds is an important consideration in the propensity for stockpiling, with the surprising result that very intense storms are likely to have less stockpiling than moderate storms.

With this in mind, we suggest retailers focus on disaster-related factors when pre-positioning inventory during the hurricane season. The NOAA produces a “cone of uncertainty” each time a tropical cyclone becomes a named storm. The cone contains information, such as current hurricane center position, forecast center positions, potential 1-3 day track areas, potential 4-5 day track areas, and maximum sustained winds for each forecast lead time (12, 24, 36, 48, 72, 96, and 120 hours). An important factor to consider is that the track and intensity forecast errors increase with forecast lead time (Avila and Cangialosi 2011, Berg 2009, Berg 2015, Blake et al. 2013). For example, the NHC official forecasts (OFCL) for hurricane Sandy 120 hours in advance had average track error of 148.9 nautical miles and windspeed error of 14.5 knots (Blake et al. 2013). The objective of disaster management is not profit-seeking; instead, it is reducing human suffering (Gupta et al. 2016). In the days leading to potential landfall, (socially-aware) retailers could consider stockpiling propensity when positioning inventory based on the forecast cone. Moreover, retailers should remain flexible when pre-positioning inventory given hurricane path uncertainties.

Local governments should account for factors associated with consumer stockpiling behavior when assessing community risk and planning operational capacity. First, on the demand side, local governments should realize that members of low-income communities may not have the means to vacate

areas in the track of hurricanes and, therefore, may need to provide essential items as hurricanes approach. On the supply side, local governments should facilitate inbound logistics networks, thus enhancing the supply of essential items to areas in hurricane tracks. This may require exceptions to highway lane reversals that may impede inbound traffic into areas in a hurricane's path. Moreover, governments could facilitate communication channels between hurricane meteorologists and retail operation managers to help retailers better understand hurricane forecast information and accurately pre-position inventories. Lastly, governments can improve their disaster-relief capabilities by utilizing efficient supply chains in private sectors; for example, by contracting with private-sector retailers to strategically position inventory during the hurricane season. Overall, civil authorities and retailers could benefit greatly from collaboration that will allow for better coordination when prepositioning inventory and directing disaster-relief efforts.

7. Conclusions

Matching demand and supply is a challenging task for retailers attempting to provide goods or services when faced with the threat of hurricanes (Pedraza-Martinez and Van Wassenhove 2016). This work disentangles a disaster management problem from the perspective of consumer stockpiling behavior and retail operations performance using hurricane disasters as a natural experiment. Specifically, we integrate critical elements in disaster preparedness: retail network and product assortment on the supply side, disaster experience and household income on the demand side, and hazard proximity and hazard intensity relating to the disaster. We show how these elements contribute to consumer stockpiling propensity, and how consumer stockpiling propensity affects in-store product availability over the course of hurricane disasters.

Our work enables retailers and policymakers to more accurately pre-position inventories and direct disaster-relief efforts during the hurricane season. In particular, this work can help professional managers in private and public sectors anticipate counties that are more likely to experience high stockpiling propensity so that they can prepare in advance of a hurricane landfall. As product availability

during the EARLY event period is positively associated with product availability during the LATE and POST event periods, anticipating stockpiling by increasing EARLY period availability can pay off in the LATE and POST periods with higher availability.

We note several limitations. First, we limit our study to the bottled water category, an essential emergency item in hurricane preparedness. Future research could extend our study beyond bottled water and compare consumer stockpiling propensity for other essential items; for example, medications. Second, we investigate how consumer stockpiling propensity of an individual store outlet is affected by its chain network. Future research could study the impacts of both retail store networks and distribution centers (Holmes 2008, Rajagopalan 2013). This will require access to additional data that is generally not publicly available. Third, we note that the speed of information diffusion is critical to combating uncertainties and complexities in disaster relief operations (Yoo et al. 2016). Future research could use content analysis methodology studying how consumer stockpiling interacts with the diffusion of positive and negative information from social media over the course of hurricane events. This, unfortunately, can only be applied to study impact of social media on future events.

Appendix

Table A1: Correlation Matrix

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 STOCK_PROP_EARLY	1.000													
2 PROD_AVAIL_LATE	-0.148	1.000												
3 PROD_AVAIL_POST_W1	-0.162	0.306	1.000											
4 PROD_AVAIL_POST_W2	-0.080	0.278	0.427	1.000										
5 PROD_AVAIL_POST_W3	-0.044	0.249	0.370	0.446	1.000									
6 PROD_AVAIL_POST_W4	0.018	0.242	0.337	0.404	0.455	1.000								
7 INTRA_NTW_COUNTY	-0.043	0.019	0.073	0.048	0.055	0.040	1.000							
8 INTER_NTW_COUNTRY	0.121	-0.004	-0.026	-0.049	-0.027	0.015	0.219	1.000						
9 PROD_VAR_SKU	-0.117	0.060	0.098	0.100	0.091	0.034	0.029	-0.615	1.000					
10 HUR_EXP_STATE	-0.232	0.012	0.121	0.079	0.070	0.068	0.035	0.107	-0.059	1.000				
11 PER_CAPITA_INC	0.175	0.007	-0.006	0.043	0.044	0.066	0.355	-0.047	0.212	-0.218	1.000			
12 HUR_LANDFALL_DIST	-0.440	0.053	0.175	0.076	0.068	0.015	0.203	0.131	-0.009	0.340	-0.208	1.000		
13 HUR_TRACK_DIST	-0.408	0.080	0.111	0.051	0.017	0.008	-0.102	0.049	-0.059	0.360	-0.235	0.416	1.000	
14 HUR_TRACK_WIND	0.007	0.006	0.012	0.046	0.019	0.036	-0.044	0.020	0.018	0.186	0.047	-0.201	0.175	1.000

Table A2: Robustness Check I (Consumer Stockpiling Propensity)

Dependent Variable	Model A1.1	Model A1.2	Model A1.3
LN(STOCK_PROP) × 1000	Quantile (.25)	Quantile (.50)	Quantile (.75)
<u>Supply-Side Characteristics</u>			
INTRA_NTW_COUNTY	-74.411*(31.180)	-173.577*** (27.774)	-252.011*** (38.668)
(INTRA_NTW_COUNTY) ²	13.495 (10.748)	29.326** (11.285)	28.792* (14.782)
INTER_NTW_COUNTRY	22.612*** (2.649)	23.743*** (2.059)	27.843*** (1.770)
(INTER_NTW_COUNTRY) ²	-0.162*** (0.019)	-0.197*** (0.016)	-0.244*** (0.013)
PROD_VAR_SKU	1.117*** (0.295)	0.230 (0.314)	-0.520 (0.390)
(PROD_VAR_SKU) ²	-0.004*** (0.001)	-0.001* (0.001)	0.001 (0.001)
<u>Demand-Side Characteristics</u>			
HUR_EXP_STATE	-9.112** (2.822)	-18.885*** (3.735)	-22.389*** (4.178)
(HUR_EXP_STATE) ²	1.177*** (0.194)	1.990*** (0.307)	2.457*** (0.340)
PER_CAPITA_INC	81.767*** (5.569)	72.465*** (7.366)	74.559*** (6.593)
(PER_CAPITA_INC) ²	-4.737*** (0.386)	-4.269*** (0.502)	-4.454*** (0.467)
<u>Disaster Characteristics</u>			
HUR_LANDFALL_DIST	-169.212*** (4.449)	-162.340*** (5.946)	-145.935*** (5.488)
(HUR_LANDFALL_DIST) ²	9.081*** (0.398)	8.341*** (0.535)	7.187*** (0.487)
HUR_TRACK_DIST	-133.743*** (10.678)	-175.741*** (11.373)	-197.530*** (10.269)
(HUR_TRACK_DIST) ²	21.772*** (2.174)	28.573*** (2.271)	30.805*** (2.110)
HUR_TRACK_WIND	19.373*** (1.635)	19.584*** (1.309)	21.473*** (1.503)
(HUR_TRACK_WIND) ²	-0.173*** (0.012)	-0.172*** (0.010)	-0.181*** (0.012)
<u>Retail Format</u>			
CHAIN_GROC	-253.342*** (47.948)	-315.628*** (29.465)	-351.831*** (97.154)
CHAIN_WHS	110.667*** (32.708)	92.700*** (27.052)	168.393*** (34.452)
CHAIN_DISC	59.242 (93.128)	102.633* (59.243)	282.392** (101.004)
CHAIN_DOLLAR	-403.432*** (105.768)	-222.389** (72.965)	-110.335 (67.087)
CHAIN_DRUG	233.230*** (45.539)	328.050*** (50.576)	521.999*** (42.264)
CHAIN_LIQ	39.526 (71.697)	136.760 (109.950)	303.743*** (63.061)
<u>Retail Chain</u>			
RETAIL_CHAIN	Included	Included	Included
<u>Hurricane Influence</u>			
DAYS_BEF_INFL_EARLY	4.851 (5.389)	21.578*** (3.591)	31.055*** (5.370)
DAYS_INFL_AFT_LANDFALL	-29.098*** (4.327)	-25.762*** (3.729)	-20.975*** (3.418)
<u>Category Competition</u>			
VOL_COUNTY	1.144 (1.441)	4.820** (1.466)	9.556*** (1.525)
VOL_STATE	5.154*** (0.331)	3.774*** (0.362)	2.084*** (0.340)
HHI_COUNTY	-24.555 (16.287)	-10.709 (15.177)	19.235 (17.157)
HHI_STATE	2,908.394*** (238.989)	2,684.218*** (310.251)	2,299.957*** (325.613)
<u>Geodemographic Feature</u>			
POP_DEN_COUNTY	-0.050 (0.056)	-0.102** (0.038)	-0.170*** (0.044)
LAND_AREA_COUNTY	1.887* (0.854)	2.360*** (0.514)	2.636** (0.871)
WATER_AREA_COUNTY	4.664*** (0.521)	5.956*** (1.065)	7.066*** (1.362)
POP_DEN_STATE	-3.384*** (0.259)	-4.019*** (0.505)	-4.104*** (0.468)
LAND_AREA_STATE	-0.528*** (0.041)	-0.579*** (0.034)	-0.602*** (0.034)
WATER_AREA_STATE	0.746*** (0.184)	0.853*** (0.182)	0.203 (0.133)
CONSTANT	-427.472*** (97.170)	-274.919*** (67.448)	-277.159*** (76.007)
Observations	38,418	38,418	38,418
Pseudo R2	0.2346	0.3161	0.3693

Note: Bootstrap standard errors in parentheses. * p<0.1, ** p<0.01, *** p<0.001.

Table A3: Robustness Check II (In-Store Product Availability)

Dependent Variable	Model A2.1	Model A2.2	Model A2.3	Model A2.4	Model A2.5
LN(PRODUCT_AVAIL) × 1000	LATE Week	POST Week 1	POST Week 2	POST Week 3	POST Week 4
PREDICTED_STOCK_PROP	-0.244*** (0.016)	-0.102*** (0.015)	-0.043** (0.016)	-0.074*** (0.016)	-0.026 (0.016)
<u>Supply-Side Characteristics</u>					
INTRA_NTW_COUNTRY	-24.202* (9.571)	33.271*** (9.302)	51.797*** (9.397)	18.603* (9.527)	13.113 (9.700)
(INTRA_NTW_COUNTRY) ²	7.120* (3.410)	-6.404* (3.315)	-12.557*** (3.353)	0.193 (3.403)	4.959 (3.455)
INTER_NTW_COUNTRY	17.431*** (0.816)	8.746*** (0.796)	7.265*** (0.803)	2.265** (0.818)	4.314*** (0.826)
(INTER_NTW_COUNTRY) ²	-0.121*** (0.007)	-0.074*** (0.007)	-0.062*** (0.007)	-0.023*** (0.007)	-0.029*** (0.007)
PROD_VAR_SKU	0.669*** (0.109)	1.241*** (0.106)	1.048*** (0.107)	1.329*** (0.109)	0.803*** (0.110)
(PROD_VAR_SKU) ²	-0.002*** (0.000)	-0.003*** (0.000)	-0.002*** (0.000)	-0.003*** (0.000)	-0.002*** (0.000)
<u>Demand-Side Characteristics</u>					
HUR_EXP_STATE	-10.382*** (1.246)	7.716*** (1.213)	-0.310 (1.226)	-4.778*** (1.241)	-0.771 (1.263)
(HUR_EXP_STATE) ²	0.809*** (0.098)	-0.524*** (0.096)	0.122 (0.096)	0.497*** (0.098)	0.224* (0.099)
PER_CAPITA_INC	24.941*** (2.768)	15.342*** (2.699)	13.943*** (2.699)	21.493*** (2.723)	18.814*** (2.803)
(PER_CAPITA_INC) ²	-1.494*** (0.176)	-0.814*** (0.171)	-0.634*** (0.171)	-1.105*** (0.171)	-0.894*** (0.178)
<u>Disaster Characteristics</u>					
HUR_LANDFALL_DIST	-16.500*** (2.936)	-3.128 (2.853)	9.698*** (2.879)	0.697 (2.919)	3.049 (2.973)
(HUR_LANDFALL_DIST) ²	-0.312 (0.203)	-0.135 (0.197)	-1.475*** (0.199)	-0.838*** (0.202)	-1.134*** (0.205)
HUR_TRACK_DIST	-13.263** (4.433)	-15.240*** (4.310)	-8.007* (4.349)	-31.411*** (4.418)	-13.243** (4.483)
(HUR_TRACK_DIST) ²	-0.825 (0.802)	2.003* (0.781)	-0.436 (0.788)	4.830*** (0.801)	1.977* (0.812)
HUR_TRACK_WIND	5.473*** (0.639)	0.919 (0.625)	3.018*** (0.628)	2.511*** (0.637)	2.347*** (0.647)
(HUR_TRACK_WIND) ²	-0.052*** (0.005)	-0.014** (0.005)	-0.031*** (0.005)	-0.025*** (0.005)	-0.026*** (0.005)
<u>Retail Format</u>					
CHAIN_GROC	61.691 (38.572)	-11.451 (37.699)	28.895 (37.978)	-16.277 (38.739)	18.772 (38.995)
CHAIN_WHS	109.200*** (11.747)	68.868*** (11.671)	38.728*** (11.595)	58.029*** (11.858)	27.480* (11.746)
CHAIN_DISC	-124.038*** (25.271)	-149.601*** (24.713)	-258.004*** (24.895)	-216.084*** (25.446)	-268.114*** (25.564)
CHAIN_DOLLAR	-558.599*** (23.157)	-262.904*** (22.635)	-249.671*** (22.812)	-104.967*** (23.287)	-244.091*** (23.419)
CHAIN_DRUG	78.472*** (15.270)	4.312 (14.908)	-53.253*** (15.027)	-66.407*** (15.329)	-123.225*** (15.449)
CHAIN_LIQ	-56.624** (20.986)	-78.317*** (20.532)	-169.661*** (20.686)	-152.209*** (21.143)	-215.496*** (21.229)
<u>Retail Chain</u>					
RETAIL_CHAIN	Included	Included	Included	Included	Included
<u>Hurricane Influence</u>					
DAYS_BEF_INFL_EARLY	-11.287*** (1.568)	-19.491*** (1.523)	-25.777*** (1.534)	-16.014*** (1.561)	-22.187*** (1.580)
DAYS_INFL_AFT_LANDFALL	-6.335*** (1.204)	-10.709*** (1.172)	-6.121*** (1.181)	-6.779*** (1.199)	-7.245*** (1.218)
<u>Category Competition</u>					
VOL_COUNTRY	1.333 (0.839)	-1.685* (0.819)	-1.366* (0.824)	-1.033 (0.840)	0.396 (0.847)
VOL_STATE	0.729*** (0.120)	0.454*** (0.118)	0.309** (0.118)	0.740*** (0.121)	0.385** (0.122)
HHI_COUNTRY	-11.779* (5.786)	-34.910*** (5.656)	-34.753*** (5.684)	-27.289*** (5.783)	-42.381*** (5.861)
HHI_STATE	658.251*** (106.087)	432.293*** (103.345)	349.052*** (104.313)	420.996*** (105.838)	400.589*** (107.505)
CHANGE_VOL_LATE_POST_W1, 2, 3, 4	Included	Included	Included	Included	Included
CONSTANT	-178.619*** (25.269)	-30.908 (24.586)	-58.193 (24.815)	-91.445*** (25.213)	-26.890 (25.542)
Sigma_u	11.725*** (1.495)	9.483*** (1.457)	9.995*** (1.330)	8.224*** (1.291)	12.387*** (1.530)
Sigma_e	140.873*** (0.509)	137.861*** (0.498)	138.859*** (0.502)	141.979*** (0.513)	142.492*** (0.515)
Rho	0.007	0.005	0.005	0.003	0.007
Observations	38,418	38,418	38,418	38,418	38,418
Wald Chi2	6,405.49***	8,210.21***	7,163.24***	6,748.14***	5,863.83***

Note: Standard errors in parentheses. * p<0.1, ** p<0.01, *** p<0.001.

References

- Avila, L. A., J. Cangialosi. 2011. *Tropical Cyclone Report: Hurricane Irene (AL092011), 21-28 August 2011*. National Hurricane Center. Retrieved from https://www.nhc.noaa.gov/data/tcr/AL092011_Irene.pdf. Viewed February 1, 2018.
- Baker, E. J. 2011. Household preparedness for the aftermath of hurricanes in Florida. *Applied Geography*, 31(1), 46–52.
- Beatty, T. K. M., J. P. Shimshack, R. J. Volpe. 2018. Disaster preparedness and disaster response: Evidence from bottled water sales before and after hurricanes. *SSRN Electronic Journal*.
- Bendoly, E., R. Croson, P. Goncalves, K. Schultz. 2010. Bodies of knowledge for research in behavioral operations. *Production and Operations Management*, 19(4), 434–452.
- Berg, R. 2009. *Tropical Cyclone Report: Hurricane Ike (AL092008), 1-14 September 2008*. National Hurricane Center. Retrieved from https://www.nhc.noaa.gov/data/tcr/AL092008_Ike.pdf. Viewed February 1, 2018.
- Berg, R. 2015. *Tropical Cyclone Report: Hurricane Arthur (AL012014), 1-5 July 2014*. National Hurricane Center. Retrieved from https://www.nhc.noaa.gov/data/tcr/AL012014_Arthur.pdf. Viewed February 1, 2018.
- Blake, E. S., T. B. Kimberlain, R. J. Berg, J. P. Cangialosi, J. L. Beven II, 2013. *Tropical Cyclone Report: Hurricane Sandy (AL182012), 22-29 October 2012*. National Hurricane Center. Retrieved from https://www.nhc.noaa.gov/data/tcr/AL182012_Sandy.pdf. Viewed February 1, 2018.
- Bleichrodt, H., U. Schmidt, H. Zank. 2009. Additive utility in prospect theory. *Management Science*, 55(5), 863–873.
- Boudreau, J., W. Hopp, J. O. McClain, L. J. Thomas. 2003. On the interface between operations and human resources management. *Manufacturing & Service Operations Management*, 5(3), 179–202.

- Brock, T. C. 1968. *Implications of commodity theory for value change*. New York: Academic Press.
- Brown, S. J., J. B. Warner. 1985. Using daily stock returns: The case of event studies. *Journal of Financial Economics*, 14(1), 3–31.
- Bustos-Reyes, C. A., Ó. González-Benito. 2008. Store and store format loyalty measures based on budget allocation. *Journal of Business Research*, 61(9), 1015–1025.
- Cachon, G. P., M. Olivares, 2010. Drivers of finished-goods inventory in the U.S. automobile industry. *Management Science*, 56(1), 202–216.
- Cangialosi, J. P., C. W. Landsea. 2016. An examination of model and official national hurricane center tropical cyclone size forecasts. *Weather and Forecasting*, 31(4), 1293–1300.
- Carrasco, C. A., C. W. Landsea, Y.-L. Lin. 2014. The influence of tropical cyclone size on its intensification. *Weather and Forecasting*, 29(3), 582–590.
- Cavallo, A., E. Cavallo, R. Rigobon. 2014. Prices and supply disruptions during natural disasters. *Review of Income and Wealth*, 60(S2), S449–S471.
- Chen, L., E. L. Plambeck. 2008. Dynamic inventory management with learning about the demand distribution and substitution probability. *Manufacturing & Service Operations Management*, 10(2), 236–256.
- Croson, R., K. Schultz, E. Siemsen, M. L. Yeo. 2013. Behavioral operations: The state of the field. *Journal of Operations Management*, 31(1-2), 1–5.
- CSIMarket Company. 2012. Target Inventory Turnover Ratio (COS). Retrieved from <https://csimarket.com/stocks/singleEfficiencyit.php?code=TGT&hist=25>
- CSIMarket Company. 2012. Kroger Co Inventory Turnover Ratio (COS). Retrieved from <https://csimarket.com/stocks/singleEfficiencyit.php?code=KR&hist=25>
- CSIMarket Company. 2012. Costco Wholesale Inventory Turnover Ratio (COS). Retrieved from <https://csimarket.com/stocks/singleEfficiencyit.php?code=COST&hist=25>
- CSIMarket Company. 2012. CVS Health Inventory Turnover Ratio (COS). Retrieved from <https://csimarket.com/stocks/singleEfficiencyit.php?code=CVS&hist=25>

- CSIMarket Company. 2012. Dollar Tree Inc Inventory Turnover Ratio (COS). Retrieved from <https://csimarket.com/stocks/singleEfficiencyit.php?code=DLTR&hist=25>
- Davis, L. B., F. Samanlioglu, X. Qu, S. Root. 2013. Inventory planning and coordination in disaster relief efforts. *Int. J. Prod. Econ.* 141(3): 561–573.
- Demuth, J. L., M. DeMaria, J. A. Knaff. 2006. Improvement of advanced microwave sounding unit tropical cyclone intensity and size estimation algorithms. *Journal of Applied Meteorology and Climatology*, 45(11), 1573–1581.
- Dunning, T. 2012. *Natural experiments in the social sciences: a design-based approach*. Cambridge, UK: Cambridge University Press.
- Fothergill, A., L. A. Peek. 2004. Poverty and disasters in the United States: A review of recent sociological findings. *Natural Hazards*, 32(1), 89–110.
- Galino, S., A. Moreno, L. Stamatopoulos. 2016. Channel integration, sales dispersion, and inventory management. *Management Science*, 63(9), 2813–2831.
- Gaur, V., M. L. Fisher, A. Raman. 2005. An econometric analysis of inventory turnover performance in retail services, *Management Science*, 51(2), 181–194.
- Gilland, W. G., H. S. Heese. 2013. Sequence matters: Shelf-space allocation under dynamic customer-driven substitution. *Production and Operations Management*, 22(4), 875–887.
- Gino, F., G. Pisano. 2008. Toward a theory of behavioral operations. *Manufacturing & Service Operations Management*, 10(4), 676–691.
- González-Benito, O. S., P. A. Muñoz-Gallego, P. K. Kopalle. 2005. Asymmetric competition in retail store formats: Evaluating inter- and intra-format spatial effects. *Journal of Retailing*, 81(1), 59–73.
- Gupta, S., M. K. Starr, R. Z. Farahani, N. Matinrad. 2016. Disaster management from a POM perspective: Mapping a new domain. *Production and Operations Management*, 25(10), 1611–1637.
- Hendel, I., A. Nevo. 2006. Measuring the implication of sales and consumer inventory behavior. *Econometrica*. 74(6), 1637–1673.

- Hendricks, K. B., B. Jacobs, V. R. Singhal. 2017. Stock market reaction to supply chain disruptions from the 2011 Great East Japan Earthquake. *SSRN Electronic Journal*.
- Hobfoll, S. E. 1988. *The ecology of stress*. New York: Hemisphere Pub. Corp.
- Hobfoll, S. E. 1989. Conservation of resources: A new attempt at conceptualizing stress. *The American Psychologist*, 44(3), 513–524.
- Holmes, T. J. 2008. The diffusion of Wal-Mart and economies of density. *Econometrica*, 79(1), 253–302.
- Honhon, D. D. E., S. Seshardi. 2013. Fixed vs. random proportions demand models for the assortment planning problem under stockout-based substitution. *Manufacturing & Service Operations Management*, 15(3), 378–386.
- Hu, X., H. Gurnani, L. Wang. 2013. Managing risk of supply disruptions: incentives for capacity restoration. *Production and Operations Management*, 22(1), 137–150.
- Huchzermeier, A., A. Iyer, J. Freiheit. 2002. The supply chain impact of smart customers in a promotional environment. *Manufacturing & Service Operations Management*, 4(3), 228–240.
- Kahn, B. E. 1998. Dynamic relationships with customers: High-variety strategies. *Journal of the Academy of Marketing Science*, 26(1), 45–53.
- Kahneman, D., A. Tversky. 1979. Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2), 263–292.
- King, D., R. Devasagayam. 2017. An endowment, commodity, and prospect theory perspective on consumer hoarding behavior. *Journal of Business Theory and Practice*, 5(2), 77–88.
- Kleindorfer, P. R., G. H. Saad. 2005. Managing disruption risks in supply chains. *Production and Operations Management*, 14(1), 53–68.
- Koenker, R., K. F. Hallock. 2001. Quantile regression. *Journal of Economic Perspectives*, 15(4), 143–156.
- Koenker, R., G. Bassett. 1978. Regression Quantiles. *Econometrica*, 46(1), 33–50.
- Kraiselburd, S., V. G. Narayanan, A. Raman. 2004. Contracting in a supply chain with stochastic demand and substitute products. *Production and Operations Management*, 13(1), 46–62.

- Kunz, N., G. Reiner, S. Gold. 2014. Investing in disaster management capabilities versus pre-positioning inventory: A new approach to disaster preparedness. *International Journal of Production Economics*, 157, 261–272.
- Lal, R., J. D. C. Little, J. M. Villas-Boas. 1996. A theory of forward buying, merchandising, and trade deals. *Marketing Science*, 15(1), 21–37.
- Landsea, C. W., J. L. Franklin. 2013. Atlantic Hurricane Database Uncertainty and Presentation of a New Database Format. *Mon. Wea. Rev.*, 141, 3576–3592.
- Lim, M. K., H.-Y. Mak, Z.-J. M. Shen. 2017. Agility and proximity considerations in supply chain design. *Management Science*, 63(4), 1026–1041.
- Lindell, M. K., R. W. Perry. 1992. *Behavioral foundations of community emergency planning*. Washington, D.C.: Hemisphere Pub.
- Lodree, E. J., K. N. Ballard, C. H. Song. 2012. Pre-positioning hurricane supplies in a commercial supply chain. *Socio-Economic Planning Sciences*, 46(4), 291–305.
- Lodree, E. J., S. Taskin. 2009. Supply chain planning for hurricane response with wind speed information updates. *Computers and Operations Research*, 36(1), 2–15.
- Lynn, M. 1991. Scarcity effects on value: A quantitative review of the commodity theory literature. *Psychology & Marketing*, 8(1), 43–57.
- McAlister, L., E. Pessemier. 1982. Variety seeking behavior: An interdisciplinary review. *Journal of Consumer Research*, 9(3), 311-322.
- McKinnon, G., M. E. Smith, H. K. Hunt. 1985. Hoarding behavior among consumers: Conceptualization and marketing implications. *Journal of the Academy of Marketing Science*, 13(1-2), 340–351.
- Messinger, P. R., C. Narasimhan. 1997. A model of retail formats based on consumers' economizing on shopping time. *Marketing Science*, 16(1), 1–23.
- Meyer, R. J., J. Baker, K. Broad, J. Czajkowski, B. Orlove. 2014. The dynamics of hurricane risk perception: real-time evidence from the 2012 Atlantic hurricane season. *Bulletin of the American Meteorological Society*, 95(9), 1389–1404.

- Moffatt, S., B. Hoeldke, T. Pless-Mulloli. 2003. Local environmental concerns among communities in North-East England and South Hessen, Germany: the influence of proximity to industry. *Journal of Risk Research*, 6(2), 125–144.
- Morrice, D. J., P. Cronin, F. Tanrisever, J. C. Butler. 2016. Supporting hurricane inventory management decisions with consumer demand estimates. *Journal of Operations Management*, 45, 86–100.
- National Hurricane Center. Glossary of NHC Terms. Retrieved from <https://www.nhc.noaa.gov/aboutgloss.shtml>. Viewed August 15, 2019.
- Peacock, W. G., S. D. Brody, W. Highfield. 2005. Hurricane risk perceptions among Florida's single family homeowners. *Landscape and Urban Planning*, 73(2), 120–135.
- Pedraza-Martinez, A. J., L. N. Van Wassenhove. 2016. Empirically grounded research in humanitarian operations management: The way forward. *Journal of Operations Management*, 45, 1–10.
- Rajagopalan, S. 2013. Impact of variety and distribution system characteristics on inventory levels at U.S. retailers. *Manufacturing & Service Operations Management*, 15(2), 191–204.
- Rawls, C. G., M. A. Turnquist. 2010. Pre-positioning of emergency supplies for disaster response. *Transportation Research Part B*, 44(4), 521–534.
- Remler, D. K., G. G. Van Ryzin. 2011. *Research methods in practice: strategies for description and causation*. Thousand Oaks, Calif.: SAGE Publications.
- Ren, C. R., Y. Hu, J. Hausman. 2011. Managing product variety and collocation in a competitive environment: An empirical investigation of consumer electronics retailing. *Management Science*, 57(6), 1009–1024.
- Sattler, D. N., C. F. Kaiser, J. B. Hittner. 2000. Disaster preparedness: Relationships among prior experience, personal characteristics, and distress. *Journal of Applied Social Psychology*, 30(7), 1396–1420.
- Simon, H. A. 1969. *The sciences of the artificial*. Cambridge: MIT Press.
- Simon, H. A. 1982. *Models of bounded rationality*. Cambridge: MIT Press.

- Sterman, J. D., G. Dogan. 2015. "I'm not hoarding, I'm just stocking up before the hoarders get here.": Behavioral causes of phantom ordering in supply chains. *Journal of Operations Management*, 39–40, 6–22.
- Target. 2018. How Target tare responding to hurricane Florence. Retrieved from <https://corporate.target.com/article/2018/09/hurricane-florence-response>. Viewed on August 15, 2019.
- Taskin, S., E. J. Lodree. 2010. Inventory decisions for emergency supplies based on hurricane count predictions. *International Journal of Production Economics*, 126(1): 66–75.
- Taskin, S., E. J. Lodree. 2011. A Bayesian decision model with hurricane forecast updates for emergency supplies inventory management. *Journal of the Operational Research Society*, 62(6): 1098–1108.
- Ton, Z., A. Raman. 2010. The effect of product variety and inventory levels on retail store sales: A longitudinal study. *Production and Operations Management*, 19(5): 546–560.
- Trumbo, C., M. Lueck, H. Marlatt, L. Peek. 2011. The effect of proximity to hurricanes Katrina and Rita on subsequent hurricane outlook and optimistic bias. *Risk Analysis*, 31(12): 1907–1918.
- U.S. Census Bureau. 2010. U.S. Gazetteer Files [Data file]. Retrieved from <https://www.census.gov/geographies/reference-files/time-series/geo/gazetteer-files.2010.html>
- U.S. Census Bureau. 2012. U.S. Gazetteer Files [Data file]. Retrieved from <https://www.census.gov/geographies/reference-files/time-series/geo/gazetteer-files.2012.html>
- U.S. Census Bureau. 2014. U.S. Gazetteer Files [Data file]. Retrieved from <https://www.census.gov/geographies/reference-files/time-series/geo/gazetteer-files.2014.html>
- Windle, M. 2018. We all want grocery stores reopened after a disaster. The "How?" is much harder. Accessed online <https://www.linkedin.com/pulse/we-all-want-grocery-stores-reopened-after-disaster-how-michael-windle/>. Viewed December 1, 2018.
- Yoo, E., W. Rand, M. Eftekhari, E. Rabinovich. 2016. Evaluating information diffusion speed and its determinants in social media networks during humanitarian crises. *Journal of Operations Management*, 45, 123–133.

Zipkin, P. H. 2000. *Foundations of inventory management*. Boston: McGraw-Hill.