ABSTRACT

Title of Document: RETAIL OPERATIONS, CONSUMER STOCKPILING, AND LOGISTICS IT RESOURCES

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This dissertation examines research questions within two streams: (1) consumer behavior and retail operations and (2) Information Technology (IT) and operational performance. Specifically, the first two essays study the impacts of consumer stockpiling behavior on retail operations management using natural experiment methodology. The third essay explores the interaction of logistics IT resources, organizational factors, and operational performance.

The first essay examines how environmental stress affects consumer stockpiling behavior using the 2008–2009 financial crisis as a natural experiment. Although overall consumption falls due to budgetary constraints, the essay shows that environmental stress increases consumers' propensity to stockpile during promotional periods. As consumers exhibit a higher stockpiling propensity, retailers are subject to an increased demand variation between regular and promotional periods, exposing themselves to a higher

stockout risk. Moreover, the increase in demand variation is compounded if retailers adopt a randomly-priced promotion strategy. Consequently, a high-low promotion strategy coupled with greater stockpiling propensity requires more safety stock inventory during times of environmental stress due to economic downturns.

The second essay explores how retail operations performance varies in the face of consumer stockpiling behavior utilizing hurricanes as a natural experiment. The essay shows that supply-side characteristics (retail network and product variety), demand-side characteristics (hurricane experience and household income), and disaster-side characteristics (hazard proximity and hazard intensity) significantly affect consumer stockpiling propensity as the hurricane approaches. Further, increased consumer stockpiling propensity has an immediate and persistent impact on retail operations, such as higher product availability before hurricanes and lower product availability after hurricanes. Note that this impact depends on store formats. This study suggests retailers need to carefully monitor factors affecting consumer stockpiling behavior during natural disasters. This would allow retailers to better manage their inventories and increase their ability to fulfill consumer demand.

The third essay studies the interaction of logistics IT resources, organizational factors, and operating performance. The previous typology of logistics IT resources is extended into four mid-level constructs: operations-focused IT, decision-focused IT, service-focused IT, and IT development capability. The results show that operations-focused IT, decision-focused IT, and IT development capability is more related to superior operating performance than service-focused IT. Moreover, it is shown that organizational factors, such as firm size, firm age, and firm ownership, may enhance or suppress the effects of logistics IT resources on operational performance. In general, logistics firms should carefully manage IT resources according to their particular organizational environment in order to achieve competitive advantage.

The findings for the first two essays contribute to retail operations theory by proposing and testing novel questions about the impact of the presence of consumer stockpiling behavior on retail operations management using natural experiment methodology. The findings for the third essay contribute to business logistics theory by proposing a typology for logistics IT resources and testing hypotheses regarding the impact of logistics IT resources on logistics firms' operational performance.

RETAIL OPERATIONS, CONSUMER STOCKPILING, AND LOGISTICS IT RESOURCES

By

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Dedication

This dissertation is dedicated to my husband, Alex Dayong Cao, for his constant encouragement throughout my Ph.D. journey. He, in particular, made many sacrifices in order to support my Ph.D. studies. I am truly grateful for the efforts he gave toward helping me pursue my dream. This work is also dedicated to my son, Forrest Jingsen Cao, and my daughter, Judy Jingyi Cao. You have made me stronger, better, and more fulfilled than I could have ever imagined. I love you to the moon and back.

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Chapter 1: Overview

This dissertation is developed over three essays and examines research questions within the two streams: (1) consumer behavior and retail operations and (2) IT resources and operational performance. The first two essays explore how consumer stockpiling behavior affects retail operations management using a natural experiment methodology. In particular, two types of inventory accumulation activities by consumers are examined: conventional stockpiling during promotions for profit-seeking and unconventional stockpiling during disasters for loss-avoidance (McKinnon, Smith, & Hunt, 1985). The third essay examines how logistics IT resources affect logistics firm performance in a context of an emerging economy. In particular, a typology for logistics IT resources is introduced while highlighting the complementary effects of organizational factors on the effectiveness of logistics IT resources.

In the first essay, we study the impacts of environmental stress on consumer stockpiling behavior using the 2008–2009 financial crisis as a natural experiment. The two-segment household inventory theory is utilized to guide this work, which distinguishes consumers as either non-stockpilers or stockpilers (Blattberg, Eppen, & Lieberman, 1981). Specifically, two research questions are addressed: (1) How does environmental stress affect consumer stockpiling for storable goods? And (2) What are the implications of this changing behavior for retail inventory planning? Using a sample retail channel and a panel of households, fast-moving items, such as diapers, are investigated as they can attract significant consumer stockpiling behavior during promotions. The essay shows that, although overall consumption falls due to budgetary constraints, environmental stress increases consumers' propensity to stockpile during promotional periods. As consumers exhibit a higher stockpiling propensity, retailers are subject to increased demand variation between regular and promotional periods, exposing themselves to higher stockout risk. Moreover, the increased demand variation is compounded if retailers adopt a randomly-priced promotion strategy, requiring more safety stock inventory. It appears to be critical for retailers to reign in consumer stockpiling behavior and to distill consumer demand rates and therefore avoid stockouts or oversupply, especially under environmental stress.

In the second essay, we explore the impacts of consumer stockpiling behavior on in-store product availability over the different stages of a hurricane. Utilizing event study methodology, this study categorizes hurricane event periods as PRE, EARLY, LATE, and POST. Also, three research questions are addressed: (1) How do supply-side, demand-side, and disaster-side characteristics impact consumer stockpiling propensity during the EARLY event period? (2) How does expected consumer stockpiling propensity influence in-store product availability during the EARLY event period? and (3) How long do the effects of consumer stockpiling propensity on in-store product availability persist over the course of a hurricane? Focusing on bottled water, an emergency product category in hurricane disaster preparedness, four U.S. continental hurricanes are matched with various formats of retail store outlets. We show that supply-side characteristics (retail network and product variety), demand-side characteristics (hurricane experience and household income), and disaster-side characteristics (hazard proximity and hazard intensity) significantly affect consumer stockpiling propensity before a hurricane approach. Additionally, consumer stockpiling propensity positively relates to in-store product availability during the EARLY event period. This increased consumer stockpiling propensity may lead to significantly lower in-store product availability during the LATE event week and the first week of the POST event period, but the effects gradually weaken over the POST event period. During the hurricane season, retailers need to carefully monitor factors affecting consumer stockpiling behavior to plan prepositioning of inventories effectively.

In the third essay, the complementary effects of logistics IT resources and organizational factors on logistics firm performance are studied. The resource complementarity theory is utilized to guide this work, which emphasizes the marginal benefit of one resource capability being impacted by another (Bendoly, Bharadwaj, & Bharadwaj, 2012). In particular, we explore two research questions: (1) To what degree are different types of logistics IT resources related to operating performance? and (2) To what degree are these relationships contingent on organizational factors, such as the firm's size, age, and ownership? We empirically validate the theoretical model using a cross-sectional sample of secondary data from domestic logistics firms in China. The study contributes to previous research in three ways. The previous typology of logistics IT resources is extended into four mid-level constructs: operations-focused IT, decision-focused IT, service-focused IT, and IT development capability. We show that operations-focused IT, decision-focused IT, and IT development capability are more related to superior operating performance than service-focused IT. Moreover, organizational factors, including the firm's size, age, and ownership, may enhance or suppress the effects of logistics IT resources on operational performance. Logistics firms should carefully manage IT resources according to their particular organizational environment to achieve competitive advantage.

Chapter 2: Inventory Planning, Consumer Stockpiling, and Environmental Stress

ABSTRACT

We study how environmental stress affects consumer stockpiling behavior using the 2008–2009 financial crisis as a natural experiment. Environmental stress disturbs the psychological equilibria of consumers; thus; consumers may be incentivized to stockpile to take advantage of promotional prices. However, limited financial resources may reduce the ability of consumers under economic stress to stockpile. Using retail- and household-level samples, we find that in a high-low promotional retail environment, the former effect dominates. Although overall consumption falls due to budgetary constraints, environmental stress increases consumers' propensity to stockpile during promotional periods. This change in behavior affects retail inventory planning. In the face of higher environmental stress and lower consumption rates during economic downturns, retail inventories need to be decreased to correspond with the decrease in demand. However, as consumers exhibit a higher stockpiling propensity, retailers are subject to increased demand variation between regular and promotional periods, thus exposing themselves to higher stockout risk. Moreover, the increase in demand variation is compounded if retailers adopt a randomly-priced promotion strategy. Consequently, a high-low promotion strategy coupled with greater stockpiling propensity requires more safety stock inventory during economic downturns.

INTRODUCTION

Focusing on one of the top domains of environmental stressors, financial and economic events (Hobson, Kamen, Szostek, Nethercut, Tiedmann, & Wojnarowicz, 1998), we examine how environmental stress affects consumer stockpiling behavior by utilizing the 2008–2009 financial crisis as a natural experiment. Environmental stress disturbs a person's normal state of psychological equilibrium, leading to an imbalance between demands and resources (Lazarus, 1966; Lazarus & Folkman, 1984). Specifically, the financial demands may stimulate consumers to save money through stockpiling when products are on sale, whereas their financial limitations may restrict their ability to stockpile, and thus, deters them to spend large amounts of money on promotions. Thus, consumers need to rebalance their consumption trade-off. Accordingly, in the face of the changing consumer behavior under financial and economic stress, how should retailers adjust their inventories? Budgetary constraints imply lower consumer spending and consequently lead to a decrease in retail inventories. However, if consumer stockpiling increases at the same time (Sterman & Dogan, 2015), then this downward adjustment could lead to lower service levels during promotions. In this work, we discuss the impact of consumer stockpiling propensity and retail promotional strategy on inventory stocking decisions during times of environmental stress.

Consumer stockpiling is a well-accepted consumer behavior; however, not all consumers stockpile. This distinction is captured by the household inventory theory (Blattberg, Buesing, Peacock, & Sen, 1978) which classifies consumers in a high-low promotional environment as stockpilers, who leverage promotions to stockpile goods at lower prices, and non-stockpilers, whose purchasing decisions are not significantly affected by promotional activities. Thus, consumer stockpiling is leveraged by retailers as a mechanism to shift inventory from retailers to consumers while discriminating between the two types of consumers (Blattberg, Eppen, & Lieberman, 1981). An important related measure is stockpiling propensity, which at the household level, is the ratio of deal purchases to non-deal purchases (Blattberg et al., 1981). At the retail level, stockpiling propensity can be measured as the ratio of the consumption rate of the stockpiler segment to the consumption rate of the non-stockpiler segment.

Conducive to consumer stockpiling are high-low or promotional pricing environments, in which retailers often adopt a random promotion strategy over predictable pricing policies, as the latter can be underbid by competitors (Bell, Iyer, & Padmanabhan, 2002; Breiter & Huchzermeier, 2015; Lal, Little, & Villas-Boas, 1996; Wiehenbrauk, 2010). Specifically, retailers often determine the timing of the promotion in advance but vary promotional prices randomly before the promotion starts. For example, Breiter and Huchzermeier (2015) point out Real, a major German retail chain, relies on Comosoft technology in promotion campaign, which allows Real to adjust prices until five minutes before printing the promotional leaflets. Although consumer stockpiling helps reduce retailers' inventory holding costs (Blattberg et al., 1981), the random promotion strategy requires more safety stock to protect against the demand volatility induced by the stockpilers. Notably, if consumer stockpiling increases with environmental stress (Sterman & Dogan, 2015), the random promotion strategy may amplify the retailers' inventory risks over time.

Earlier, we asked: What is the impact of environmental stress on consumer stockpiling behavior? We use the 2008–2009 financial crisis as a natural experiment to examine the effects of changes in environmental stress on consumer stockpiling behavior. We first investigate the impact of environmental stress on stockpiling propensity at the retail level and then examine these behavioral changes at the household level. Using the consumption of diapers as a case study, we reveal that environmental stress is likely to stimulate stockpiling behavior even though overall diaper consumption falls during the financial downturn.

The second question we address is: How should retailers make inventory stocking decisions in light of changing stockpiling and purchasing behavior during financial downturns? Based on numerical illustrations, we show that lower consumption rates reduce the retailer's required mean inventory and safety stock levels, while higher stockpiling propensity needs an upward adjustment to the mean inventory and safety stock for the stockpiler segment. Specifically, a random promotion strategy amplifies retailers' stockout risks as stockpiling propensity increases with environmental stress. Therefore, retail managers must consider the purchasing effects from the promotion strategy, as well as dynamic changes in both overall demand and stockpiling propensities during economic downturns when determining safety stock levels.

Our contributions are threefold. First, from a methodology perspective, we explore the relationship between environmental stress and consumer stockpiling utilizing a natural experiment methodology (Hobson et al., 1998), which enhances the generalizability and relevance of the estimation results (Remler & Ryzin, 2011). Second, from a theoretical perspective, we find that environmental stress stimulates consumers to stockpile, but budgetary constraints reduce their ability to consume, reflected by a higher stockpiling propensity coupled with a lower consumption rate from individual consumers. Last, from a managerial perspective, as stockpiling propensity rises with environmental stress, retailers have to face greater possibilities of stockouts during promotions. In particular, a random promotion policy combined with a higher stockpiling propensity amplifies safety stock needs for the stockpiler segment. In general, we propose that retailers need to monitor their consumer markets closely as environmental conditions change. The existence of the two consumer segments, non-stockpilers and stockpilers, requires retailers to account for changes in stockpiling propensity and manage inventory more efficiently.

THEORETICAL FOUNDATIONS

We survey two streams of literature that relate to consumer stockpiling and the household inventory model, and to retail inventory planning and environmental stress.

Consumer Stockpiling and the Household Inventory Model

A vast literature shows how consumer stockpiling behavior is impacted due to significant promotional demands (Bell, Chiang, & Padmanabhan, 1999; Gupta, 1988). In practice, two types of pricing formats are widely adopted by the retail industry: high-low pricing (HILO) and everyday low pricing (EDLP). HILO is characterized by higher demand variation between regular (non-promotional) periods and promotional periods; while EDLP is characterized by lower demand variation through the setting of low average prices with little price variability (Wiehenbrauk, 2010). Helsen and Schmittlein (1992) show that consumer stockpiling relies on the promotional environment, including the availability of deals, the expected deal discount, and the uncertainty of deal prices. In general, long-term exposure to a HILO pricing environment stimulates consumers to stockpile.

Research on consumer stockpiling decisions commonly assumes that consumers seek an optimal purchasing policy by implementing the household inventory model, in which a household chooses an optimal purchase level of a storable product depending on storage costs, current inventory levels, and promotion prices. The two-segment household inventory model (Blattberg et al., 1981) distinguishes between non-stockpiling and stockpiling consumers. Non-stockpilers value convenience over savings from promotions and thus are not willing to stockpile. They ignore promotional prices and purchase a consistent quantity each period, forming the base demand for a retailer (Breiter & Huchzermeier, 2015). In contrast, stockpilers value savings over convenience and thus are willing to stockpile. In the face of the high price variability in a HILO environment, they may decide to stockpile their inventory, postpone a purchase, or buy a lesser quantity, depending on the promotion available at that time (Ho, Tang, & Bell, 1998).

Blattberg and colleagues (1981) described promotional pricing by retailers as a means of transferring inventory carrying costs from the retailer to the consumer. In doing so, they illustrated a household inventory model in which both consumers and retailers act to minimize their costs. Assunção and Meyer (1993) explored the effect of price variation on household consumption in the face of uncertain future prices. They derived an optimal ordering policy as a function of the observed price of the goods, the distribution of future prices, and the nature of current inventory. Boizot, Robin, and Visser (2001) utilized a household inventory model to predict the correlations between inter-purchase durations, current and past prices, and the expectation of purchasing quantities. Hendel and Nevo (2006a, 2006b) presented a household inventory model to generate predictions about household purchasing patterns and store-level demand patterns. They suggested that static demand estimates may overstate own-price elasticities and understate cross-price elasticities in the presence of stockpiling. In this study, we utilize the household inventory model to determine how stockpilers and non-stockpilers react to environmental stress originating from financial and economic events (Hobson et al., 1998).

Retail Inventory Planning and Environmental Stress

The operations management (OM) literature has explored the implications of stockpiling behavior on retail inventory management. For instance, Iyer and Ye (2000) assessed the value of information sharing in a two-level manufacturer and retailer promotional environment. They found that information sharing can mitigate the manufacturer’s inventory costs for supporting promotions. Huchzermeier, Iyer, and Freiheit (2002) built a demand model in which only stockpilers react to promotions through inventory stockpiling. They showed that capturing the stockpilers’ responses to promotions is beneficial for retailers in reducing their inventory costs. Breiter and Huchzermeier (2015) explored promotional planning and supply chain contracting in a HILO pricing environment. They found that a hedging approach can be deployed to distribute demand risk efficiently over the whole supply chain. Su (2010) studied the seller’s optimal dynamic pricing strategies and consumers’ optimal stockpiling strategies. The results suggested that stockpiling behavior can initiate the bullwhip effect in supply chains.

Previous OM literature has studied retail operational strategy under environmental uncertainty originating from financial and economic events. For example, focusing on long-term economic cycles, Kesavan and Kushwaha (2014) found that during expansion periods, high-service-level retailers increase their inventory investment significantly more than low-service-level retailers, whereas low-service-level retailers curtail their inventory investment substantially more than high-service-level retailers during contraction periods. A subsequent study by Kesavan, Kushwaha, and Gaur (2016) concluded that high-inventory-turnover retailers respond quickly to economic conditions by changing their purchase quantities to manage demand shocks, whereas low-inventory-turnover retailers rely primarily on price changes to manage demand shocks. While focusing on short-term economic shocks such as the 2008–2009 financial crisis, Dooley, Yan, Mohan, and Gopalakrishnan (2010) found that wholesalers respond late and drastically, indicative of bullwhip effects, while retailers respond quickly and conservatively, indicative of inventory smoothing.

There is limited literature on behavioral operations focusing on consumer stockpiling behavior during times of environmental stress. Sterman and Dogan (2015) studied hoarding and phantom ordering in supply chains by extending the experiment of Croson, Donohue, Katok, and Sterman (2014) with the Beer Distribution Game. They discussed psychiatric and neuroanatomical evidence to find that environmental stress stimulates the impulse to stockpile. The OM literature offers two explanations for stockpiling behavior (Sterman & Dogan, 2015): rational and boundedly rational. The rational theory assumes that humans make optimal decisions given local information and incentives. For example, stockpiling can be rational when customers compete for limited supply under environmental uncertainty or capacity constraints. The boundedly rational theory argues that humans use heuristics with imperfect mental models of situational factors such as environmental complexity (Bendoly, Croson, Goncalves, & Schultz, 2010; Boudreau, Hopp, McClain, & Thomas, 2003; Croson, Schultz, Siemsen, & Yeo, 2013; Gino & Pisano, 2008; Simon, 1969, 1982). Thus, consumer stockpiling may be viewed as a behavioral and emotional response to environmental stress (Sterman & Dogan, 2015).

This study is built on behavioral explanations of consumer stockpiling under environmental stress (Sterman & Dogan, 2015). Stress is a physically and emotionally draining reaction to tensions that arise when previously balanced states become disrupted through either internal or external stressors (Hobfoll, 1988). Environmental stress disturbs a person's internal psychological equilibrium, leading to an imbalance between demands and resources (Lazarus, 1966, Lazarus & Folkman, 1984). Hobson and colleagues (1998) revised the Social Readjustment Scale of Holmes and Rahe (1967) and listed 51 major life events that precipitate significant stress, with the top 20 being classified into five themes: death and dying, health care, crime and criminal justice system, financial and economic events, and family-related issues. Our study focuses on environmental stress originating from financial and economic events (Hobson et al., 1998).

RESEARCH METHODOLOGY

Natural Experiment

The financial crisis, with its exogenous nature, provides a natural experiment for testing the impact of environmental stress on consumer stockpiling behavior. A natural experiment is an empirical or observable study based on reactions to exogenous events (Dunning, 2012). In particular, subjects exposed to the experimental conditions are not artificially manipulated by researchers but instead are determined by nature or by other factors outside the control of researchers and subjects. In this natural experiment, the treatment (environmental stress, the independent variable of interest) varies through naturally occurring or unplanned events (the financial crisis) which is exogenous to the outcome (stockpiling propensity, the dependent variable of interests) (Remler & Ryzin, 2011). Using a natural experiment methodology allows us to compare stockpiling propensity over time and to relate stockpiling propensity variations to environmental stress over the period of study.

We construct the treatment variable, environmental stress, based on the Conference Board's monthly Present Situation Index, which represents the degree of optimism that consumers feel about the current situation based on the overall state of the economy and their financial situation[1]. The Present Situation Index is compiled from a survey of 5,000 households, in which participants are asked if they feel that current business conditions are good, bad or normal, and if they feel that current employment conditions are plentiful, not so plentiful or hard to get. It is regarded as a positive signal if the households view current business conditions as good and current employment conditions as plentiful. Thus, the Present Situation Index is a reasonable indicator reflecting how consumers feel about environmental stress in the face of financial and economic events. We measure environmental stress, $\mathrm{STRESS\_CCIP}_t$, with a simple index

[1] The Conference Board utilizes two indices to construct the Consumer Confidence Index: 1) the Present Situation Index and 2) the Expectation Index. The Present Situation Index reflects consumers' current shopping and stockpiling behavior, while the Expectations Index indicates their expectations for the future, for example in six months, and is hence beyond the scope of the stockpiling behavior.

by first 1) setting the index as the negative value of the Present Situation Index, and then 2) normalizing the index to a value of one on the first period under this study.

Sample Description

We focus on diapers as the sample product category. Although diapers appear to be a "necessity" by households with infants, they have been found to be one of the first costs that households cut during recessions (Lubin, 2011). Moreover, diapers are an ideal product category for studying consumer stockpiling behavior for a number of reasons (Huchzermeier et al., 2002; Wiehenbrauk, 2010): 1) diapers represent rather "expensive" fast-moving items that attract significant stockpiling behavior during promotions; 2) brand switching is not typical for diapers as parents maintain brand loyalty throughout usage time; and 3) consumer stockpiling of diapers does not induce consumption acceleration (i.e., unlike cookies, stockpiling diapers does not promote extra consumption). Our data is sourced from the Nielsen retail scanner dataset, which consists of weekly pricing, volume, and store environment information, generated by point-of-sale systems from participating retail chains[2].

We test the impact of environmental stress on stockpiling behavior utilizing natural experiment methodology. An essential requirement for the experiment is the stability of the promotional policy during the study period, as a change in promotional patterns (e.g., frequencies of promotions, or intervals between promotions) may affect consumer stockpiling behavior. We focus on a drugstore channel that utilized a stable but

[2] Calculated (or derived) based on data from The Nielsen Company (US), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researchers and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

irregular HILO promotional pattern for the sample diaper brand during the period 2007Q4 to 2009Q4. We do not find any evidence for significant adjustment in the retailer's promotional "pattern" during the study period[3].

This sample retail channel utilizes a centralized HILO pricing scheme of a uniform price across all states in which it operates. We aggregate the sales volumes of a network of small-scale stores to the state-market level. To eliminate the influences of newly-opened stores or stores that closed during the study period, we only capture data from stores that operated from 2006 to 2009. We focus on the top six state markets for this retailer's sales of this diaper brand, including New York (NY), California (CA), Michigan (MI), Ohio (OH), New Jersey (NJ), and Pennsylvania (PA), with each accounting for at least 5% of chain sales and their total for 75% of chain sales. We aggregate sales data to the brand-level and calculate prices on a per-diaper basis (Breiter & Huchzermeier, 2015). The chain-level average price of a diaper was $0.21, the highest price was $0.25, and the lowest price was $0.15, during our sample period.

Model Foundation

We estimate dynamic changes in consumer stockpiling behavior utilizing the two-segment household inventory model consisting of the two segments: stockpilers and non-stockpilers (Blattberg et al., 1981). As non-stockpilers purchase to meet their per-period consumption, the base demand is only determined by the base consumption rate of the non-stockpiler segment. Since stockpilers purchase to satisfy their future consumption, they induce a spike in demand during each promotional period, which is jointly

[3] We refer the reader to Table A1 in the Appendix, where we estimate promotion frequency as the number of promotions within a quarter, and promotion interval as the number of weeks between two consecutive promotions. Since the sample retailer utilized a centralized pricing scheme, we examine its promotion pattern at the chain level.

determined by the base consumption rate and the number of stocking periods of the stockpiler segment. Hence, the total demand during promotions reflects both the base demand of the non-stockpiler segment and the spiking demand of the stockpiler segment.

We first briefly review the foundations of the two-segment household inventory model. Our modeling assumptions are based on the findings of Blattberg and colleagues (1981) and Breiter and Huchzermeier (2015). We assume consumers shop in a retail channel on a periodic basis. The retail channel utilizes HILO pricing for a storable product over a horizon of T periods. Out of these T periods ($\mathrm{t} = 1, 2, \dots, \mathrm{T}$), N are promotional pricing periods ($\mathrm{n} = 1, 2, \dots, \mathrm{N}$) during which the product is offered at a discount, while the remaining $\mathrm{T} - \mathrm{N}$ periods are regular pricing periods during which the product is sold at its full price.

Consumers differ in their stockpiling behavior. Let C^{ns} and C^{s} denote the consumption rates of the non-stockpiler segment and the stockpiler segment, respectively, which are assumed to be constant over the T periods. The consumption rate of the non-stockpiler (stockpiler) segment is the quantity consumed by all consumers in the segment during a unit time period, expressed as $\mathrm{C}^{\mathrm{ns}} = \mathrm{c} \cdot \mathrm{S}^{\mathrm{ns}}$ ($\mathrm{C}^{\mathrm{s}} = \mathrm{c} \cdot \mathrm{S}^{\mathrm{s}}$), with c representing the mean consumption rate of an individual consumer and S^{ns} (S^{s}), the size of consumers in the non-stockpiler (stockpiler) segment (Blattberg et al., 1981).

The non-stockpiler segment forms the base of the periodic demand. The demand of the non-stockpiler segment during a purchase period is set at a constant, $\mathrm{D}_{\mathrm{t}}^{\mathrm{ns}} = \mathrm{C}^{\mathrm{ns}}$. The stockpiler segment induces a demand spike during each promotional period. Stockpilers follow an order-up-to policy in their stockpiling decisions such that they purchase sufficient units to meet future τ_{n}^{*} periods of consumption, reaching a stockpiling level Q_n^s, where the subscript n indicates the corresponding promotion period. The optimal τ_n^* is a function of the reservation price, w^s, the holding costs, h^s, and the promotional price, p_n (Blattberg et al., 1981). We have:

$$Q_n^s = C^s \cdot \tau_n^*,$$

where

$$\tau_n^* = \frac{w^s - p_n}{h^s}. \tag{1}$$

In practice, price promotions may take place before or after households stock out. While stockpilers stock inventory for the τ_{n-1}^* period at the n-1st promotion, the next promotion, the nth, may occur before or after the τ_{n-1}^* period has concluded. We distinguish between two scenarios:

- If the nth promotion occurs too early, $\tau_{n-1} \leq \tau_{n-1}^*$, then stockpilers have an inventory level of $I_n^s(p_{n-1})$ at the beginning of the nth promotion, resulting in a lower demand spike during the nth promotion:

$$I_n^s(p_{n-1}) = C^s \cdot [\tau_{n-1}^* - \tau_{n-1}]^+. \tag{2}$$

- If the nth promotion occurs too late, $\tau_{n-1} > \tau_{n-1}^*$, then stockpilers will run out of inventory before the beginning of the nth promotion, resulting in lost sales for HILO retailers (i.e., consumers may fill needed demand at the EDLP retailer) (Iyer & Ye, 2000).

During the nth promotion period, the actual demand for stockpilers $D_t^s(p_t)$ equals the difference between the optimal order-up-to level, $Q^s(p_n)$, and their inventory at the beginning of the nth promotion, $I_n^s(p_{n-1})$. According to (2), the stockpiler demand during the nth promotion is $[Q_n^s(p_n) - I_n^s(p_{n-1})]^+ = [\tau_n^* - [\tau_{n-1}^* - \tau_{n-1}]^+]^+ \cdot C^s$, where the first term represents the number of periods that the actual demand of the stockpiler segment can satisfy given its constant consumption rate, C^s . We let $STOCKING\_PERIOD_t^s \equiv [\tau_n^* - [\tau_{n-1}^* - \tau_{n-1}]^+]^+$ if t is a promotional period; otherwise we set $STOCKING\_PERIOD_t^s$ as zero if t is a regular period. Accordingly, we can express the actual demand of the stockpiler segment at any purchase period, t, as:

$$D_t^s(p_t) = C^s \cdot STOCKING\_PERIOD_t^s. \tag{3}$$

The non-stockpilers continue purchasing the same periodic quantity, $D_t^{ns}(p_t) = C^{ns}$, to accommodate per-period consumption. The total demand during any purchase period, $D_t(p_t)$, is the sum of the demands from the non-stockpiler and stockpiler segments, $D_t^{ns}(p_t)$ and $D_t^s(p_t)$. Thus,

$$D_t(p_t) = C^{ns} + C^s \cdot STOCKING\_PERIOD_t^s \tag{4}$$

The consumption rates for each of the segments can be estimated using a regression model, where the estimated coefficients, β_0 and β_1, represent C^{ns} and C^s, respectively.

$$D_t(p_t) = \beta_0 + \beta_1 \cdot STOCKING\_PERIOD_t^s \tag{5}$$

Stockpiling propensity represents the ratio of consumption rate of the stockpiler segment to the consumption rate of the non-stockpiler segment. Thus, we can derive the stockpiling propensity, ρ, as:

$$\rho = \frac{C^s}{C^{ns}} = \frac{\beta_1}{\beta_0} \tag{6}$$

Estimation Model

We extend the equations described above in (4), (5) and (6) to estimate the impact of environmental stress on stockpiling propensity. First, we observe the weekly demand of the sample retailer in week t for each state market s, $D_{t,s}(p_{t,s})$, from the sample data, which reflects the sum of the weekly demands from the non-stockpiler and stockpiler segments. Second, we assume that the weekly consumption rates of the non-stockpiler (superscript ns) and stockpiler (superscript s) segments are constant over a monthly period m for each state market (subscript s), $\mathrm{C}^{\mathrm{ns}}_{\mathrm{m,s}}$ and $\mathrm{C}^{\mathrm{s}}_{\mathrm{m,s}}$, which vary with environmental stress, $\mathrm{STRESS\_CCIP_t}$, for each monthly period m under the study[4]. Thus, we modify (5) to obtain the weekly demand of the sample retailer, $\mathrm{D_{t,s}}(\mathrm{p_{t,s}})$, as follows:

$$\mathrm{D_{t,s}}(\mathrm{p_{t,s}}) = \beta_0 + \beta_2 \cdot \overline{\mathrm{STATE}} + \beta_4 \cdot \mathrm{STRESS\_CCIP_t} + (\beta_1 + \beta_3 \cdot \overline{\mathrm{STATE}} + \beta_5 \cdot \mathrm{STRESS\_CCIP_t}) \cdot \mathrm{STOCKING\_PERIOD^s_{t,s}} \quad (7)$$

where $\overline{\mathrm{STATE}}$ is a vector of dummy variables indicating the six sample sate markets, NY, CA, MI, OH, NJ, and PA. Thus, β_2 (β_3) is a vector of coefficients for the corresponding sample state markets.

According to (7), we can estimate the weekly consumption rate of the non-stockpiler segment, $\mathrm{C}^{\mathrm{ns}}_{\mathrm{m,s}} = \beta_0 + \beta_2 \cdot \overline{\mathrm{STATE}} + \beta_4 \cdot \mathrm{STRESS\_CCIP_m}$, and the weekly consumption rate of the stockpiler segment, $\mathrm{C}^{\mathrm{s}}_{\mathrm{m,s}} = \beta_1 + \beta_3 \cdot \overline{\mathrm{STATE}} + \beta_5 \cdot \mathrm{STRESS\_CCIP_m}$, for each monthly period m.

Stockpiling propensity represents the relative ratio of the consumption rate of the stockpiler segment to the consumption rate of the non-stockpiler segment. Likewise, we can modify (6) to derive the stockpiling propensity in month m for each sample state market, $\rho_{\mathrm{m,s}}$, as:

$$\rho_{\mathrm{m,s}} = \frac{\mathrm{C}^{\mathrm{s}}_{\mathrm{m,s}}}{\mathrm{C}^{\mathrm{ns}}_{\mathrm{m,s}}} = \frac{\beta_1 + \beta_3 \cdot \overline{\mathrm{STATE}} + \beta_5 \cdot \mathrm{STRESS\_CCIP_m}}{\beta_0 + \beta_2 \cdot \overline{\mathrm{STATE}} + \beta_4 \cdot \mathrm{STRESS\_CCIP_m}} \quad (8)$$

[4] The weekly measure of the sample retailer is Sunday to Saturday. Accordingly, we set the weekly environmental stress index, $STRESS\_CCIP_t$ to the monthly environmental stress index, $STRESS\_CCIP_m$, of the corresponding month containing this Saturday.

Note that the expression of stockpiling propensity provided in (8) is nonlinear in terms of the estimated coefficients in (7). To examine how environmental stress affects the stockpiling propensity, we have:

$$\rho_{m,s} = \gamma_0 + \gamma_1 \cdot \overline{\mathrm{STATE}} + \gamma_2 \cdot \mathrm{STRESS\_CCIP}_m + \gamma_3 \cdot \mathrm{STRESS\_CCIP}_m \cdot \overline{\mathrm{STATE}} \qquad (9)$$

Parameter Estimation

To calculate $\mathrm{STOCKING\_PERIOD}_{t,s}^{s}$ in the estimation model (7), we first estimate the reservation price, w^s, and the holding cost, h^s, of the stockpiler segment. Using grid search, we set w^s at 50%, 55%, …, 100% of the maximum retail price during the study period and h^s at 1%, 2%, …, 10% of the maximum retail price. We then calculate $\mathrm{STOCKING\_PERIOD}_{t,s}^{s}$ using each combination of w^s and h^s for each week in the dataset from 2007Q4 to 2009Q4, assuming zero household inventory in the first week of 2007Q4. We choose the parameter values of w^s and h^s that maximize the explanatory power of the estimation model, yielding the highest value of adjusted R^2 (Greenleaf, 1995). We assume the reservation prices and the holding costs of the stockpiler segment are the same across the regional markets. Our estimated reservation price is approximately 85% of the maximum retail price; that is, about $0.21 per diaper. The estimated holding cost is about 6% of the maximum retail price. Table 1 displays statistics of the variables. The correlation matrix is provided in Table A2.

Table 1: Data Description (Sample Retailer)

Variable	Unit	Obs	Mean	Std. Dev.	Min	Max
$D_{t,s}$	unit diapers	702	30,885.91	32,924.53	7,126.00	243,436.00
$\mathrm{STOCKING\_PERIOD}_{t,s}^{s}$	weeks	702	0.34	0.87	0.00	4.17
$\mathrm{STRESS\_CCIP}_t$	-	702	1.54	0.29	1.00	1.83

EMPIRICAL RESULTS

In Table 2, we set the weekly demand, $\mathrm{D_{t,s}}$, as the dependent variable. In Model 2.1.1 and Model 2.1.2, we ignore the effects of the environmental stress. In Model 2.1.3 and Model 2.1.4, we highlight the effects of the environmental stress. We explain the results utilizing Model 2.1.4, the complete model. In Model 2.1.4, the coefficient of $\mathrm{STRESS\_CCIP_t}$ is negative and significant, β_4 =-7,768.13; the coefficient of $\mathrm{STOCKING\_PERIOD^s_{t,s}} \cdot \mathrm{STRESS\_CCIP_t}$ is negative and significant, β_5=-1,947.06. We can estimate the weekly consumption rate of the two segments for each sample state market s using the estimated coefficients in Model 2.1.4, $\mathrm{C^{ns}_{m,s}} = \beta_0 + \beta_2 \cdot \overline{\mathrm{STATE}} + \beta_4 \cdot \mathrm{STRESS\_CCIP_m}$ and $\mathrm{C^{s}_{m,s}} = \beta_1 + \beta_3 \cdot \overline{\mathrm{STATE}} + \beta_5 \cdot \mathrm{STRESS\_CCIP_m}$. Thus, the results indicate that environmental stress is negatively associated with the consumption rates of each of the segments (non-stockpiler and stockpiler).

Table 2: Regression Results (Weekly Sales Volume at the Retailer Level)

Variables	Weekly Sales Volume (DV: $D_{t,s}$)			
	Model 2.1.1 (OLS Regression)	Model 2.1.2 (OLS Regression)	Model 2.1.3 (OLS Regression)	Model 2.1.4 (OLS Regression)
Intercept	28,947.01*** (2,523.93)	20,821.10*** (724.01)	46,321.39***(5,974.96)	32,818.12***(1,622.69)
NY	31,652.00*** (3,569.38)	22,719.58*** (1,023.52)	31,652.00***(3,545.86)	22,718.63***(962.05)
CA	22,033.32*** (3,569.38)	15,361.24*** (1,024.04)	22,033.32***(3,545.86)	15,317.08***(962.55)
MI	-11,917.03*** (3,569.38)	-8,781.03*** (1,021.31)	-11,917.03***(3,545.86)	-8,825.11***(959.98)
OH	-14,640.32*** (3,569.38)	-10,533.25*** (1,021.38)	-14,640.32***(3,545.86)	-10,561.98***(960.04)
NJ	-15,494.53*** (3,569.38)	-10,960.66*** (1,022.83)	-15,494.53***(3,545.86)	-10,963.03***(961.40)
STRESS_CCIP_t			-11,304.03***(3,528.56)	-7,768.13***(954.68)
$\text{STOCKING\_PERIOD}^s_{t,s}$		23,714.91*** (772.66)		26,454.01***(1,663.82)
$\text{STOCKING\_PERIOD}^s_{t,s} \cdot \text{NY}$		25,322.54*** (1081.62)		25,332.68***(1016.66)
$\text{STOCKING\_PERIOD}^s_{t,s} \cdot \text{CA}$		17,090.26*** (1,064.02)		17,296.16***(1,000.69)
$\text{STOCKING\_PERIOD}^s_{t,s} \cdot \text{MI}$		-8,050.31*** (1,111.60)		-7,859.20***(1,045.43)
$\text{STOCKING\_PERIOD}^s_{t,s} \cdot \text{OH}$		-11,166.14*** (1,109.13)		-11,049.08***(1,042.75)
$\text{STOCKING\_PERIOD}^s_{t,s} \cdot \text{NJ}$		-12,396.08*** (1,127.51)		-12,397.54***(1,059.79)
$\text{STOCKING\_PERIOD}^s_{t,s} \cdot \text{STRESS\_CCIP}_t$				-1,947.06*(1,002.48)
Observations	702	702	702	702
R^2	0.317	0.952	0.327	0.958
Adjusted R^2	0.312	0.951	0.321	0.957

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

We calculate stockpiling propensity according to (8) in Table A3 and Table A4 in the Appendix. In Table 3, we set the monthly stockpiling propensity of each state market s, $\rho_{m,s}$, as the dependent variable. In Model 2.2.1, Model 2.2.2, and Model 2.2.3, we focus on the monthly stockpiling propensity highlighting the effects of environmental stress. In Model 2.2.2 and Model 2.2.3, the coefficients of $STRESS\_CCIP_m$ are positive and significant, 0.43 and 0.31, revealing that stockpiling propensity increases with environmental stress. Figure 1 illustrates the causal relationship between stockpiling propensity and environmental stress.

Table 3: Regression Results (Consumer Stockpiling Propensity at the Retailer Level)

Variables	Consumer Stockpiling Propensity (DV: $\rho_{m,s}$)		
	Model 2.2.1 (OLS Regression)	Model 2.2.2 (OLS Regression)	Model 2.2.3 (OLS Regression)
Intercept	1.13***(0.03)	0.48***(0.03)	0.66***(0.02)
NY	-0.01(0.04)	-0.01(0.02)	0.23***(0.03)
CA	-0.00(0.04)	-0.00(0.02)	0.19***(0.03)
MI	0.20*** (0.04)	0.20***(0.02)	-0.30***(0.03)
OH	0.11**(0.04)	0.11***(0.02)	-0.44***(0.03)
NJ	0.02(0.04)	0.02(0.02)	-0.47***(0.03)
$STRESS\_CCIP_m$		0.43***(0.02)	0.31***(0.01)
$STRESS\_CCIP_m \cdot NY$			-0.16***(0.02)
$STRESS\_CCIP_m \cdot CA$			-0.13***(0.02)
$STRESS\_CCIP_m \cdot MI$			0.32***(0.02)
$STRESS\_CCIP_m \cdot OH$			0.36***(0.02)
$STRESS\_CCIP_m \cdot NJ$			0.32***(0.02)
Observations	162	162	162
R^2	0.224	0.826	0.986
Adjusted R^2	0.199	0.820	0.985

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

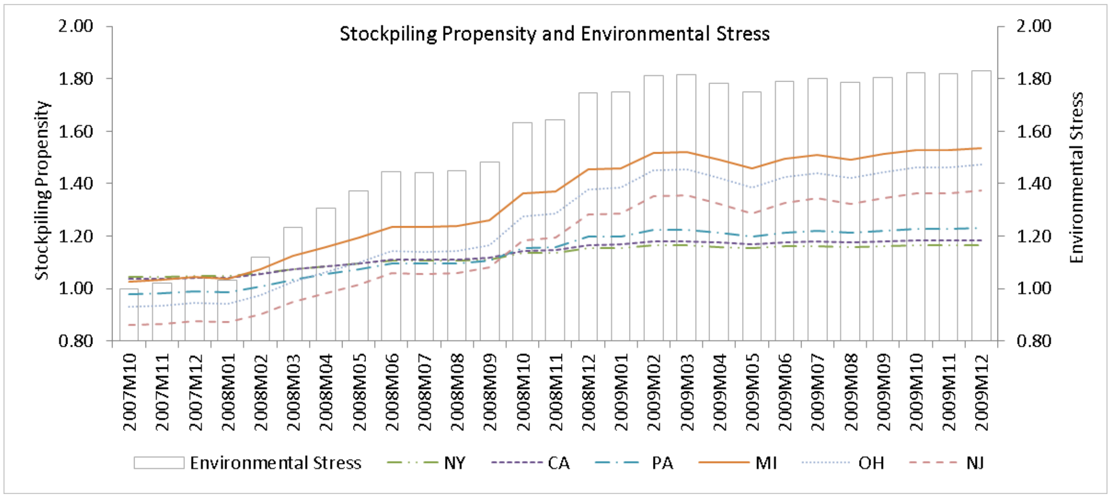

Figure 1: Stockpiling Propensity in the Face of Environmental Stress

SUPPLEMENTARY ANALYSIS

To better determine how changes in environmental stress impact stockpiling behavior, we use household expenditure data to estimate stockpiling propensity. Specifically, we focus only on diapers purchased by the sample households.

Sample Description

Our data is sourced from the Nielsen consumer panel dataset[5]. The Nielsen panelists use in-home scanners to record all household purchases of fast-moving consumer goods. Nielsen samples all US states and major markets with approximately 60,000 panelists each year, geographically dispersed and demographically balanced. Some consumers stay on the panel for several years, while others join or drop off each year. The dataset includes information on shopping trips and purchase transactions, as

[5] Calculated (or derived) based on data from The Nielsen Company (US), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researchers and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

well as demographic and geographic data. We focus on diapers as the sample product category.

We collect data from all households with one child who is up to two years of age and with purchase records of diapers during the period 2007Q4 to 2009Q4. We drop those households that also have children who are three or four years old. We define a one-year-old (two-year-old) child as a child who is up to 12 months (13 to 24 months) old at the beginning of the sample year. Households with children who are three or four years old are omitted since the diaper consumption rate shows more variation among older children. We keep those households within the 1% to 99% percentile range of quarterly diaper demand. This provides a sample of 2,932 households, around 4.9% of the total Nielsen panelists. According to the U.S. Census Bureau in 2012, households with children under three (one) years old are around 7.0% (2.5%) of total households. Thus, our sample provides a reasonable representation of the national demographic distribution. The longitudinal and geographic distributions of the sample households are provided in Table A5 and Table A6 in the Appendix.

Estimation Results

We look to uncover the degree to which households change their consumption rates and stockpiling propensity in the face of environmental stress. We assume the household's quarterly diaper demand is a proxy for the quarterly diaper consumption rate per child. We measure the quarterly household stockpiling propensity as the ratio of deal purchases to non-deal purchases (Blattberg et al., 1981). We define a dummy variable One-Year-Old that equals one if the child is up to 12 months old at the beginning of the sample year. We control for key observable household characteristics that may affect household price sensitivity, including household size and household income (Hendel & Nevo, 2006a, 2006b). Table 4 displays statistics on household demographics and diaper purchases. The correlation matrix is provided in Table A7.

Table 4: Data Description (Sample Households)

	2,932 Sample Households					
	Obs	Mean	Median	Std	Min	Max
Demographics						
Size of household (number of persons)	2,932	4.03	4.00	1.21	2.00	9.00
Average income per head (000's of $)	2,932	21.23	17.50	14.22	0.83	83.33
One year old (dummy variable)	2,932	0.29	0	0.46	0.00	1.00
Diapers Purchases						
Quarterly household stockpiling propensity	7,158	0.35	0.14	0.40	0.00	1.00
Quarterly diaper consumption rate (units/quarter)	7,158	283	256	177	24	958

In Table 5 and Table 6, we present the estimation results at the household level. In Model 2.3.1 and Model 2.3.2, we focus on the periodic consumption rate of a child highlighting the effects of environmental stress[6]. In Model 2.3.2, the coefficient of $\mathrm{STRESS\_CCIP_q}$ is negative and significant, -79.35, indicating that the periodic consumption rate is negatively associated with environmental stress. In Model 2.4.1 and Model 2.4.2, we focus on the household stockpiling propensity highlighting the effects of the environmental stress[7]. In Model 2.4.2, the coefficient of $\mathrm{STRESS\_CCIP_q}$ is positive and significant, 0.15, illustrating that household stockpiling propensity is positively associated with environmental stress.

[6] We utilize fixed effects model estimating periodic consumption rate of a child, $\boldsymbol{c_q}$,. The Hausman test results suggest the fixed effects models are more appropriate than random effects models.
[7] We apply fraction regression model estimating household stockpiling propensity, $\boldsymbol{\rho_q}$, which has a boundary between zero and one (Williams 2016, Wooldridge 2011).

Table 5: Regression Results (Periodic Consumption Rate at the Household Level)

Variables	Periodic Consumption Rate (DV: c_q) Model 2.3.1 (Fixed Effects)	Model 2.3.2 (Fixed Effects)
Intercept	182.92**(66.47)	317.05***(69.31)
HOUSEHOLD_SIZE	11.02(13.94)	9.41(13.88)
AVG_INCOME_HEAD	2.04*(1.22)	2.01*(1.22)
ONE_YEAR_OLD	40.49***(6.82)	9.74(8.27)
$STRESS\_CCIP_q$		-79.35***(12.19)
Observations	7,158	7,158
F test	12.37	19.95

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

Table 6: Regression Results (Consumer Stockpiling Propensity at the Household Level)

Variables	Consumer Stockpiling Propensity (DV: ρ_q) Model 2.4.1 (Fraction Regression)	Model 2.4.2 (Fraction Regression)
Intercept	-0.33***(0.06)	-0.55***(0.09)
HOUSEHOLD_SIZE	-0.06***(0.01)	-0.06***(0.01)
AVG_INCOME_HEAD	0.01***(0.00)	0.01***(0.00)
ONE_YEAR_OLD	0.09***(0.03)	0.09**(0.03)
$STRESS\_CCIP_q$		0.15***(0.04)
Observations	7,158	7,158
F test		
Wald chi2	122.40	138.11

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

ROBUSTNESS CHECKS

In our primary analysis, we construct a simple environmental stress index based on the Conference Board’s Present Situation Index. As a robustness check, we utilize actual changes, or “economic shocks” in the gross domestic product (GDP) to measure environmental stress. To determine the shocks, we isolate the long-term trend from the cyclical component of GDP. We collect quarterly GDP data from the Bureau of Economic Analysis (BEA) for 1947−2015. The GDP series can be decomposed into a linear component (GDP_t^l) and a cyclical component (GDP_t^c), $\mathrm{GDP}_t = \mathrm{GDP}_t^l + \mathrm{GDP}_t^c$, in which decreases or increases in the cyclical component GDP_t^c correspond to economic shocks at time point t. We take the natural log-transformation on the GDP series (Kesavan & Kushwaha, 2014) and apply the Hodrick-Prescott (HP) filter to extract the trend and the cyclical components (Lamey, Dekimpe, Deleersnyder, & Steenkamp, 2007; Lamey, Deleersnyder, Dekimpe, & Steenkamp, 2012). The extracted cyclical components, GDP_t^c, feed into (10) and yield the value of economic shocks, SHOCK_t.

$$\mathrm{SHOCK}_t = \begin{cases} \mathrm{GDP}_t^c - \mathrm{GDP}_{\mathrm{PriorTrough}}^c & \text{if t within an expansion cycle} \\ \mathrm{GDP}_t^c - \mathrm{GDP}_{\mathrm{PriorPeak}}^c & \text{if t within a contraction cycle} \end{cases} \quad (10)$$

The expression $\mathrm{GDP}_t^c - \mathrm{GDP}_{\mathrm{PriorTrough}}^c$ measures the expansion shock by calculating how much a cyclical component GDP_t^c within an expansion cycle has increased relative to the trough of its previous contraction cycle (Lamey et al., 2007). The expression $\mathrm{GDP}_t^c - \mathrm{GDP}_{\mathrm{PriorPeak}}^c$ measures the contraction shock by calculating how much a cyclical component GDP_t^c within a contraction cycle has dropped relative to the peak of its previous expansion cycle (Lamey et al., 2007). The conceptual reasoning underlying the definition of economic shock is that consumers evaluate the current state of the economy by comparing it with the previous best or previous worst of recent times (Kesavan & Kushwaha, 2014). Thus, economic shocks could be used to approximate environmental stress. Environmental stress based on the actual economic shocks, $\mathrm{STRESS\_SHOCK}_t$, is constructed in a similar way to that based on the Present Situation Index, $\mathrm{STRESS\_CCIP}_t$.

Table 7 presents the regression results based on the sample retailer. In Model 2.5.1, Model 2.5.2, and Model 2.5.3, we focus on the quarterly stockpiling propensity highlighting the effects of environmental stress. In Model 2.5.2 and Model 2.5.3, the coefficients of $\mathrm{STRESS\_SHOCK_q}$ are significantly positive, which is consistent with our primary analysis at the retailer level.

Table 7: Robustness Checks (Consumer Stockpiling Propensity at the Retailer Level)

Variables	Consumer Stockpiling Propensity (DV: $\rho_{q,s}$)		
	Model 2.5.1 (OLS Regression)	Model 2.5.2 (OLS Regression)	Model 2.5.3 (OLS Regression)
Intercept	1.12***(0.03)	0.94***(0.02)	1.00***(0.01)
NY	-0.01(0.04)	-0.01(0.02)	0.06***(0.01)
CA	0.00(0.04)	0.00(0.02)	0.06***(0.01)
MI	0.19***(0.04)	0.19***(0.02)	0.02**(0.01)
OH	0.10*(0.04)	0.10***(0.02)	-0.07***(0.01)
NJ	0.01(0.04)	0.01(0.02)	-0.13***(0.01)
$\mathrm{STRESS\_SHOCK_q}$		0.08***(0.01)	0.06***(0.00)
$\mathrm{STRESS\_SHOCK_q} \cdot \mathrm{NY}$			-0.03***(0.00)
$\mathrm{STRESS\_SHOCK_q} \cdot \mathrm{CA}$			-0.02***(0.00)
$\mathrm{STRESS\_SHOCK_q} \cdot \mathrm{MI}$			0.07***(0.00)
$\mathrm{STRESS\_SHOCK_q} \cdot \mathrm{OH}$			0.08***(0.00)
$\mathrm{STRESS\_SHOCK_q} \cdot \mathrm{NJ}$			0.06***(0.00)
Observations	54	54	54
R^2	0.402	0.860	0.997
Adjusted R^2	0.339	0.842	0.997

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

Table 8 illustrates the regression results based on the sample households. In Model 2.6.1 and Model 2.6.2, we focus on the household stockpiling propensity highlighting the effects of environmental stress. Specifically, in Model 2.6.2, the coefficient of $\mathrm{STRESS\_SHOCK_q}$ is significantly positive, which is consistent with our supplementary analysis at the household level.

Table 8: Robustness Checks (Consumer Stockpiling Propensity at the Household Level)

Variables	Consumer Stockpiling Propensity (DV: ρ_q)	
	Model 2.6.1 (Fraction Regression)	Model 2.6.2 (Fraction Regression)
Intercept	-0.33***(0.06)	-0.42***(0.07)
HOUSEHOLD_SIZE	-0.06***(0.01)	-0.06***(0.01)
AVG_INCOME_HEAD	0.01***(0.00)	0.01***(0.00)
ONE_YEAR_OLD	0.09***(0.03)	0.09**(0.03)
$\mathrm{STRESS\_SHOCK}_q$		0.05***(0.01)
Observations	7,158	7,158
Wald chi2	122.40	137.43

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

Overall, the evidence reveals that consumer stockpiling propensity increases with environmental stress. The estimation results regarding weekly sales volume (retailer-level) and periodic consumption rate (household-level) are presented in Table A8 and Table A9 in the Appendix, respectively.

MANAGERIAL IMPLICATIONS

How should retailers respond to changes in stockpiling behavior due to environmental stress? Similar to Su (2010), we suggest retailers employ a combination of regular orders to fulfill the demand from the non-stockpiler segment and jumbo orders to fulfill the demand from the stockpiler segment during promotional periods. In the absence of inventory counts of the sample retailer, we follow the methodology of Gallino, Moreno, and Stamatopoulos (2016) by applying operations theory (namely, the safety stock formula) to explore inventory implications using sales data as a proxy for consumer demand. We first derive mean inventory and safety stock expressions for the two segments. Next, we illustrate dynamic changes to the mean inventory and safety stock of the sample retail channel. Last, we provide managerial implications to address a retailer's need to capture stockpiling behavior to manage inventory efficiently.

Inventory Planning

In practice, a retailer can plan promotional inventory by setting the expected stocking periods for the stockpiler segment, based on either known promotion prices or random promotion prices. For example, under a random promotion strategy, retailers may decide the promotion timing in advance, but vary promotional prices on the promotional events. In this case, the retailer can estimate the expected stocking periods by stockpiler segment, $\overline{\mathrm{STOCKING\_PERIOD}^{s}_{t,s}}$, based on expected promotional prices, while allowing certain variability due to the randomness in promotion prices. We assume the variance of the stocking periods by the stockpiler segment is proportional to the expected stocking periods, $\omega \cdot \overline{\mathrm{STOCKING\_PERIOD}^{s}_{t,s}}$. To simplify our analysis, we assume the forecast error of the actual weekly segment consumption rate is proportional to the estimated weekly segment consumption during month m as, $\sigma \cdot \mathrm{C}^{ns}_{m,s}$ and $\sigma \cdot \mathrm{C}^{s}_{m,s}$.

To identify the subsequent effects on inventory management, we derive the mean inventory and safety stock to address the demand of the non-stockpiler segment. As the non-stockpiler segment purchases only to fulfill per-period consumption, the mean inventory to fulfill the weekly demand of the non-stockpiler segment in month m is given by

$$\mathrm{INV}^{ns}_{m,s} \cong \mathrm{C}^{ns}_{m,s}. \tag{11}$$

Accordingly, the retailer's safety stock for the non-stockpiler segment needs to protect against the forecast error in segment consumption rate, $\sigma \cdot \mathrm{C}^{ns}_{m,s}$. The weekly safety stock for the non-stockpiler segment during month m is given by

$$SS^{ns}_{m,s} \cong z \cdot \sigma \cdot C^{ns}_{m,s}. \tag{12}$$

Next, we derive the mean inventory and safety stock to account for the demand of the stockpiler segment. As the stockpiler segment purchases during promotional periods for multi-period consumption, the retailer needs to use two components to determine the expected demand: the mean weekly segment consumption rate, $C^{s}_{m,s}$, and the expected stocking periods, $\overline{STOCKING\_PERIOD^{s}_{t,s}}$. The mean inventory to fulfill the stockpiler segment during a promotion in month m is

$$INV^{s}_{m,s} \cong C^{s}_{m,s} \cdot \overline{STOCKING\_PERIOD^{s}_{t,s}} = \rho_{m,s} \cdot C^{ns}_{m,s} \cdot \overline{STOCKING\_PERIOD^{s}_{t,s}}. \tag{13}$$

Recalling the definition of the stockpiling propensity, we can express $C^{s}_{m,s} = \rho_{m,s} \cdot C^{ns}_{m,s}$.

Consequently, the safety stock for the stockpiler segment should protect against two types of variability: the forecast error in the segment consumption rate and the variability in the expected stocking periods. The weekly safety stock for the stockpiler segment during a promotion in month m is given by

$$SS^{s}_{m,s} \cong z \cdot \overline{STOCKING\_PERIOD^{s}_{t,s}} \cdot \sigma \cdot C^{s}_{m,s} + z \cdot \sqrt{\omega \cdot \overline{STOCKING\_PERIOD^{s}_{t,s}}} \cdot C^{s}_{m,s} \tag{14}$$

Before illustrating the inventory stocking decisions for the non-stockpiler segment and the stockpiler segment, we derive two additional inventory measures, the mean inventory ratio and the safety stock ratio of the stockpiler to the non-stockpiler segments. Explicitly, these two ratios are given by:

$$\frac{INV^{s}_{m,s}}{INV^{ns}_{m,s}} = \rho_{m,s} \cdot \overline{STOCKING\_PERIOD^{s}_{t,s}}, \tag{15}$$

$$\frac{SS^{s}_{m,s}}{SS^{ns}_{m,s}} = \rho_{m,s} \cdot \overline{STOCKING\_PERIOD^{s}_{t,s}} + \rho_{m,s} \cdot \frac{1}{\sigma} \cdot \sqrt{\omega \cdot \overline{STOCKING\_PERIOD^{s}_{t,s}}} \tag{16}$$

In the next section, we demonstrate dynamic changes in the mean inventory ratio and safety stock ratio as stockpiling propensity increases with environmental stress during economic downturns.

Numerical Illustration

We consider a hypothetical scenario where the retailer pursues a service level of 0.95. To obtain the estimations, we first recover the main parameters using the estimation results from Model 2.1.4 in Table 2. Since the mean of the stocking periods by the stockpiler segment, $\overline{\mathrm{STOCKING\_PERIOD}^{s}_{t,s}}$, is 2.3 weeks, and the variance of the stocking periods by the stockpiler segment, $\omega \cdot \overline{\mathrm{STOCKING\_PERIOD}^{s}_{t,s}}$, is approximately 0.63, we assume the maximum value of ω is 0.27. Without actual weekly segment consumption rate information, we utilize Mean Absolute Percentage Error (MAPE) of the estimation model as an approximate value for σ, about 0.13. Next, we compare the dynamic changes in inventories for the two segments, with known promotion prices and random promotion prices, setting $\omega = 0$ and $\overline{\omega} = 0.27/2 = 0.135$, respectively[8]. We demonstrate the primary inventory management insights using the State of Michigan. In Table 9, we demonstrate dynamic changes in the mean inventory and safety stock of the two segments with known promotion prices and random promotion prices in the face of environmental stress.

[8] The estimation of $\omega = 0.27$ reflects the ratio of the variance of the stocking periods to the mean of the stocking periods by the stockpiler segment over the whole study period, 2007Q4 to 2009Q4. We apply the mean of the ratio, $\overline{\omega} = 0.135$, in our hypothetical scenario.

Table 9: Inventory Planning for Non-Stockpiler and Stockpiler Segments (Michigan)

MTH	$\mathrm{STRESS\_CCIP}_{m,s}$	$\rho_{m,s}$	Non-Stockpiler Segment		Stockpiler Segment Known Promotion Prices ($\omega = 0$)				Stockpiler Segment Random Promotion Prices ($\omega = 0.135$)			
			$\overline{\mathrm{INV}_{m,s}^{ns}}$	$\overline{\mathrm{SS}_{m,s}^{ns}}$	$\overline{\mathrm{INV}_{m,s}^{s}}$	$\overline{\mathrm{SS}_{m,s}^{s}}$	$\frac{\overline{\mathrm{INV}_{m,s}^{s}}}{\overline{\mathrm{INV}_{m,s}^{ns}}}$	$\frac{\overline{\mathrm{SS}_{m,s}^{s}}}{\overline{\mathrm{SS}_{m,s}^{ns}}}$	$\overline{\mathrm{INV}_{m,s}^{s}}$	$\overline{\mathrm{SS}_{m,s}^{s}}$	$\frac{\overline{\mathrm{INV}_{m,s}^{s}}}{\overline{\mathrm{INV}_{m,s}^{ns}}}$	$\frac{\overline{\mathrm{SS}_{m,s}^{s}}}{\overline{\mathrm{SS}_{m,s}^{ns}}}$
2007M10	1.00	1.03	16,225	3,480	38,290	8,213	*2.36*	*2.36*	38,290	23,519	*2.36*	*6.76*
2007M11	1.02	1.03	16,073	3,448	38,203	8,194	*2.38*	*2.38*	38,203	23,466	*2.38*	*6.81*
2007M12	1.04	1.04	15,889	3,408	38,096	8,172	*2.40*	*2.40*	38,096	23,401	*2.40*	*6.87*
2008M01	1.03	1.04	15,981	3,428	38,149	8,183	*2.39*	*2.39*	38,149	23,433	*2.39*	*6.84*
2008M02	1.12	1.07	15,303	3,283	37,759	8,099	*2.47*	*2.47*	37,759	23,193	*2.47*	*7.07*
2008M03	1.23	1.12	14,421	3,093	37,250	7,990	*2.58*	*2.58*	37,250	22,881	*2.58*	*7.40*
2008M04	1.31	1.16	13,848	2,970	36,920	7,919	*2.67*	*2.67*	36,920	22,678	*2.67*	*7.63*
2008M05	1.37	1.19	13,341	2,862	36,628	7,857	*2.75*	*2.75*	36,628	22,498	*2.75*	*7.86*
2008M06	1.45	1.24	12,762	2,737	36,294	7,785	*2.84*	*2.84*	36,294	22,293	*2.84*	*8.14*
2008M07	1.44	1.23	12,788	2,743	36,309	7,788	*2.84*	*2.84*	36,309	22,303	*2.84*	*8.13*
2008M08	1.45	1.24	12,736	2,732	36,278	7,782	*2.85*	*2.85*	36,278	22,284	*2.85*	*8.16*
2008M09	1.48	1.26	12,479	2,677	36,130	7,750	*2.90*	*2.90*	36,130	22,193	*2.90*	*8.29*
2008M10	1.63	1.36	11,320	2,428	35,462	7,607	*3.13*	*3.13*	35,462	21,783	*3.13*	*8.97*
2008M11	1.64	1.37	11,241	2,411	35,417	7,597	*3.15*	*3.15*	35,417	21,755	*3.15*	*9.02*
2008M12	1.74	1.46	10,445	2,240	34,958	7,498	*3.35*	*3.35*	34,958	21,473	*3.35*	*9.58*
2009M01	1.75	1.46	10,412	2,233	34,939	7,494	*3.36*	*3.36*	34,939	21,461	*3.36*	*9.61*
2009M02	1.81	1.52	9,925	2,129	34,658	7,434	*3.49*	*3.49*	34,658	21,289	*3.49*	*10.00*
2009M03	1.81	1.52	9,898	2,123	34,643	7,431	*3.50*	*3.50*	34,643	21,279	*3.50*	*10.02*
2009M04	1.78	1.49	10,135	2,174	34,779	7,460	*3.43*	*3.43*	34,779	21,363	*3.43*	*9.83*
2009M05	1.75	1.46	10,412	2,233	34,939	7,494	*3.36*	*3.36*	34,939	21,461	*3.36*	*9.61*
2009M06	1.79	1.50	10,103	2,167	34,760	7,456	*3.44*	*3.44*	34,760	21,352	*3.44*	*9.85*
2009M07	1.80	1.51	9,991	2,143	34,696	7,442	*3.47*	*3.47*	34,696	21,312	*3.47*	*9.94*
2009M08	1.78	1.49	10,129	2,173	34,776	7,459	*3.43*	*3.43*	34,776	21,361	*3.43*	*9.83*
2009M09	1.81	1.51	9,971	2,139	34,684	7,440	*3.48*	*3.48*	34,684	21,305	*3.48*	*9.96*
2009M10	1.82	1.53	9,846	2,112	34,612	7,424	*3.52*	*3.52*	34,612	21,261	*3.52*	*10.07*
2009M11	1.82	1.53	9,852	2,113	34,616	7,425	*3.51*	*3.51*	34,616	21,263	*3.51*	*10.06*
2009M12	1.83	1.54	9,787	2,099	34,578	7,417	*3.53*	*3.53*	34,578	21,240	*3.53*	*10.12*

First, according to (11)-(14), the lower consumption rates of the two segments require lower inventories in the face of higher environmental stress due to financial and economic events. As shown in Table 9, for the non-stockpiler segment, the mean inventory and the safety stock declines from 16,225 and 3,480, respectively, in October 2007 to 9,787 and 2,099, respectively, in December 2009; for the stockpiler segment, when planning inventory with known (random) promotion prices, the mean inventory and safety stock declines from 38,290 and 8,213 (23,290), respectively, in October 2007 to 34,578 and 7,417 (21,240), respectively, in December 2009.

Second, according to (15), a higher stockpiling propensity requires an upward adjustment in mean inventories for the stockpiler segment, $\rho_{m,s} \cdot \overline{\mathrm{STOCKING\_PERIOD}^{s}_{t,s}}$. In Figure 2, we demonstrate the dynamic changes in the mean inventory ratio (stockpiler segment to non-stockpiler segment) as stockpiling propensity increases with environmental stress. For instance, with either known promotion prices ($\omega = 0$) or random promotion prices ($\omega = 0.135$), the mean inventory ratio increases from 2.36 during October 2007 to 3.53 during December 2009 as stockpiling propensity increases from 1.03 to 1.54 with environmental stress.

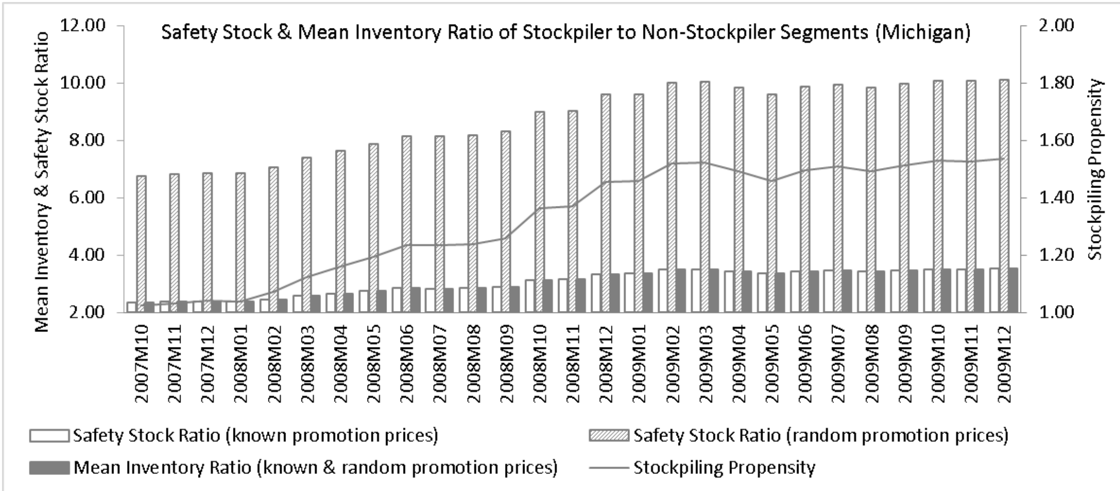

Figure 2: Mean Inventory Ratio and Safety Stock Ratio of Stockpiler to Non-Stockpiler Segments (Michigan)

Lastly, according to (16), inventory policy with random promotion prices (leading to variability in the expected stocking periods by the stockpiler segment) requires an upward adjustment of the safety stock for the stockpiler segment, $\rho_{m,s} \cdot \overline{\mathrm{STOCKING\_PERIOD}_{t,s}^{s}} + \rho_{m,s} \cdot \frac{1}{\sigma} \cdot \sqrt{\omega \cdot \overline{\mathrm{STOCKING\_PERIOD}_{t,s}^{s}}}$. In Figure 2, we illustrate the dynamic changes in the safety stock ratio (stockpiler segment to non-stockpiler segment) as stockpiling propensity increases with environmental stress. For example, comparing random promotion pricing ($\omega = 0.135$) to known promotion pricing ($\omega = 0$), the safety stock ratio increases from 2.36 to 6.76 in October 2007, and from 3.53 to 10.12 in December 2009.

Managerial Implications

A critical insight relates to the correction of mean inventories and safety stocks to match consumer stockpiling behavior affected by environmental stress. For example, as illustrated in Table 9, the estimated stockpiling propensity for Michigan ranges from a minimum of 1.03 to a maximum of 1.54 due to dynamic changes in environmental stress. Unless this differential is considered, a retailer will likely fail to meet its target service level as stockpiling propensity increases. Therefore, retailers need to carefully monitor how their customers respond to environmental stress, such as financial and economic events. Specifically, retailers must consider not only how demand dwindles, but also how customers increasingly exhibit stockpiling behavior. Accordingly, retailers need to be careful when ordering inventory for promotions in the face of changing stockpiling behavior under environmental stress.

Another valuable insight of this study is related to inventory risks due to the interaction of promotion strategy and stockpiling propensity. A random promotion strategy amplifies the inventory risks as stockpiling propensity increases with environmental stress. For example, in Figure 2, we contrast our estimation results with known and random promotion prices. We find that as the stockpiling propensity of Michigan increased by 50% from October 2007 to December 2009, the safety stock ratio rose from 2.36 to 3.53 and from 6.76 to 10.12 under the two scenarios. To reduce the risk of the higher stockpiling propensity on inventory planning, retailers may control for the randomness of promotion prices (reducing the variability of the expected stocking periods by the stockpiler segment). Overall, to manage these effects with environmental stress, retailers need to pay close attention to the compound effects of promotion strategy and stockpiling propensity.

CONCLUSIONS

In this study, we address two important research questions: (1) How does environment stress affect consumer stockpiling for storable goods? And (2) What are the implications of this changing behavior for retail inventory management? We focus on one of the top environmental stressors, financial and economic events (Hobson et al., 1998), utilizing the 2008–2009 financial crisis as a natural experiment. We explore our research questions by investigating a fast-moving item, diapers, which can attract significant consumer stockpiling behavior during promotions. Using a sample retail channel and a panel of households, we propose that it is critical for retailers to capture consumer stockpiling behavior to distill consumer demand rates to avoid stockouts or oversupplies, especially under environmental stress.

Our contributions are as follows: First, we employ natural experiment methodology to explore the relationship between environmental stress and stockpiling propensity. The sample retailer and sample households exposed to the experimental conditions are determined by naturally occurring events, which enhance the generalizability and relevance of the estimation results. Second, we investigate the impact of environmental stress originating from financial and economic events on stockpiling propensity. Distinguishing between non-stockpiler and stockpiler segments in HILO pricing environments, we find that environmental stress is positively associated with stockpiling propensity, coupled with lower consumption rates from individual consumers. Third, we demonstrate the linkage between stockpiling behavior and inventory planning. Although the lower consumption rates require lower mean inventory and safety stock, to the extent that there is a shift to stockpiling behavior, mean inventory and safety stock need to be adjusted upwards. Last, we illustrate risks in stocking decisions in the face of the interaction of promotion strategy and stockpiling propensity. Due to stockpiling through a randomly-priced promotion strategy, retailers may increase the required safety stock to protect against demand variability induced by the stockpilers.

Our findings are valuable to retailers as they monitor inventories in the face of the impact of environmental stress on consumers. Similar to Sterman and Dogan (2015), we find that stockpiling propensity is likely to increase with environmental stress. This implies that retailers ignoring environmental stress may underestimate stockpiling propensity, leading to higher possibilities of inventory shortages during economic downturns. In practice, retailers can plan promotional inventory through setting expected stock periods of the stockpiler segment while allowing some degree of variability when employing the random promotion prices. In the face of higher stockpiling propensity, retailers can reduce inventory risks by controlling the variability in the stockpiler segment’s stock periods. In general, to optimize inventory management, retailers should carefully monitor the environmental conditions and assess the corresponding impacts on consumer stockpiling behavior by matching inventory supply with consumer demand.

Chapter 3: Product Availability, Consumer Stockpiling, and Hurricane Disasters

ABSTRACT

As exogenous events, hurricanes provide a natural experiment to test retail operations performance in the face of natural disasters. We study consumer stockpiling behavior prior to the onset of four U.S. continental hurricanes, with a focus on the impact of this behavior on in-store product availability for various formats of retail store outlets. We find that supply-side characteristics (retail network and product variety), demand-side characteristics (hurricane experience and household income), and disaster-side characteristics (hazard proximity and hazard intensity) significantly affect consumer stockpiling propensity as the hurricanes approach. The increased consumer stockpiling propensity has immediate and persistent impacts on retail operations such as higher in-store product availability before hurricanes and lower in-store product availability following hurricanes. Among various retail formats, drugstores are associated with the highest consumer stockpiling propensity before hurricanes, while dollar stores are associated with the lowest in-store product availability following hurricanes. Our study points to the need for retailers to carefully monitor factors affecting consumer stockpiling behavior during the hurricane season that will allow them to better preposition inventories and fulfill consumer demand.

INTRODUCTION

Hurricane disasters affect a large number of people and cause untolled damage. No wonder they have drawn urgent attention from government, industry, and academia. One of the key humanitarian concerns in the wake of anticipated hurricane disasters relates to retail operations with an emphasis on the emergency supply of critical groceries (Morrice et al., 2016). Pedraza-Martinez and Van Wassenhove (2016) pointed out that most of the humanitarian operations challenges are practical in nature; however, there is a lack of sufficiently empirically grounded research in observations. Our work relates to Morrice, Cronin, Tanrisever, and Butler (2016) who empirically studied how to match retail inventory with consumer demand during hurricane disasters. In particular, we contribute to the macro level "architectural blueprint" for disaster operations research (Gupta, Starr, Farahani, & Matinrad, 2016). The focus of this study is on consumer stockpiling behavior in advance of hurricanes and the impacts of this behavior on in-store product availability over the course of hurricane events.

The behavior of consumers as they choose or not choose to stockpile supplies in anticipation of hurricanes deserves attention from retailers who can forecast consumer demands and plan their inventory. Consumer stockpiling for hurricane disasters refers to a type of nonconventional inventory accumulation activity motivated by a desire to minimize loss or perceived loss (McKinnon et al., 1985). During the time lag between storm formation and landfall, some people anticipate the storm and take preventive action; however, others are blindly confident that the hurricane will not strike their location. As a result, some people choose not to purchase enough essential supplies, while others may purchase adequate supplies or even too much as they prepare for the worst. Thus, from the perspective of disaster operations, it is critical for retailers to identify supply-side, demand-side, and disaster-side factors that may affect consumer stockpiling behavior.

We study in-store product availability in light of consumer stockpiling behavior utilizing hurricane disasters as a natural experiment. Focusing on bottled water, suggested as an essential emergency supply, we match four hurricanes making landfall in the continental U.S. (Ike in 2008, Irene in 2011, Sandy in 2012, and Arthur in 2014) with retail store outlets located along the hurricane's path to obtain 38,418 store-event observations. Using event study methodology, we categorize the course of a hurricane disaster into four event periods: EARLY and LATE, corresponding to the weeks before and after the hurricane landfall, and PRE and POST, corresponding to the time periods before and after the EARLY and the LATE periods, respectively. We set the PRE event period as the benchmark and then examine consumer stockpiling propensity during the EARLY event period and its impacts on in-store product availability over the course of hurricane events, namely, the EARLY, the LATE, and the POST event periods.

We address the first question: How do supply-side, demand-side, and disaster-side characteristics impact consumer stockpiling propensity during the EARLY event period? From a supply-side perspective, we find that consumer stockpiling propensity is associated with factors that influence store desirability and operations constraints, such as intra-regional store network, inter-regional store network, and product variety. From a demand-side perspective, we show that consumer stockpiling propensity is related to factors that affect risk perception and purchasing power such as recent hurricane experience and household income level. From a disaster-side perspective, we identify that consumer stockpiling propensity is linked to factors that impact risk awareness and consumer response such as distance to points of landfall, distance to path of the hurricane, and intensity of storm wind.

Consumer stockpiling is likely to affect the availability of stock-keeping units (SKUs) over the course of hurricane disasters. Hence, from a managerial perspective, the second question is: How does expected consumer stockpiling propensity affect in-store product availability during the EARLY event period? Consequently, the third question is*:* How long do the impacts of consumer stockpiling propensity during the EARLY event period on in-store product availability continuously exist during the LATE and the POST event periods?

We show that consumer stockpiling propensity is positively associated with in-store product availability during the EARLY event period as the time lag between the hurricane's formation and landfall allows retailers to plan pre-positioning of inventory in potentially affected markets. However, the increased consumer stockpiling propensity is likely to lead to significantly lower in-store product availability during the LATE event week and the first week of the POST event period, but then the effects gradually weaken over the POST event period.

Interestingly, consumer stockpiling propensity and in-store product availability vary across retail formats over the course of a hurricane. First, at such times, we find that consumers are likely to stockpile based on the variety of store formats offer. For example, drugstores offer 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 capability are likely to achieve superior performance in in-store product availability over the course of hurricane events. For instance, grocery stores are related to the highest in-store product availability during the EARLY event period, while 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 EARLY, the LATE, and the POST event periods.

Our contributions are fourfold. First, we contribute to the macro level "architectural blueprint" of disaster management research (Gupta et al., 2016), developing an empirically grounded work in humanitarian operations (Pedraza-Martinez & Van Wassenhove, 2016). In particular, we investigate in-store product availability in light of consumer stockpiling behavior utilizing hurricane disasters as a natural experiment. Second, we triangulate the research questions with multiple data sources and research methods (Pedraza-Martinez & 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 real-time hurricane data from four recent hurricanes with a wide range of impacts. Next, from a theoretical perspective, we integrate supply-side characteristics (retail network and product variety), demand-side characteristics (hurricane experience and household income), and disaster-side characteristics (hazard proximity and hazard intensity). We found that these factors significantly affect consumer stockpiling propensity prior to hurricanes. Last, from a managerial perspective, we show that consumer stockpiling propensity has immediate and persistent effects on retail operations, such as higher in-store product availability before hurricanes and lower in-store product availability following hurricanes, although the effects vary across retail formats. In general, we propose that retailers should carefully monitor factors affecting consumer stockpiling behavior that will allow them to better manage retail operations during hurricane disasters.

THEORETICAL FOUNDATIONS

In this study, we investigate consumer stockpiling behavior and its impacts on in-store product availability over the course of hurricane disasters. We survey literature related to consumer stockpiling behavior and retail operations management in the context of hurricane disasters. Figure 3 illustrates the theoretical model of this study.

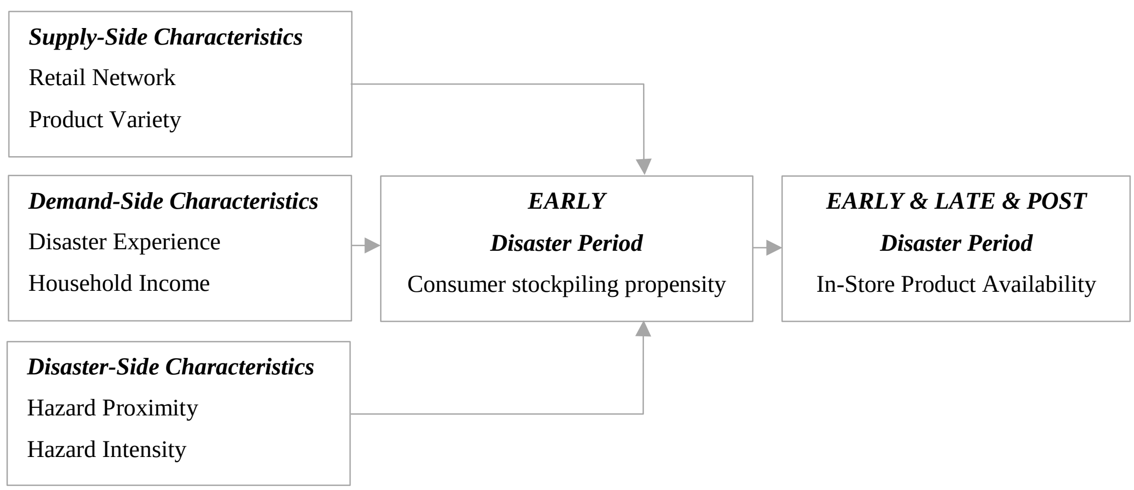

Figure 3: Theoretical Model

Theory of Consumer Stockpiling for Natural Disasters

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 and colleagues (1985) distinguished 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 nonconventional. Inventory accumulation activity is equally relevant when viewed from the perspectives of individual, household, or organization (McKinnon et al., 1985). The focus of this study is on inventory accumulation behavior by consumers at various formats of retail store outlets in the face of hurricane disasters. Specifically, based on future information about potential disasters, consumers may perceive high risks from being unable to obtain particular emergency products, and therefore, due to loss aversion, they may try to obtain abnormally high quantities of these products and hold them for non-profit purposes.

According to King & Devasagayam (2017), consumer stockpiling for natural disasters can be explained using commodity theory (Brock, 1968) and prospect theory (Kahneman & Tversky, 1979). Commodity theory deals with the psychological effects of scarcity (Lynn, 1991), and that any commodity will be valued to the degree it is unavailable (Brock, 1968). In other words, scarcity enhances the value of products that can be possessed, is useful to the possessor, and is transferable from one person to another (Brock, 1968; Lynn, 1991). During natural disasters, the potential of the scarcity of products is likely to affect consumers' attitude and behavior (Brock, 1968; Lynn, 1991), and thus stimulate stockpiling desirability. Moreover, prospect theory (Kahneman & Tversky, 1979) describes the way people choose between probabilistic alternatives that involve risk and uncertainty. The theory states that people make decisions based on the potential value of losses and gains rather than the final outcome. In the face of risk and uncertainty of natural disasters, consumers associate greater psychological discomfort due to loss aversion; thus, they may stockpile more than what would be predicted based on perceived losses.

Factors Affecting Consumer Stockpiling for Natural Disasters

Supply-Side Characteristics

During hurricane disasters, consumer stockpiling may be related to supply-side characteristics which influence store desirability and operational constraints. These characteristics include such factors as retail network and product variety.

For an individual store outlet, consumer stockpiling for disaster preparedness may be linked to the broad chain network within and between regional markets. Intuitively, a broad intra-regional or inter-regional store network is likely to attract more consumers to stores due to name recognition and hence more stockpiling at individual store outlets. However, the more important factor is the operational decision making. According to inventory theory (Zipkin, 2000), retailers with a dense intra-regional network are likely to carry fewer inventories for individual store outlets due to inventory pooling effects, which limit retailers' capability to respond to demand-side shocks; in contrast, retailers with a dense inter-regional store network are likely to carry more inventory in that network (Cachon & Olivares, 2010; Gaur, Fisher, & Raman, 2005; Rajagopalan, 2013), which allows retailers to quickly respond to demand-side shock (Holmes, 2011; Lim, Mak, & Shen, 2017). However, a dense network between regional markets can only accommodate consumer stockpiling to a certain extent due to transshipment costs. Accordingly, we expect a retailer's intra-regional and inter-regional store network may negatively and positively affect consumer stockpiling during hurricane disasters in a nonlinear relationship.

For an individual store outlet, consumer stockpiling could be linked to supply-side characteristics such as the variety of product offered. A wide variety of products is likely to attract more stockpiling at individual store outlets. The pursuit of product variety can be explained by psychology-based (Kahn, 1998; McAlister & Pessemier, 1982; Ren, Hu, & Hausman, 2011), stockout-based (Chen & Plambeck; 2008, Gilland & Heese, 2013; Honhon & Seshadri, 2013; Kraiselburd; Narayanan, & Raman, 2004) and budget-based motivations (Huchzermeier et al., 2002). With the growing perception of hurricane risks, consumers may gravitate towards store outlets with a wide variety of products, where they can easily switch between brands or package sizes to accumulate more items than usual. However, consumer stockpiling is subject to operational constraints. Inventory theory (Zipkin, 2000) points out that given the same total demand, higher product variety leads to an increase in total inventory (Gaur et al., 2005; Rajagopalan, 2013; Ton & Raman, 2010), but this inventory increase will be limited since retailers will take potential substitutability of demand into consideration when making stocking decisions (Gilland & Heese, 2013). We posit that there is more stockpiling involved with retail stores that have high product variety but with a decreasing rate due to demand substitutability.

Demand-Side Characteristics

In natural disasters, consumer stockpiling propensity may be related to demand-side characteristics that influence risk perception and purchasing power. These characteristics factor in disaster experience and household income.

From the consumers' perspective, prior experience is likely to affect consumer stockpiling propensity during natural disasters. On the one hand, prior experience may be related to more stockpiling prior to disasters. Sattler, Kaiser, and Hittner (2000) pointed out that prior experience predicts hurricane disaster preparedness, supporting both the resources stress model (Hobfoll, 1989) and the warning and response model (Lindell & Perry, 1992). Individuals with more direct or associated hurricane experience tend to have higher awareness of hurricane hazard (Trumbo, Lueck, Marlatt, & Peek, 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 stockpile due to seasonal preparedness instead of last-minute preparedness (Beatty, Shimshack, & Volpe, 2018). Moreover, consumers with significant experience may adversely affect their good judgment and 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 nonlinear relationship.

A handful of studies show that hurricane preparedness is related to household income (Baker, 2011; Fothergill & 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 households' 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 such factors as residence location, residence type, building construction, and social exclusion. However, individuals with higher income may have a lower purchasing desirability during natural disasters. Those who belong to a higher socio-economic group with abundant power and resources may have a lower purchasing desirability before and during a natural disaster

(Peacock, Brody, & Highfield, 2005). Moreover, consumers with a high-income level are more capable of fleeing from the disaster-affected area, resulting in a discounting effect on consumer stockpiling behavior. Therefore, household income may relate to consumer stockpiling propensity in a nonlinear relationship.

Disaster-Side Characteristics

Consumer stockpiling propensity may be related to disaster characteristics that influence risk awareness and consumer response. These characteristics include such factors as hazard proximity and hazard intensity. Recent studies have shown that proximity to hazard and intensity of hazard is associated with great risk awareness (Moffatt, Hoeldke, & Pless-Mulloli, 2003; Peacock et al., 2005). Prospect theory (Kahneman & Tversky, 1979) generalizes nonlinear expected utility function (Bleichrodt, Schmidt, & Zank, 2009); that is, 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 often do not make rational decisions and would stockpile more than what would be predicted based on forecasted risk and the fact that people are generally risk-averse. Notably, hazard proximity and hazard intensity also affect consumer response time. For example, storm information and forecasts specific to an area are normally issued based on hazard proximity and hazard intensity, such as hurricane and tropical storm watches, warnings, advisories, and outlooks. Overall, we expect hazard proximity (i.e., distance to landfall points and distance to path of hurricane) and hazard intensity (wind speed) may have non-linear effects on consumer stockpiling behavior.

Effects of Consumer Stockpiling on In-Store Product Availability

Consumer stockpiling accompanying hurricane disasters may have immediate and persistent effects on retail operations. First, expected consumer stockpiling might lead to high in-store product availability before the hurricane strikes. Pre-positioning of emergency supplies of critical groceries has become an important humanitarian problem (Morrice et al., 2016). In practice, retailers in a supply chain can plan inventory based on hurricane information updates while setting expectations for operations costs and service quality (Lodree & Taskin, 2009; Lodree, Ballard, & Song, 2012; Morrice et al., 2016; Taskin & Lodree, 2010, 2011; Taskin & Lodree, 2011; Rawls & Turnquist, 2010). However, as with natural disasters, the root source of massive supply disruptions may be exogenous and beyond the control of firms (Hendricks, Jacobs, & Singhal, 2017; Hu, Gurnani, & Wang, 2013; Kleindorfer & Saad, 2005). Thus, the increased consumer stockpiling may result in lower in-store product availability following disasters (Cavallo, Cavallo, & Rigobon, 2014; Hu et al., 2013; Kleindorfer & Saad, 2005). Depending on supply readiness, these effects could persist for several order cycles. For example, Cavallo and colleagues (2014) found 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. Overall, we expect that retailers with various formats may vary in operational performance during times of hurricane disasters.

RESEARCH METHODOLOGY

We study in-store product availability of bottled water in light of consumer stockpiling behavior during hurricane disasters. Using event study methodology, we match four U.S. continental hurricane events with various formats of retail stores affected to obtain 38,418 store-event observations.

Data Collection

We collect data from recent continental hurricanes making landfalls in the U.S. between 2008 and 2014. To compare consumer stockpiling behavior across geographic markets, we focus on those hurricane events with a wide range of effects, which include Ike in 2008, Irene in 2011, Sandy in 2012, and Arthur in 2014. The hurricane data is collected from NOAA's National Hurricane Center Atlantic Basin Best Tracks HURDAT2 database as well as NOAA's Tropical Cyclone Reports (Avila & Cangialosi, 2011; Berg, 2009; Berg, 2018; Blake et al., 2013). For each hurricane event, we gather data on landfall date, landfall location, path of hurricane, 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 Nielsen Retail Scanner Data, which captures a substantial proportion of total grocery sales from major retail chains across all U.S. markets[9]. The dataset consists of information on the product category, weekly pricing, sales volume, and store environment generated by point-of-sale systems from the participating retail chains. Specifically, we collect data on the bottled water product category, an essential emergency category in hurricane preparedness. Moreover, we compare various formats of store outlets impacted by the four sample hurricane events.

[9] Calculated (or derived) based on data from The Nielsen Company (US), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researchers and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

Sample Description

We match each hurricane event with the corresponding affected states and keep all store outlets within the affected states as our initial sample to generate 60,146 store-event observations. As hurricanes vary in paths, sizes, and duration, we utilize the following steps to formalize the samples to obtain 38,418 store-event observations.

Hurricane landfall. We first utilize distance to landfall points to a preliminarily determined geographic area affected by the sample hurricane events (Beatty et al., 2018). Distance to landfall points is used as a spatial dimension to study disaster preparedness. For example, Beatty and colleagues (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. National Hurricane Center (NHC) issues a five-day "cone of uncertainty" each year to indicate the probable track of the center of a tropical cyclone [10]. The radii of the cone circles are set to enclose 2/3 of the historical track forecast errors, namely, "2/3 probability circle"; that is, there is still a 1/3 probability that the center of the storm could track outside of the cone. In practice, the potential hazardous condition may occur inside or outside of the cone; for example, storm surge may stretch around 1,000 miles wide. Therefore, to study consumer stockpiling during hurricane disasters, we keep those store outlets within 1,000 miles to the expected landfall points.

Hurricane sizes. We further refine the geographic area affected by the sample hurricane events based on the size of the hurricanes. The size of the NHC's annual "cone

[10] The National Hurricane Center define 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.*"

of uncertainty" is fixed for all storms and does not vary for forecasts throughout the season. In other words, the cone only contains the probable path of the storm center but does not show 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 tropical cyclone (Cangialosi & Landsea, 2016; Carrasco, Landsea, & Lin, 2014; Demuth, DeMaria, & Knaff, 2006)[11]. It is measured as the average of the radii from the center of the storm to its outermost closed isobar. The values are determined in every six hours in real time. The value generally delimits the outermost extent of a tropical cyclone's wind circulation. The hurricane size data were collected from the Extended Best Tracks (EBT) dataset by Demuth and colleagues (2006). We refine the boundary of the hurricane-affected area utilizing the median of ROCI of 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 to apply the event study method. Event clustering may render the independence assumption of the variables of interest incorrect (Brown & Warner, 1985). As two successive hurricane events may affect the same geographic areas within a short time window, such event clustering may contaminate the movement of the variables of interest (in particular, consumer stockpiling propensity and in-store product availability). For example, Ike made landfall on September 13, 2008, while Gustav made landfall on September 1, 2008. Among the fourteen states affected by Ike, four states (FL, LA, TX, and AR) were also affected by Gustav. The overlapped area affected by the two hurricanes can bias the

[11] 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.

estimation with respect to individual hurricane events. Thus, for hurricane Ike, we do not incorporate these four states with event-clustering concerns. In this study, Gustav was not included in our sample hurricane events due to its limited range of impacts.

Event Study

Similar to Beatty and colleagues (2018), we utilize the event study approach to estimate the two variables of interest: consumer stockpiling propensity and in-store product availability. Essentially, for these two variables, we investigate whether its pattern of movement surrounding a hurricane event differs from its behavior during non-event periods (Beatty et al., 2018). To match the retail-level data with the hurricane event data, we define four periods for each sample hurricane event as follows based on our weekly retail data availability:

1) A hurricane event lasts around two weeks surrounding the landfall date. We split this event duration into two periods: an EARLY event week and a LATE event week. The EARLY event week contains at least five days before the landfall date.[12,13] The LATE event week is the week after the EARLY event week.
2) We then define a PRE event period including M weeks preceding the EARLY event week and a POST event period including N weeks following the LATE event week. Utilizing the PRE event week as a benchmark, we estimate consumer

[12] The estimation of consumer stockpiling propensity requires the EARLY event week to contain most of days during the week before the landfall date. For example, if the landfall is on Friday or Saturday, we use the week containing the landfall date as the EARLY event week, but if it is Sunday or Monday, we take the previous week as the EARLY event week.
[13] Some hurricanes may make multiple landfalls. For example, hurricane Irene in 2011 made landfalls in Cape Lookout, NC at 12:00 on Aug 27, Brigantine Island, NJ at 09:35 on Aug 28, and Coney Island, NY at 13:00 on Aug 28. We use the first landfall date, while controlling for the elapsed time from the first landfall to when hurricane track is in proximity to the store in the observation.

stockpiling propensity during the EARLY event period and in-store product availability during the EARLY, LATE, and POST event periods.

Table 10 illustrates the four event periods surrounding the four sample hurricane events. The weeks in the table correspond to the sales weeks in the Nielsen Retail Scanner Dataset. For this study, we pre-define a four-week PRE event period (M=4 weeks) and a four-week POST event period (N=4 weeks) for all four hurricane events to keep a similar degree of demand subject to seasonality. Larger values might bias the estimates and smaller ones might not be sufficient.

Table 10: Illustration of Event Periods for the Four Sample Hurricanes

Name	Landfall	PRE Period (4 Weeks)	EARLY Period (1 Week)	LATE Period (1 Week)	POST Period (4 Weeks)
Ike	2008/09/13 (Sat)	08/10 (Sun) - 09/06 (Sat)	09/07 (Sun) - 09/13 (Sat)	09/14 (Sun) - 09/20 (Sat)	09/21 (Sun) - 10/18 (Sat)
Irene	2011/08/27 (Sat)	07/24 (Sun) - 08/20 (Sat)	08/21 (Sun) - 08/27 (Sat)	08/28 (Sun) - 09/03 (Sat)	09/04 (Sun) - 10/01 (Sat)
Sandy	2012/10/29 (Mon)	09/23 (Sun) - 10/20 (Sat)	10/21 (Sun) - 10/27 (Sat)	10/28 (Sun) - 11/03 (Sat)	11/04 (Sun) - 12/01 (Sat)
Arthur	2014/07/04 (Fri)	06/01 (Sun) - 06/28 (Sat)	06/29 (Sun) - 07/05 (Sat)	07/06 (Sun) - 07/12 (Sat)	07/13 (Sun) - 08/09 (Sat)

Variable Definitions

Dependent Variables

We address our research questions by investigating two variables of interest for individual store outlets under the study:

Consumer stockpiling propensity. This is estimated for the EARLY event week. For each sample store outlet affected by a hurricane event, it represents the ratio of the sales volume of the bottled water category during the EARLY event week to the average of weekly sales volume during the four PRE event weeks.

In-store product availability. This is estimated for the EARLY event week, LATE event week, and each of the POST event weeks. For each sample store outlet affected by a hurricane event, it is the ratio of the number of product SKUs in the bottled water category sold during the EARLY event week (LATE event week and each of the POST event weeks) to the weekly average of the number of product SKUs sold during the PRE event period.

Independent Variables

Retail network. This 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 and inter-regional store network at the country-level.

Product variety. This is defined as the number of product SKUs in the bottled water category sold by a sample store outlet over the whole year of the corresponding hurricane event.

Disaster experience. This variable 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 continental hurricanes making landfalls in the United States since 1851.

Household income. This 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-income in the analysis. We collect the household income data from the U.S. Census Bureau.

Landfall distance. This variable indicates the minimum distance from the county where a sample store outlet is located to landfall points. We collect the latitude and longitude of the affected counties from the U.S. Census Bureau and the latitude and longitude of hurricane landfall locations from NOAA.

Track distance. This variable measures the minimum distance from the county where the store outlet is located to the hurricane track. We collect the latitude and longitude of the hurricane track from NOAA, which tracks the hurricane every six hours from hurricane formation to dissipation.

Wind speed. This variable measures the intensity of the storm wind when the hurricane is in close proximity to a sample store outlet. We collect the wind speed information associated with each documented hurricane track location from NOAA.

Control Variables

Retail format. This is defined as a vector of dummy variables indicating various types of store formats, such as grocery stores, warehouse clubs, discount stores, dollar stores, drug stores, liquor stores, and convenience stores. We utilize the convenience store format as the base case in our analysis.

Retail chain. This is defined as a vector of dummy variables indicating the retail chain the sample store outlets belong to. Since we already incorporate retail formats in our analysis, we need to utilize only one retail channel under each retail format as the base cases in our analysis.

Category volume. This variable 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. We calculate category volume at two levels: county-level and state-level.

Category competition. We measure market competition for the bottled water category using the Herfindahl-Hirschman index (HHI) at the county-level and state-level. Individual store outlets are the units for calculating HHI measures of individual geographic markets.

Track days after landfall. Since a hurricane can be tracked for several days from formation to dissipation, this variable measures the elapsed time from the first landfall to when the hurricane is in proximity to the observed sample store outlet.

Sales days before landfall. Since consumer stockpiling propensity is measured based on weekly sales volume of bottled water, this measure captures the number of sales days before the landfall of the hurricane during the EARLY event week.

Geodemographic feature. These are variables reflecting geodemographic features of the county and the state where a sample store outlet is located. They include population density, land area, and water area. We collect the geodemographic data from the U.S. Census Bureau.

Table 11 illustrates the descriptive statistics. Table A10 in the Appendix presents the correlation matrix after data transformation. For the dependent variables, stockpiling propensity during the EARLY event week ranges from 0.396 to 5.728, averaging at 1.581 (i.e., sales volume ranges between 40% and 570% compared to the PRE period, averaging 158%); product availability during the EARLY event period ranges from 0.320 to 3.795, averaging at 1.021 (i.e. bottled water SKUs sold range from 32 to 380% of the PRE SKUs available, averaging at 102%); product availability during the LATE event week ranges from 0.057 to 3.692, averaging at 0.983 (i.e., bottled water SKUs sold range from 5.7 to 369% compared to the PRE period, averaging at 98%); and product availability during the four POST event weeks ranges from 0.020 to 4.513, averaging at around 0.950 (i.e., bottled water SKUs sold range from 2 to 450% of the PRE SKUs available, averaging at 95%).

The independent variables include supply-side, demand-side, and disaster-side characteristics. For supply-side characteristics, the county-level chain network ranges from 1 to 266 stores with an average of 19 stores; the country-level chain network ranges from 1 to 8,484 stores with an average of 3,846 stores; and the number of product SKUs ranges from 1 to 340 with an average of 94 product SKUs. For demand-side characteristics, recent hurricane experience ranges from 0 to 14 landfalls with an average of four landfalls, and per capita income ranges from $17,100 to $153,210 with an average of $46,470. For disaster-side characteristics, distance to hurricane landfall ranges from 3.6 to 996.9 miles with an average of 356 miles; distance to hurricane track ranges from

2.9 to 482 miles with an average of 171 miles; and the speed of wind ranges from 30 to 90 miles per hour with an average of 61 miles per hour.

Table 11: Data Description

Variable	Unit	Mean	Std. Dev.	Min	Max
Dependent Variable					
Consumer Stockpiling Propensity					
STOCKPILING_PROP_EARLY	Ratio	1.581	0.909	0.396	5.728
In-Store Product Availability					
PRODUCT_AVAIL_EARLY	Ratio	1.021	0.123	0.320	3.795
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	0.127	0.048	4.513
PRODUCT_AVAIL_POST_W4	Ratio	0.952	0.126	0.020	4.513
Independent Variable					
Supply-Side Characteristics					
INTRA_NTW_COUNTY	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
Demand-Side Characteristics					
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
Disaster-Side Characteristics					
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
Control Variable					
Retail Format					
CHAIN_GROC	Dummy Variable	0.280	0.449	0.000	1.000
CHAIN_WHS	Dummy Variable	0.013	0.113	0.000	1.000
CHAIN_DISC	Dummy Variable	0.076	0.265	0.000	1.000
CHAIN_DOLLAR	Dummy Variable	0.191	0.393	0.000	1.000
CHAIN_DRUG	Dummy Variable	0.381	0.486	0.000	1.000
CHAIN_LIQ	Dummy Variable	0.009	0.092	0.000	1.000
CHAIN_CONV	Dummy Variable	0.050	0.219	0.000	1.000
Retail Chain					
RETAIL_CHAIN	60 Dummy Variables				
Hurricane Events					
TRACK_DAY_AFT_LANDFALL	Days	0.337	1.284	-3.000	2.000
SALES_DAY_BEF_LANDFALL	Days	6.122	0.743	5.000	7.000
Category Volume					
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
Category Competition					
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
Geodemographic Feature					
POP_DENSITY_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_DENSITY_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
Observations		38,418			

Estimation Model

The central task of this study is to explore how consumer stockpiling behavior affects retail operations performance during natural disasters. Specifically, we study the two variables of interest at the individual store level: consumer stockpiling propensity during the EARLY event period and in-store product availability during the EARLY, the LATE, and the POST event periods. We conduct our analysis utilizing the two-stage least square model. In the first stage, we treat consumer stockpiling propensity during the EARLY event week as the dependent variable with supply-side, demand-side, and disaster-side characteristics as independent variables. In the second stage, we treat in-store product availability during the EARLY event week; the LATE event week; and the four POST event weeks as the dependent variables while incorporating the estimated stockpiling propensity during the EARLY event week as a mediator variable.

To estimate the mediating effects of consumer stockpiling propensity on in-store product availability, we obtain the estimated value of consumer stockpiling propensity based on the first-stage analysis. Specifically, we utilize market geodemographic features as instrumental variables, which are not included in the second-stage analysis. We estimate equation (1) by utilizing fixed effects models. $\mathrm{X_{ich}}$ represents the dependent variables observed for individual store outlet i located in county c affected by hurricane event h; α_c is the unobserved county-invariant individual effects; μ_{ich} is the error term. Specifically, we have a one-to-one relationship between a hurricane event and an event year, a many-to-one relationship between individual store outlets and a county, and a many-to-one relationship between individual store outlets and a retail chain.

$$\mathrm{LN(X_{ich})} = \beta_0 + (\alpha \cdot \overline{\mathrm{STOCKPILING\_PROP_{ich}}})$$

$$+\beta_1 \cdot \mathrm{INTRA\_NTW\_COUNTY}_{ich} + \beta_2 \cdot (\mathrm{INTRA\_NTW\_COUNTY}_{ich})^2$$

$$+\beta_3 \cdot \mathrm{INTER\_NTW\_COUNTRY}_{ich} + \beta_4 \cdot (\mathrm{INTER\_NTW\_COUNTRY}_{ich})^2$$

$$+\beta_5 \cdot \mathrm{PROD\_VAR\_SKU}_{ich} + \beta_6 \cdot (\mathrm{PROD\_VAR\_SKU}_{ich})^2$$

$$+\beta_7 \cdot \mathrm{HUR\_EXP\_STATE}_{ich} + \beta_8 \cdot (\mathrm{HUR\_EXP\_STATE}_{ich})^2$$

$$+\beta_9 \cdot \mathrm{PER\_CAPITA\_INC}_{ich} + \beta_{10} \cdot (\mathrm{PER\_CAPITA\_INC}_{ich})^2$$

$$+\beta_{11} \cdot \mathrm{HUR\_LANDFALL\_DIST}_{ich} + \beta_{12} \cdot (\mathrm{HUR\_LANDFALL\_DIST}_{ich})^2$$

$$+\beta_{13} \cdot \mathrm{HUR\_TRACK\_DIST}_{ich} + \beta_{14} \cdot (\mathrm{HUR\_TRACK\_DIST}_{ich})^2$$

$$+\beta_{15} \cdot \mathrm{HUR\_WIND\_SPEED}_{ich} + \beta_{16} \cdot (\mathrm{HUR\_WIND\_SPEED}_{ich})^2$$

$$+\beta_{17} \cdot \mathrm{RETAIL\_FORMAT}_{ich} + \beta_{18} \cdot \mathrm{RETAIL\_CHAIN}_{ich}$$

$$+\beta_{19} \cdot \mathrm{TRACK\_DAYS\_AFT\_LANDFALL}_{ish}$$

$$+\beta_{20} \cdot \mathrm{SALES\_DAYS\_BEF\_LANDFALL}_{h}$$

$$+\beta_{21} \cdot \mathrm{VOL\_COUNTY}_{ich} + \beta_{22} \cdot \mathrm{VOL\_STATE}_{ich}$$

$$+\beta_{23} \cdot \mathrm{HHI\_COUNTY}_{ich} + \beta_{24} \cdot \mathrm{HHI\_STATE}_{ich}$$

$$(+\gamma_1 \cdot \mathrm{POP\_DEN\_COUNTY}_{ich} + \gamma_2 \cdot \mathrm{LAND\_AREA\_COUNTY}_{ich}$$

$$+\gamma_3 \cdot \mathrm{WATER\_AREA\_COUNTY}_{ich}$$

$$+\gamma_4 \cdot \mathrm{POP\_DEN\_STATE}_{ich} + \gamma_5 \cdot \mathrm{LAND\_AREA\_STATE}_{ich}$$

$$+ + \gamma_6 \cdot \mathrm{WATER\_AREA\_STATE}_{ich})$$

$$+\alpha_c + \mu_{ich}$$

$$\text{where } X_{ich} = \{\mathrm{STOCKPILING\_PROP}_{ich}, \mathrm{PRODUCT\_AVAIL}_{ich}\} \qquad (1)$$

EMPIRICAL RESULTS

Consumer Stockpiling Propensity

From a theoretical perspective, the first research question addressed in this paper is: How do supply-side, demand-side, and disaster-side characteristics affect consumer stockpiling propensity during the EARLY event period? In Table 12, we set consumer stockpiling propensity during the EARLY event week, STOCKPILING_PROP, as the dependent variable. Model 3.1.1 contains only the control variables; Model 3.1.2, Model 3.1.3, and Model 3.1.4, in turn, add the supply-side, demand-side, and disaster-side characteristics. We utilize Model 3.1.4, the complete model, to describe our results. Accordingly, in Figure 4, Figure 5, and Figure 6, we depict the impacts of supply-side, demand-side, and disaster-side characteristics on consumer stockpiling propensity, respectively[14]. Overall, we illustrate that, for an individual store outlet in a hurricane-affected geographic market, consumer stockpiling propensity depends on supply-side characteristics (retail network and product variety), demand-side characteristics (disaster experience and household income), and disaster-side characteristics (hazard proximity and hazard intensity) characteristics, all with non-linear relationships.

[14] As we utilize semi log regression model in Equation (1), Figure 4Figure 4, Figure 5, and Figure 6 reflect the effects of unit changes in the independent variables on percentage changes in the dependent variable, that is, consumer stockpiling propensity during the EARLY event week.

Table 12: Estimation Results (Step 1: Consumer Stockpiling Propensity)

Dependent Variable LN(STOCKPILING_PROP) × 1000	Model 3.1.1 EARLY Week	Model 3.1.2 EARLY Week	Model 3.1.3 EARLY Week	Model 3.1.4 EARLY Week
Independent Variable				
Supply-Side Characteristics				
INTRA_NTW_COUNTY		-376.764*** (24.411)	-406.923*** (24.368)	-277.673*** (21.770)
$(\text{INTRA\_NTW\_COUNTY})^2$		69.445*** (9.445)	82.942*** (9.376)	68.143*** (8.348)
INTER_NTW_COUNTRY		1.370 (1.939)	3.208* (1.900)	25.699*** (1.730)
$(\text{INTER\_NTW\_COUNTRY})^2$		0.005 (0.016)	-0.044** (0.015)	-0.230*** (0.014)
PROD_VAR_SKU		3.170*** (0.306)	3.444*** (0.301)	2.045*** (0.267)
$(\text{PROD\_VAR\_SKU})^2$		-0.011*** (0.001)	-0.011*** (0.001)	-0.007*** (0.001)
Demand-Side Characteristics				
HUR_EXP_STATE			96.535*** (3.589)	15.614*** (3.596)
$(\text{HUR\_EXP\_STATE})^2$			-7.844*** (0.289)	-0.693* (0.291)
PER_CAPITA_INC			244.995*** (7.646)	101.685*** (6.929)
$(\text{PER\_CAPITA\_INC})^2$			-15.176*** (0.553)	-5.830*** (0.499)
Disaster-Side Characteristics				
HUR_LANDFALL_DIST				-133.124*** (5.123)
$(\text{HUR\_LANDFALL\_DIST})^2$				6.417*** (0.459)
HUR_TRACK_DIST				-165.653*** (8.941)
$(\text{HUR\_TRACK\_DIST})^2$				16.992*** (1.900)
HUR_TRACK_WIND				23.027*** (1.284)
$(\text{HUR\_TRACK\_WIND})^2$				-0.197*** (0.010)

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

Table 12 Continued: Estimation Results (Step 1: Consumer Stockpiling Propensity)

Dependent Variable LN(STOCKPILING_PROP) × 1000	Model 3.1.1 EARLY Week	Model 3.1.2 EARLY Week	Model 3.1.3 EARLY Week	Model 3.1.4 EARLY Week
Control Variable				
Retail Format				
CHAIN_GROC	-465.159*** (108.005)	-600.028*** (108.842)	-527.954*** (106.652)	-275.790** (94.720)
CHAIN_WHS	304.205*** (31.098)	248.377*** (31.687)	202.509*** (31.122)	196.591*** (27.604)
CHAIN_DISC	-122.753* (72.741)	-52.315 (72.532)	-25.015 (71.073)	133.843* (63.122)
CHAIN_DOLLAR	527.499*** (25.237)	494.573*** (64.283)	572.998*** (63.139)	-43.036 (57.768)
CHAIN_DRUG	454.295*** (38.849)	462.715*** (39.168)	404.855*** (38.430)	434.843*** (34.120)
CHAIN_LIQ	160.985** (58.064)	264.322*** (59.012)	165.744** (57.933)	219.064*** (51.375)
Retail Chain				
RETAIL_CHAIN	Included	Included	Included	Included
Hurricane Events				
TRACK_DAY_AFT_LANDFALL	45.191*** (2.534)	45.667*** (2.589)	16.026*** (2.902)	-31.487*** (2.853)
SALES_DAY_BEF_LANDFALL	39.773*** (2.925)	40.958*** (3.010)	67.447*** (3.090)	41.573*** (3.691)
Category Volume				
VOL_COUNTY	-22.241*** (2.011)	3.236 (2.372)	0.128 (2.332)	4.427* (2.067)
VOL_STATE	4.914*** (0.370)	4.896*** (0.369)	4.424*** (0.365)	3.109*** (0.324)
Category Competition				
HHI_COUNTY	-114.858*** (15.251)	-178.825*** (15.840)	63.835*** (17.073)	18.915 (15.164)
HHI_STATE	1,943.760*** (288.912)	1,963.647*** (287.625)	2,643.441*** (282.840)	2,325.372*** (251.300)
Geodemographic Feature				
POP_DENSITY_COUNTY	0.152*** (0.038)	0.343*** (0.040)	0.765*** (0.054)	-0.008 (0.049)
LAND_AREA_COUNTY	-4.354*** (0.615)	-3.775*** (0.613)	2.064*** (0.625)	4.734*** (0.559)
WATER_AREA_COUNTY	1.031 (1.272)	4.668*** (1.290)	-5.157*** (1.295)	0.063 (1.157)
POP_DENSITY_STATE	-0.614* (0.354)	-0.924** (0.352)	-2.316*** (0.350)	-3.389*** (0.311)
LAND_AREA_STATE	-0.928*** (0.033)	-0.845*** (0.033)	-0.819*** (0.033)	-0.617*** (0.030)
WATER_AREA_STATE	0.706*** (0.134)	0.472*** (0.136)	1.775*** (0.152)	0.709*** (0.136)
CONSTANT	-181.154*** (30.237)	-314.599*** (33.295)	-1307.823*** (42.363)	-770.833*** (58.358)
Observations	38,418	38,418	38,418	38,418
F	181.92***	176.69***	194.88***	351.65***

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

Supply-Side Characteristics

Consumer stockpiling propensity may be related to supply-side characteristics such as store network and product variety. In Table 12 and Figure 4, we show that for an individual store outlet, consumer stockpiling propensity is associated with intra-regional store network at the county level in a convex relationship, inter-regional store network at the country level in a concave relationship, and product variety carried by the store outlet in a concave relationship, respectively.

We first examine the linkage between intra-regional store network and consumer stockpiling propensity. For an individual store outlet, a broader intra-regional store network belonging to the same chain may relate to more stockpiling due to store desirability or less stockpiling due to inventory pooling. In Model 3.1.4, the coefficient of $\mathrm{INTRA\_NTW\_COUNTY}$ is significantly negative (-277.673, p<0.001) and the coefficient of $(\mathrm{INTRA\_NTW\_COUNTY})^2$ is significantly positive (68.143, p<0.001). The results indicate a convex relationship at the critical value $\mathrm{INTRA\_NTW\_COUNTY}$ =203. As 99% of observations have a county-level store network less than 203 stores, intra-regional chain store network generally accommodates consumer stockpiling with a decreasing convex relationship. For example, as the county-level store network increases from 0 to 203 stores, consumer stockpiling propensity changes by 75%. Overall, inventory constraint at individual store outlets is likely to dominate the impacts of intra-regional store network on consumer stockpiling propensity but with a decreasing rate because of the increase in store desirability.

Next, we explore the linkage between inter-regional store network and consumer stockpiling propensity. For an individual store outlet, a broader inter-regional store network belonging to the same chain may accommodate more stockpiling due to inventory availability of the network or less stockpiling due to transshipment-related costs. In Model 3.1.4, at the country level, the coefficient of $\mathrm{INTER\_NTW\_COUNTRY}$ is significantly positive (25.699, p<0.001) and the coefficient of $(\mathrm{INTER\_NTW\_COUNTRY})^2$ is significantly negative (-0.230, p<0.001). The results demonstrate a concave relationship at the critical value $\mathrm{INTER\_NTW\_COUNTRY}$=5,586 stores. Among the 60 sample retail chains, we find only two chains operate with a network of over 5,586 stores; therefore, inter-regional store network generally accommodates consumer stockpiling with an increasing concave relationship. For example, when the country-level store network increases from 0 to 5,586 stores, consumer stockpiling propensity changes by 200%. Overall, inventory availability of the network is likely to dominate the effects of inter-regional store network on consumer stockpiling propensity but with a decreasing rate due to transshipment costs.

Last, 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 to the substitutability of demand, which correspondingly affects consumer stockpiling propensity. In Model 3.1.4, the coefficient of $\mathrm{PROD\_VAR\_SKU}$ is significantly positive (2.045, p<0.001) and the coefficient $(\mathrm{PROD\_VAR\_SKU})^2$ is significantly negative (-0.007, p<0.001). The results imply a concave relationship at the critical value $\mathrm{PROD\_VAR\_SKU}$=146 SKUs. As close to 75% of the sample store outlets carry less than 140 SKUs, there is an increasing concave relationship between product SKU variety and consumer stockpiling propensity for most of the sample store outlets. For instance, when product SKUs carried by a store outlet increases from 0 to 146 SKUs, consumer stockpiling propensity changes by 116%. Overall, a higher variety of product assortment is likely to accommodate more stockpiling but only to a certain extent due to the constraint of inventory availability.

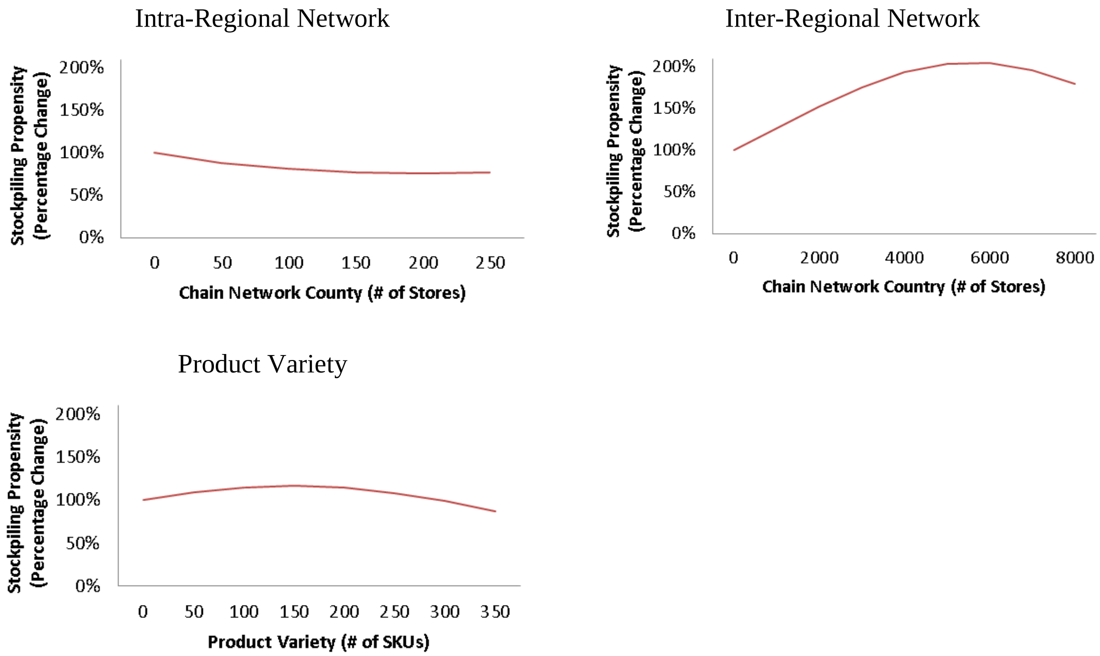

Figure 4: Supply-Side Characteristics and Consumer Stockpiling Propensity

Demand-Side Characteristics

Consumer stockpiling propensity may be related to demand-side characteristics such as disaster experience and household income. As represented in Table 12 and Figure 5, for an individual sample store outlet, consumer stockpiling propensity is related to recent hurricane experience in a concave relationship and household income level in a concave relationship, respectively.

We first explore the relationship between recent hurricane experience and consumer stockpiling propensity. Individuals with more hurricane experience may stockpile more due to high perceived risk or stockpile less due to seasonal preparedness or psychological inoculation. In Model 3.1.4, the coefficient of HUR_EXP_STATE is positive and significant (15.614, $p<0.001$) and the coefficient of $(\text{HUR\_EXP\_STATE})^2$ is negative and significant (-0.693, $p<0.1$). The results demonstrate a concave relationship at the critical value HUR_EXP_RECT=11 landfalls. We find that among the 25 sample states, Florida is the only state that experienced over 11 landfalls during the past 20 years; therefore, for most of the geographic markets, there is an increasing concave relationship between recent hurricane experience and consumer stockpiling propensity. For example, when recent hurricane experience increases from 0 to 11 landfalls, consumer stockpiling propensity changes by around 109%. Overall, high-risk perception due to recent hurricane experience is likely to stimulate consumer to stockpile but with a decreasing rate due to seasonal preparedness and psychological inoculation.

Next, we investigate the relationship between household income level and consumer stockpiling propensity. Consumers with a high-income level may stockpile more due to high purchasing power or stockpile less due to low purchasing desirability. In Model 3.1.4, the coefficient of PER_CAPITA_INC is positive and significant (101.685, $p<0.001$) and the coefficient of $(\text{PER\_CAPITA\_INC})^2$ is negative and significant (-5.830, $p<0.001$). The results imply a concave relationship at the critical value PER_CAPITA_INC=87,200 dollars. Among the 963 counties, four counties have per capita income over 87,200 dollars: Westchester and New York of New York State, Nantucket of Massachusetts State, and Fairfield of Connecticut. Thus, for most of the geographic markets, there is an increasing concave relationship between household income and stockpiling propensity. For example, when household income increases from 0 to 87,200 dollars, consumer stockpiling propensity changes by 155%. Generally, purchasing power dominates the impact of household income on consumer stockpiling propensity but with a diminishing effect due to low purchasing desirability of high-income consumers.

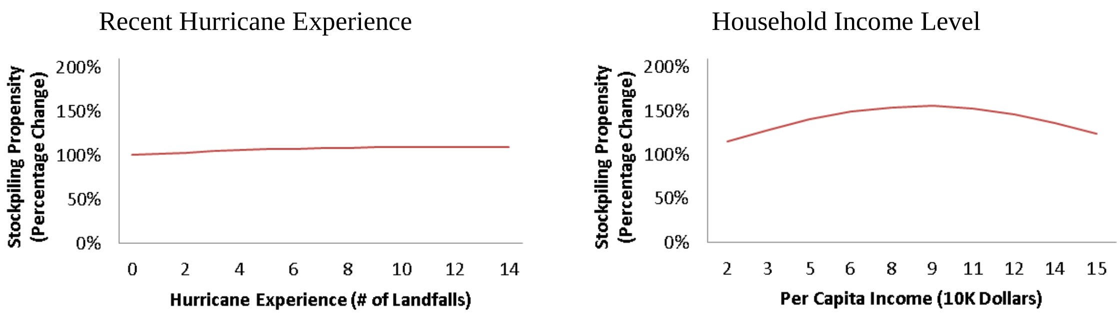

Figure 5: Demand-Side Characteristics and Consumer Stockpiling Propensity

Disaster-Side Characteristics

Consumer stockpiling propensity may be related to disaster-side characteristics such as hazard proximity and hazard intensity. In Table 12 and Figure 6, we illustrate that, for an individual sample store outlet, consumer stockpiling propensity is related to distance to hurricane landfall in a convex relationship, distance to hurricane track in a convex relationship, and the intensity of storm wind when hurricane track is in proximity to the store outlet in a concave relationship, respectively.

We first examine the relationship between hazard proximity and consumer stockpiling propensity. In Model 3.1.4, the coefficient of HUR_LANDFALL_DIST is negative and significant (-133.124, $p<0.001$) and the coefficient of $(\text{HUR\_LANDFALL\_DIST})^2$ is positive and significant (6.417, $p<0.001$). As the distance to landfall points ranges from 3.6 to 996.9 miles, there is a decreasing convex relationship between distance to landfall points and consumer stockpiling propensity. For instance, when the distance to landfall points increases from 0 to 1,000 miles, consumer stockpiling propensity changes by 50%. Moreover, the coefficient of HUR_TRACK_DIST is negative and significant (-165.653, $p<0.001$) and the coefficient of $(\text{HUR\_TRACK\_DIST})^2$ is positive and significant (16.992, $p<0.001$). As the distance to the hurricane track ranges from 2.9 to 482 miles, there is a decreasing convex relationship between distance to hurricane track and consumer stockpiling propensity. For instance, as the distance to hurricane track increases from 0 to 500 miles, consumer stockpiling propensity changes by 67%. In general, the results support the prospect theory (Kahneman & Tversky, 1979); that is, consumers associate greater psychological discomfort with losses than gains (Bleichrodt et al., 2009) in the face of risk and uncertainty, resulting with a higher stockpiling propensity when closer to hurricane hazard.

Next, we investigate the relationship between hazard intensity and consumer stockpiling propensity. The coefficient of HUR_TRACK_WIND is positive and significant (23.027, $p<0.001$) and the coefficient of $(\text{HUR\_TRACK\_WIND})^2$ is negative and significant (-0.197, $p<0.001$). The results indicate two types of concave relationships: an increasing concave relationship when HUR_TRACK_WIND <58 miles per hour and a decreasing concave relationship when HUR_TRACK_WIND >58 miles per hour. The wind associated with hurricanes is one of the main reasons that cause damage and loss of life. When hurricane tracks are in proximity to the sample store outlets, there are three main development stages: tropical storm (with wind speed from 35 to 60 miles per hour), hurricane (with wind speed from 65 to 90 miles per hour), and extratropical (with wind speed from 30 to 75 miles per hour). Notably, the NOAA National Hurricane Center (NHC) issues hurricane watches 48 hours before it anticipates tropical storm force winds, as it is not safe to prepare for a hurricane once winds reach tropical storm force.

Therefore, from the perspective of hurricane development, the results imply that more stockpiling behavior is tied to tropical storm stage or extratropical stage instead of hurricane stage.

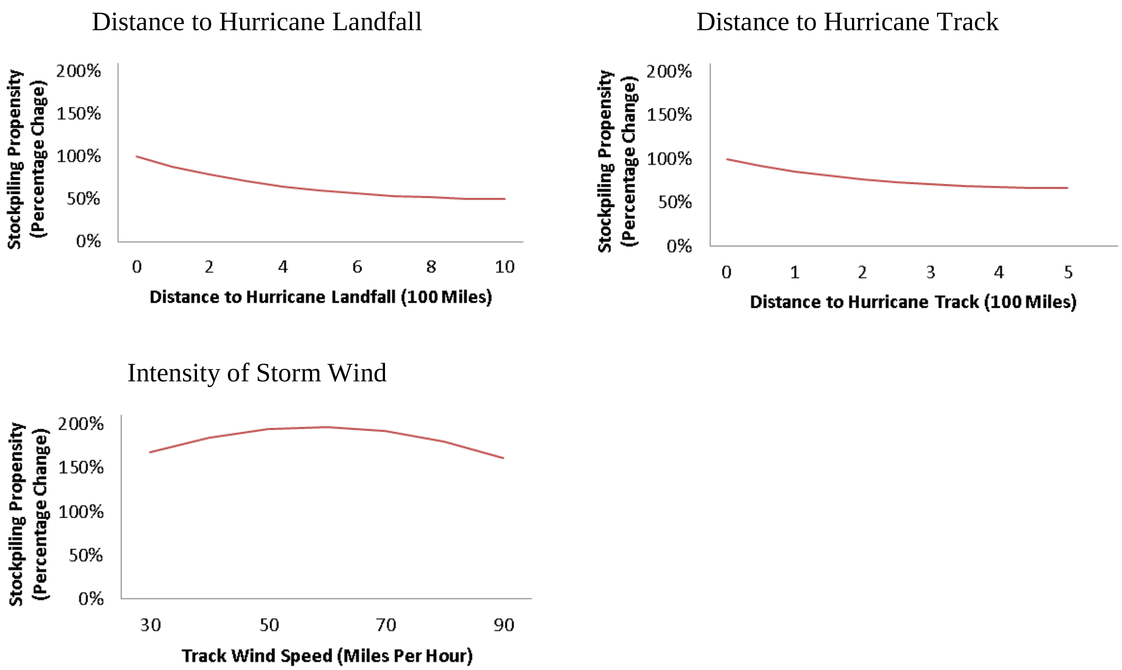

Figure 6: Disaster-Side Characteristics and Consumer Stockpiling Propensity

In-Store Product Availability

From a managerial perspective, the second research question posed in this study is: How does expected consumer stockpiling propensity influence product availability during the EARLY event period? And subsequently, the third research question raised in this study is: How does consumer stockpiling propensity during the EARLY event period relate to product availability during the LATE and the POST event periods? In Table 13, we set product availability during the EARLY, LATE, and POST event periods as dependent variables, while incorporating the mediation effects of consumer stockpiling propensity during the EARLY event period. We obtained the estimated value of consumer stockpiling propensity from the first-stage analysis.

We seek to explain how expected consumer stockpiling propensity affects product availability during the EARLY event period and how the effects of consumer stockpiling propensity continuously exist during the LATE and the POST event periods. In Table 13, we find that consumer stockpiling propensity during the EARLY event period is positively related to product availability during the EARLY event period (0.103, p<0.001) but is negatively related to product availability during the LATE event week (-0.251, p<0.001) and the first (-0.113, p<0.001), second (-0.056, p<0.001), third (-0.077, p<0.001), and fourth (-0.034, p<0.1) weeks of the POST event period. Figure 7 illustrates the coefficients of $\overline{\text{STOCKPILING\_PROP}}$ of Models 3.2.1-3.2.6, which represent dynamic changes in the effects of stockpiling propensity on product availability over the EARLY, LATE, and POST event periods.

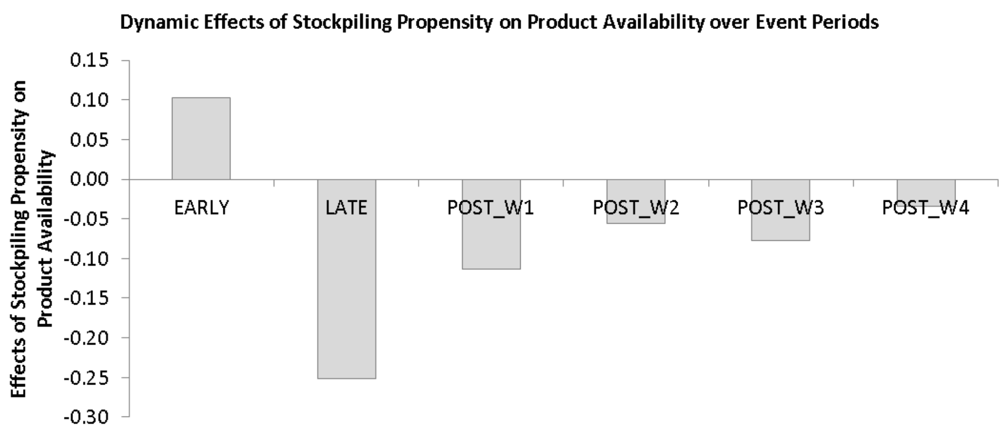

Figure 7: Stockpiling Propensity and Product Availability over Event Periods

The results demonstrate that consumer stockpiling propensity has immediate and persistent effects on in-store product availability over hurricane event periods. Similar to Beatty and colleagues (2018), we define four event periods surrounding hurricane landfall: PRE, EARLY, LATE, and POST. Hurricane landfalls are largely determined by weather patterns in place as the hurricanes approach. During the time lag between hurricane formation and landfall, the expected high stockpiling propensity is likely to motivate retailers to improve product availability for disaster preparedness. For example, compared to unpredictable disasters such as an earthquake, retailers can use weather forecasting information to plan inventory needs and accelerate inventory flow before hurricanes approach. However, the increased consumer stockpiling propensity may lead to lower product availability following hurricanes, specifically, during the first two weeks following the hurricanes, defined as the LATE event week and the first week of the POST event period in this study. These effects gradually weaken over the POST event period.

Table 13: Estimation Results (Step 2: In-Store Product Availability)

Dependent Variable LN(PRODUCT_AVAIL) × 1000	Model 3.2.1 EARLY Week	Model 3.2.2 LATE Week	Model 3.2.3 POST Week 1
Mediating Variable			
$\overline{\text{STOCKPILING\_PROP}}$	0.103*** (0.013)	-0.251*** (0.016)	-0.113*** (0.015)
Independent Variable			
Supply-Side Characteristics			
NTW_COUNTY	19.173* (8.108)	-29.764** (9.861)	22.374* (9.386)
$(\text{NTW\_COUNTY})^2$	-5.838* (2.853)	5.487 (3.470)	-7.901* (3.302)
NTW_COUNTRY	1.473* (0.650)	17.932*** (0.791)	12.737*** (0.753)
$(\text{NTW\_COUNTRY})^2$	-0.016** (0.005)	-0.125*** (0.007)	-0.104*** (0.006)
PROD_VAR_SKU	-0.573*** (0.089)	-0.026 (0.108)	0.545*** (0.103)
$(\text{PROD\_VAR\_SKU})^2$	0.002*** (0.000)	-0.000 (0.000)	-0.002*** (0.000)
Demand-Side Characteristics			
HUR_EXP_STATE	-3.224** (1.111)	-5.607*** (1.352)	6.354*** (1.287)
$(\text{HUR\_EXP\_STATE})^2$	0.328*** (0.087)	0.348** (0.106)	-0.437*** (0.101)
PER_CAPITA_INC	1.246 (2.365)	19.177*** (2.876)	9.251*** (2.737)
$(\text{PER\_CAPITA\_INC})^2$	0.060 (0.150)	-1.188*** (0.183)	-0.482** (0.174)
Disaster-Side Characteristics			
HUR_LANDFALL_DIST	4.940* (2.361)	-6.603* (2.872)	-10.716*** (2.733)
$(\text{HUR\_LANDFALL\_DIST})^2$	-0.909*** (0.168)	-0.812*** (0.205)	0.861*** (0.195)
HUR_TRACK_DIST	-4.879 (3.624)	-14.843*** (4.407)	-10.689* (4.195)
$(\text{HUR\_TRACK\_DIST})^2$	-0.215 (0.650)	-2.527** (0.791)	2.610*** (0.753)
HUR_TRACK_WIND	0.971* (0.519)	4.325*** (0.631)	-1.191* (0.601)
$(\text{HUR\_TRACK\_WIND})^2$	-0.010* (0.004)	-0.037*** (0.005)	0.007 (0.005)
Control Variable			
Retail Format			
CHAIN_GROC	90.014** (30.943)	27.195 (37.637)	-1.490 (35.822)
CHAIN_WHS	-52.420*** (9.370)	84.701*** (11.397)	75.275*** (10.847)
CHAIN_DISC	-34.221* (20.600)	-29.696 (25.056)	-39.578* (23.848)
CHAIN_DOLLAR	-32.209* (18.720)	-501.986*** (22.770)	-310.055*** (21.671)
CHAIN_DRUG	-63.571*** (12.245)	129.907*** (14.894)	68.666*** (14.175)
CHAIN_LIQ	-29.791* (16.787)	74.328*** (20.419)	64.576*** (19.434)
Retail Chain			
RETAIL_CHAIN	Included	Included	Included
Hurricane Events			
TRACK_DAY_AFT_LANDFALL	1.267 (1.006)	-6.811*** (1.224)	-7.685*** (1.165)
SALES_DAY_BEF_LANDFALL	13.424*** (1.299)	12.080*** (1.580)	-18.034*** (1.504)
Category Volume			
VOL_COUNTY	1.100 (0.674)	1.196 (0.820)	-1.115 (0.780)
VOL_STATE	0.193* (0.096)	0.280* (0.116)	-0.055 (0.111)
Category Competition			
HHI_COUNTY	2.352 (4.823)	8.049 (5.867)	-16.211** (5.584)
HHI_STATE	-24.691 (87.003)	522.587*** (105.823)	215.907* (100.720)
CONSTANT	-86.663*** (21.325)	-253.337*** (25.938)	61.680* (24.687)
Observations	38,418	38,418	38,418
F	52.34***	43.74***	52.71***

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

Table 13 Continued: Estimation Results (Step 2: In-Store Product Availability)

Dependent Variable LN(PRODUCT_AVAIL) × 1000	Model 3.2.4 POST Week 2	Model 3.2.5 POST Week 3	Model 3.2.6 POST Week 4
Mediating Variable			
$\overline{\text{STOCKPILING\_PROP}}$	-0.056*** (0.015)	-0.077*** (0.016)	-0.034* (0.016)
Independent Variable			
Supply-Side Characteristics			
NTW_COUNTY	38.388*** (9.461)	12.927 (9.773)	6.185 (9.822)
$(\text{NTW\_COUNTY})^2$	-11.959*** (3.329)	-1.133 (3.439)	3.177 (3.456)
NTW_COUNTRY	10.765*** (0.759)	5.529*** (0.784)	7.837*** (0.788)
$(\text{NTW\_COUNTRY})^2$	-0.086*** (0.006)	-0.048*** (0.006)	-0.056*** (0.006)
PROD_VAR_SKU	0.260* (0.104)	0.547*** (0.107)	0.001 (0.108)
$(\text{PROD\_VAR\_SKU})^2$	-0.001* (0.000)	-0.001*** (0.000)	0.000 (0.000)
Demand-Side Characteristics			
HUR_EXP_STATE	-2.252* (1.297)	-5.038*** (1.340)	-1.139 (1.347)
$(\text{HUR\_EXP\_STATE})^2$	0.277** (0.102)	0.502*** (0.105)	0.218* (0.105)
PER_CAPITA_INC	5.534* (2.759)	14.324*** (2.850)	11.429*** (2.865)
$(\text{PER\_CAPITA\_INC})^2$	-0.120 (0.175)	-0.654*** (0.181)	-0.403* (0.182)
Disaster-Side Characteristics			
HUR_LANDFALL_DIST	3.954 (2.755)	-2.896 (2.846)	0.944 (2.860)
$(\text{HUR\_LANDFALL\_DIST})^2$	-0.658*** (0.196)	-0.206 (0.203)	-0.636** (0.204)
HUR_TRACK_DIST	-4.477 (4.228)	-25.275*** (4.368)	-8.512* (4.390)
$(\text{HUR\_TRACK\_DIST})^2$	-0.114 (0.759)	4.545*** (0.784)	1.878* (0.788)
HUR_TRACK_WIND	1.027* (0.606)	0.427 (0.626)	0.253 (0.629)
$(\text{HUR\_TRACK\_WIND})^2$	-0.009* (0.005)	-0.005 (0.005)	-0.004 (0.005)
Control Variable			
Retail Format			
CHAIN_GROC	42.786 (36.108)	-11.045 (37.301)	19.185 (37.488)
CHAIN_WHS	49.067*** (10.934)	40.671*** (11.295)	27.710* (11.351)
CHAIN_DISC	-145.823*** (24.038)	-105.531*** (24.832)	-170.309*** (24.957)
CHAIN_DOLLAR	-293.007*** (21.844)	-126.769*** (22.566)	-280.084*** (22.679)
CHAIN_DRUG	15.817 (14.289)	-4.441 (14.761)	-62.811*** (14.835)
CHAIN_LIQ	-29.384 (19.589)	-15.887 (20.236)	-82.260*** (20.338)
Retail Chain			
RETAIL_CHAIN	Included	Included	Included
Hurricane Events			
TRACK_DAY_AFT_LANDFALL	-5.291*** (1.174)	-4.985*** (1.213)	-6.389*** (1.219)
SALES_DAY_BEF_LANDFALL	-19.807*** (1.516)	-14.280*** (1.566)	-14.862*** (1.573)
Category Volume			
VOL_COUNTY	-1.300* (0.787)	-0.856 (0.813)	0.578 (0.817)
VOL_STATE	-0.086 (0.112)	0.249* (0.115)	0.039 (0.116)
Category Competition			
HHI_COUNTY	-18.040** (5.628)	-8.495 (5.814)	-25.256*** (5.843)
HHI_STATE	126.878 (101.524)	174.460* (104.878)	192.570* (105.404)
CONSTANT	9.290 (24.884)	5.876 (25.706)	30.909 (25.835)
Observations	38,418	38,418	38,418
F	37.73***	28.77***	28.00***

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

ROBUSTNESS CHECKS

As a robustness check, we apply the quantile regression technique. As an alternative to ordinary least squares regression (OLS) and other related techniques, quantile regression aims at estimating either the conditional median or other quantiles of the response variable (e.g., a 25% quantile stockpiling propensity regression estimates the coefficients for the explanatory variables at the 25% stockpiling propensity level, rather than the mean level of stockpiling propensity). Quantile regressions are particularly more robust to outliers than standard regression techniques. Specifically, we utilize simultaneous-quantile regressions for multiple quantiles (0.25, 0.50, and 0.75), which produce bootstrap standard errors. We illustrate the results in Table A11 in the Appendix. In general, the results are consistent with the results in Table 12.

As a second robustness check, we estimate in-store product availability by eliminating bottom product SKUs. In our primary analysis, we measure product availability by considering all product SKUs of the bottled water category. For each store outlet, we drop those product SKUs with low sales volume which makes up the bottom five percentile in terms of weekly sales volume. As illustrated in Table A12, consumer stockpiling propensity during the EARLY event week plays a critical role with significantly positive impacts on product availability during the EARLY event week, and then turned into significantly negative impacts on product availability during the LATE and POST event period. The results are consistent with the findings in Table 13.

FURTHER DISCUSSION

We further investigate how various retail formats relate to consumer stockpiling propensity and in-store product availability over the course of hurricane events. Growing heterogeneity in consumer demand has led to the significant diversification of store formats (González-Benito, Muñoz-Gallego, & Kopalle, 2005). For example, consumers are influenced by store features such as (1) product assortment, (2) pricing strategy, (3) transactional convenience, and (4) shopping experience (Messinger & Narasimhan, 1997; Bustos-Reyes & Gonzalez-Benito, 2008). From a demand-side perspective, the diversity of retail formats allows retailers to satisfy the needs of various consumer segments in different shopping situations (González-Benito et al., 2005), which may affect consumer stockpiling propensity in the face of natural disasters. From a supply-side perspective, the diversity of retail formats represents a mix of operations and distribution functions to support their business strategy, which may impact in-store product availability during the course of natural disasters.

During times of natural disasters, we expect consumer stockpiling propensity to vary between retail formats. In Model 3.1.4, we control for various store formats utilizing convenience stores as the base case. We rank the impacts of store formats on stockpiling propensity: drug store (434.843, $p<0.001$), liquor store (219.064, $p<0.001$), warehouse club (196.591, $p<0.001$), discount store (133.843, $p<0.1$), convenience store (0, base case), dollar store (-43.036, $p>0.1$), grocery store (-275.790, $p<0.01$). Among various store formats, the drugstore channel is related to the highest stockpiling propensity. This may be due to two main reasons. The drugstores can meet consumers' need for disaster preparedness by offering a combination of emergency products such emergency kits, prescription drugs, and bottled water. And drugstores are more accessible to consumers compared to the other retail formats with a high density of store network. Overall, consumer segments are likely to stockpile based on the variety of store formats offered during times of natural disasters.

Moreover, during natural disasters, we also expect that operational performance such as in-store product availability varies between retail formats. In Models 3.2.1-3.2.6, we utilize convenience stores as the base case. To compare various store formats over the course of hurricane event, we transform the coefficients of store formats into z-score separately for each event week (Model 3.2.1-3.2.6) to represent the degree of product availability of each store format relative to the market average. Figure 8 (Figure 9) illustrates the effects of retail formats on in-store product availability during the EARLY event week (the LATE week and the four POST event weeks). We find that grocery stores are associated with superior performance in in-store product availability during the EARLY event week, while warehouse clubs 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 EARLY, LATE, and POST event period.

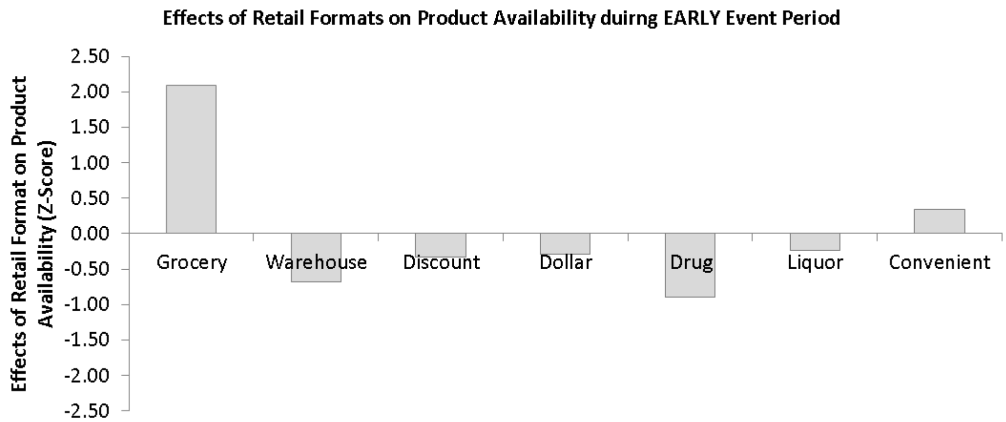

Figure 8: Retail Formats and Product Availability during EARLY Event Period

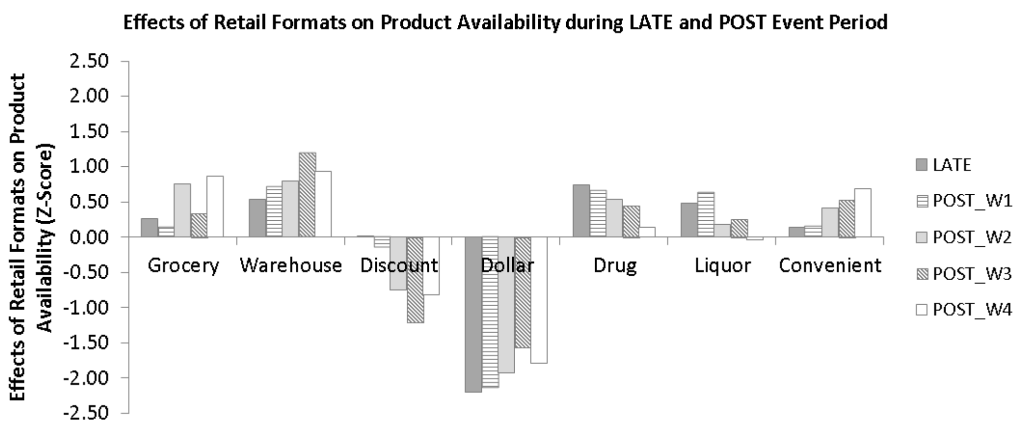

Figure 9: Retail Formats and Product Availability during LATE and POST Event Periods

Retail formats represent a mix of operations and distribution functions to support their business strategy; for example, inventory strategy varies across retail chains with various retail formats. Publicly available information showed that in the year 2017, the inventory turnover ratio and average inventory processing period were around 14 and 25 days for grocery stores like Kroger, 12 and 32 days for warehouse clubs like Costco, and 11 and 34 days for drugstore channels like CVS, 8 and 44 days for discount stores like Walmart, and 5 and 74 days for dollar stores like Dollar Tree. The inventory turnover ratio and inventory planning cycle reflect retail chains' restoration capability, which could partially explain why low-price-oriented retail channels such as discount stores and dollar stores perform differently compared to the other store formats and 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.

CONCLUSIONS

Research in disaster management from a production and operations management perspective is a relatively new field (Gupta et al., 2016; Pedraza-Martinez & Van Wassenhove, 2016). Gupta and colleagues (2016) point out that the goal of disaster operations is not to seek profit but to save lives and to reduce human suffering. One of the key humanitarian concerns in the wake of anticipated disasters relates to pre-positioning of critical groceries (Morrice et al., 2016). To respond to the call by Gupta and colleagues (2016) and Pedraza-Martinez and Van Wassenhove (2016), we explore the linkages between consumer stockpiling behavior and in-store product availability during hurricane disasters. Specifically, we construct empirical models with archival retail scanner data and real-time hurricane event data utilizing hurricane disasters as a natural experiment.

Focusing on bottled water, an emergency product category in hurricane disaster preparedness, we match four U.S. continental hurricanes with various formats of retail store outlets. We used event study methodology to categorize hurricane event windows into PRE, EARLY, LATE, and POST periods. We study consumer stockpiling propensity during the EARLY event period and its impacts on retail operations performance during the LATE and POST event periods, while using the PRE event periods as the benchmark periods. This study addresses three important research questions: 1) How do supply-side, demand-side, and disaster-side characteristics impact consumer stockpiling propensity during the EARLY event period? 2) How does expected consumer stockpiling propensity influence in-store product availability during the EARLY event period? And 3) How long do the effects of consumer stockpiling propensity during the EARLY event period on in-store product availability persist during the LATE and the POST event periods?

Our results can be summarized as follows: First, from a theoretical perspective, we find that supply-side characteristics (retail network and product variety), demand-side characteristics (hurricane experience and household income), and disaster-side characteristics (hazard proximity and hazard intensity) are related to consumer stockpiling propensity in either a convex or a concave relationship. Second, from a managerial perspective, we note that demand shocks due to consumer stockpiling have immediate and persistent impacts on retail operations performance, such as higher in-store product availability during the EARLY event week and significantly lower in-store product availability during the LATE event week and the first week of POST event period. The effects gradually weaken over the POST event period. Last, we find that consumer stockpiling propensity and in-store product availability vary between retail formats. Among various retail formats, drugstores are related to the highest consumer stockpiling propensity, while dollar stores are associated with the lowest in-store product availability. In general, we propose that retailers should carefully monitor consumer behavior when managing retail operations during hurricane disasters.

The results from this study can help retailers improve in-store product availability during hurricane disasters. In practice, matching demand and supply is a challenging task for retailers attempting to provide goods or services faced with the threat of hurricane disasters (Pedraza-Martinez & Van Wassenhove, 2016). This work disentangles a humanitarian operations problem from the perspective of consumer stockpiling behavior and retail operations performance utilizing hurricane disasters as a natural experiment. Specifically, we integrate a number of 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 are related to consumer stockpiling propensity on an individual store level and how consumer stockpiling propensity affects in-store product availability over the course of hurricane disasters. Overall, our work enables retailers, regardless of format, to more accurately plan pre-positioning of inventories prior to hurricane disasters.

We note several limitations. First, we utilize weekly sales data to obtain an approximate measure of consumer stockpiling propensity before hurricanes. Ideally, future research could utilize daily sales data to get a precise measure of consumer stockpiling propensity (Beatty et al., 2018). Second, 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 both essential items and non-essential items. Third, we conservatively estimate in-store product availability with retail sales data utilizing the average of the number of product SKUs being sold during each of the four PRE event weeks. Ideally, future research could estimate in-store product availability utilizing store inventory data. Fourth, we investigate how consumer stockpiling propensity of individual store outlet is affected by its store network belonging to the same chain. Future research could study the impacts of retailer distribution network (Rajagopalan, 2013). Last, we focus on four hurricane events with broad geographic coverage, including category 2 hurricanes Ike and Arthur; and category 1 hurricanes Sandy and Irene. Future research could investigate hurricane events with high variation in intensity.

Chapter 4: Logistics IT Resources, Organizational Factors, and Operational Performance

ABSTRACT

The prevalence of information technology (IT) has profoundly impacted the logistics industry in emerging economies. Drawing on resource complementarity, this is an exploration of the relationships of logistics IT resources, organizational factors, and operating performance. It extends the previous typology of logistics IT resources into four mid-level constructs: operations-focused IT, decision-focused IT, service-focused IT, and IT development capability. We find that operations-focused IT, decision-focused IT, and IT development capability are more related to superior operating performance than service-focused IT. Moreover, organizational factors, such as size of the firm, age of the firm, and ownership of the firm, may enhance or suppress the effects of logistics IT resources on operational performance. In general, logistics firms should carefully manage IT resources according to their particular organizational environment to achieve competitive advantage.

INTRODUCTION

The advent of new information technology (IT) has profoundly affected the logistics industry in emerging economies. For example, domestic logistics firms in China, which are the focus of this research study, are seeking extensive implementation of IT resources. A dilemma for these logistics firms is determining which type of IT resource is critical to achieving a competitive advantage. As a result, two research questions are investigated: (1) To what extent are logistics IT resources associated with operating performance? (2) To what extent are these relationships contingent on organizational factors, such as size of the firm, age of the firm, and ownership of the firm? Keen (1993) point out that, “The wide difference in competitive and economic benefits that companies gain from information technology rests on a management difference and not a technical difference.” Thus the complementary effects of IT resources and organizational factors deserve greater attention from both practitioners and researchers.

Information technology is one element of a firm’s physical resource capabilities that must be carefully managed to achieve a sustainable competitive advantage (Barney 1991). Previous operations management (OM) studies have examined the direct linkages between IT resources and firm performance (Bardhan, Mithas, & Lin, 2007; Bendoly et al., 2012; Chung& Swink, 2009; Hardgrave, Aloysius, & Goyal, 2013; Lai, Li, Wang, & Zhao, 2008; Mcafee, 2002; Setia & Patel, 2013; Wang, Lai, & Zhao, 2008; Whitaker, Mithas, & Krishnan, 2007). Others have investigated the complementary effects of IT resources and non-IT resources on firm performance (Jeffers, Muhanna, & Nault, 2008; Bendoly et al., 2012). In addition, a few studies have explored the antecedents and consequences from the adoption of logistics IT resources in the context of an emerging economy (Lai et al., 2008; Lin, 2008). This study explores the complementarity of IT resources and organizational factors within an emerging economy context.

The previous typology of logistics IT resources mainly emphasizes how IT is employed to manage functional capabilities, such as warehouse management, transportation management, customer relations management, decision supporting systems, data exchange, operations visibility, and cargo tracking. (Jeffers et al., 2008; Lin, 2008; Lai et al., 2008). In addition, the ability to develop IT capabilities (Wade & Hulland, 2004) has been identified as a significant IT resource (Day, 1994). For this paper, logistics IT resources are categorized into four mid-level constructs: operations-focused IT, decision-focused IT, service-focused IT, and IT development capabilities. Drawing on resource complementarity theory, we argue that the linkages between logistics IT resources and operational performance are contingent on organizational factors, such as firm size, firm age, and firm ownership.

The theoretical notion of complementarity emphasizes that the marginal benefit of one resource capability may be impacted by another resource capability (Bendoly et al., 2012). Black and Boal (1994) pointed out that the relationship among resources has three forms: compensatory, enhancing, and suppressing. For example, Jeffers and colleagues (2008) found that IT resources can either enhance or suppress the effects of non-IT resources on process performance. Bendoly and colleagues (2012) concluded that IT capability synergistically complements the effects of internal and external coordination of market intelligence and supply-chain intelligence.

Wade and Hulland (2004) encouraged future research focuses on how organizational factors impact the effectiveness of IT resources in a firm. In this study, we investigate the complementary effects of logistics IT resources (operations-focused IT, decision-focused IT, service-focused IT, and IT development capability) and organizational factors (firm size, firm age, and firm ownership) on operational performance, such as return on assets (ROA).

This study extends previous research in three important ways. First, the typology for logistics IT resources in previous studies emphasize logistics functional management. This study generalizes and extends the previous typology into four IT constructs as outlined above. Second, this study examines the direct relationships between these four types of logistics IT resources and operating performance. Operations-focused IT, decision-focused IT, and IT development capability have a more significant association with superior operating performance compared to service-focused IT. Third, the study examines the complementarity of logistics IT resources and organizational factors in an emerging economy context. The relationships between logistics IT resources and operating performance are partially contingent on organizational environments, such as size of the firm, age of the firm, and ownership of the firm.

The model is empirically validated using a cross-sectional sample of secondary data from domestic logistics firms in China. These data allow us to test how logistics IT resources and organizational factors are related to operating performance of third-party logistics (3PL) firms. The rest of the paper proceeds as follows. Section Two outlines a theoretical framework that highlights the underlying mechanisms concerning IT resources, organizational factors, and operating performance, leading to the research hypotheses. Section Three discusses the data and methodology. Section Four presents our empirical findings. Section Five provides a robustness check for the empirical results.

Finally, Section Six concludes with a summary and a discussion of potential future research direction.

THEORETICAL FOUNDATIONS

Theory of Resources Complementarity

The resources complementarity theory is used to guide this work. Barney (1991) pointed out that only resources deeply embedded in informal and formal decision-making processes may hold the potential for sustained competitive advantage. However, as a trait-based approach, the resource-based view (RBV) overlooks the dynamics of the interaction among firm resources particularly how a firm's performance is impacted by a resource network with specific inter- and intra-factor relationships (Black & Boal, 1994). Resource complementarity refers to how one resource factor may influence another and how the relationships between them may affect competitive advantage (Teece, 1986). For example, using a sample of 108 US logistics firms, Jeffers and colleagues (2008) found that IT resources can either enhance or suppress the effects of non-IT resources on process performance. Using a sample of publicly traded US manufacturing firms, Bendoly and colleagues (2012) noted that information system capability moderates the effects of internal and external coordination of market intelligence and supply-chain intelligence.

Black and Boal (1994) indicated that the relationship among resources has three dimensions, namely compensatory, enhancing, and suppressing. A compensatory relationship exists when a change in the degree of one factor offsets a change in the degree of another. This type of relationship focuses on changes to the mix of existing factors rather than on the replacement of existing factors with new factors. An enhancing relationship exists when the presence of one factor magnifies the impact of another factor on performance. This link may be unidirectional or asymmetric and does not require a mutual dependence. A suppressing relationship exists when the presence of one factor diminishes the impact of another. For example, the positive impact of vendor managed inventory (VMI) on a supplier's performance may be suppressed if the supplier contracts out its distribution network. Drawing on resource complementarity, we analyze the complementary effects of IT resources and organizational factors on operating performance.

Typology of Logistics IT Resources

The typology for logistics IT generally emphasizes logistics functional management. Jeffers and colleagues (2008) classified logistics IT resources into five categories; warehousing and transportation, customer interaction, network and process modeling, data exchange, and visibility and tracking. They showed that IT resources can either enhance or suppress the effects of non-IT resources on process performance. Lin (2008) classified logistics IT resources into four categories: data acquisition technology, information exchange technology, warehousing technology, and transportation technology. He found the adoption of IT resources is significantly influenced by the technological, organizational, and environmental contexts and is positively related to supply chain performance. Lai and colleagues (2008) sorted logistics IT resources into four categories: website, online transactions, shipment tracking service, and data exchange interface. They concluded that resource commitment and managerial involvement significantly affect IT capability, which in turn affects competitive advantage.

We propose a typology for logistics IT resources using four mid-level constructs: operations-focused IT, decision-focused IT, service-focused IT, and IT development capability. Logistics firms invest in various types of IT resources to manage operational knowledge and to achieve sustainable advantage (Setia & Patel, 2013). Operations-focused IT represents IT applications that help improve effectiveness, responsiveness, and partnerships through logistics operations (Day, 1994; Wade & Hulland, 2004). Decision-focused IT represents IT applications that help manage logistics and operations. Service-focused IT refers to a firm’s ability to facilitate interactions with internal and external stakeholders. Finally, IT development capability refers to the potential for development of future capabilities through IT innovation (Wade & Hulland, 2004). Table 14 shows how these categories can be used to classify various logistics functions.

Table 14: Typology for Logistics IT resources

Logistics IT Constructs	Logistics IT Applications or Capability
Operations-Focused IT	• Geographical Information System (GIS) • Global Position System (GPS) • Electronic Data Interchange (EDI) • Radio Frequency Identification System (RFID) • Barcode
Decision-Focused IT	• Transportation Management System • Warehousing Management System • Decision Supporting System
Service-Focused IT	• Online Transaction System • Ordering Management System • Cargo Tracking System
IT Development Capability	• Technology Development Award

Direct Effect of Logistics IT Resources

Logistics firms implement operations-focused IT to improve effectiveness, responsiveness, and partnerships in logistics operations (Gaiman, 2008; Wade & Hulland, 2004). This type of IT helps achieve superior operating performance through improving labor productivity, inventory visibility, product availability, delivery performance, and operational coordination (Ahmad & Schroeder, 2001; Dutta, Lee, & Whang, 2007; Hardgrave et al., 2007; Lee & Ozer, 2007). For example, Hardgrave and colleagues (2013) concluded that Radio Frequency Identification System (RFID) ameliorates the effects of known determinants of inventory record inaccuracy, although the effectiveness of RFID in reducing inventory record inaccuracy (IRI) varies by product categories. Ahmad and Schroeder (2001) noted that Electronic Data Interchange (EDI) applications have a positive impact on delivery performance after controlling for managerial and non-managerial contextual factors. Given these and other findings, we posit that broad operations-focused IT applications will help logistics firms achieve superior operating performance.

Secondly, logistics firms implement decision-focused IT to facilitate efficient employee decision making (Bloom, Garicano, Sadun, & Van Reenen, 2014). This action helps logistics firms achieve superior performance through improvement in operational efficiency and cost reductions. For example, Bardhan and colleagues (2007) found that the implementation of enterprise management systems (EMS) and operations management systems (OMS) positively affect on-time delivery rates. Chung and Swink (2009) categorized firms into four groups based on advanced manufacturing technology (AMT) utilization: traditionalists, generalists, high investors, and designers. They found that the four groups have significantly different performance regarding cost capability. But, in general, employees with access to decision support technology can better solve design and production problems on their own, and thus require less access to superiors when making decisions (Bloom et al., 2014). Therefore, it can be argued that broad decision-focused IT will help logistics firms achieve superior operating performance.

Third, logistics firms implement service-focused IT resources to manage communication with internal and external stakeholders (Wade & Hulland, 2004). On the one hand, the application of service-focused IT may lead to increased operational complexity given greater involvement through collaborative planning for example, from internal and external stakeholders. As a result, service-focused IT resources may have adverse effects on operating performance. On the other hand, the application of service-focused IT decreases communication costs with internal and external stakeholders (Bloom et al., 2014). Presumably, firms weigh the trade-offs between potential costs and benefits to implement service-focused IT when it will have positive benefits. Therefore, it can be argued that broad service-focused IT will help logistics firms to achieve superior operating performance.

Lastly, logistics firms pursue technological progress to manifest their orientation and capability in developing, experimenting with, and applying new technologies (Wade & Hulland, 2004). IT development capability represents a firm’s ability to integrate information technology to allow future progress. Setia and Patel (2013) found that integrated IT capability is an antecedent to potential operational absorptive capacity (POAC) and realized operational absorptive capacity (ROAC) capabilities. The earnings of a technology development award by a logistics firm is utilized to proxy for its capability in technology development. Although IT development capability may indirectly affect operating performance through other constructs, we generally expect that IT development capability to be directly associated with superior operating performance.

Based on the above discussion, our first four hypotheses are as follows:

H1a: Firms with a broad implementation of operations-focused IT resources are associated with superior operating performance.

H1b: Firms with a broad implementation of decision-focused IT resources are associated with superior operating performance.

H1c: Firms with a broad implementation of service-focused IT resources are associated with superior operating performance.

H1d: Firms with higher IT development capability are associated with superior operating performance.

Complementary Effects of Organizational Factors

Firm size is one of the most significant contingency variables in organizational studies. Large firms are more capable of achieving economies of scale in their operations, for example, through the broad application of IT resources. Dean, Brown, and Bamford (1998) revealed that firm size is positively associated with sunk costs, vertical integration, excess capacity, overall profitability, and technical development. As a result, financial and human resources are more likely to be a distinct competitive advantage for larger firms (Dean et al., 1998). However, IT resources in large firms are more likely to lack standardization. In many cases, large firms are formed by mergers and acquisitions, with each pre-merger firm bringing its own set of IT resources into the merged company. Therefore, coordination of IT in large firms may be difficult and could cause operational problems. Moreover, large firms typically have greater inertia which makes fundamental changes in IT capabilities more costly and harder to achieve (Dean et al., 1998; Hendricks & Singhal, 2001). Therefore, we posit that firm size may positively or negatively affect the relationships between IT resources and operating performance. Thus, our moderating hypothesis (H2) in relation to firm size is as follows:

> H2: Firm size moderates the relationships between IT resources (operations-focused, decision-focused, service-focused and development capability) and operating performance.

The age of the firm is another significant contingency variable in organizational studies. Older firms may be reluctant to adopt advanced technology or may fail to realize the benefits of implementing IT resources (Bardhan et al., 2007). In particular, older firms are likely to employ dated capital resources which can be less productive than the industry average (Lundvall & Battese, 2000). As a result, the age of the firm may suppress the benefits of operations- and decision-focused IT. On the other hand, customer relationships as a form of the firm's resources are likely to improve with age as otherwise they would be ended. Although the application of service-focus IT may increase operational complexity due to more involvement by internal and external stakeholders, better customer relationships that develop with time may decrease the adverse impacts of operation complexity. Therefore, firm age could potentially be associated with enhanced benefits from implementing service-focus IT. Finally, older firms may be more capable of generating innovative output than young firms. Resource endowment, such as knowledge accumulation (Cohen & Levinthal, 1990) and slack resources (Nohria & Gulati, 1996), tend to accumulate with age, which may enhance firm competency and generate innovative output. Therefore, it can be argued that firm age can enhance the benefits of IT development capability. Overall, firm age may enhance or suppress the direct effects of IT resources on operating performance and these effects could vary depending on the category of the main effects. Thus, our moderating hypothesis (H3) with respect to firm age is as follows:

> H3: Firm age moderates the relationships between IT resources (operations-focused, decision-focused, service-focused and development capability) and operating performance.

Firm ownership is a crucial institutional factor in emerging economies. Two types of ownership, state-owned and non-state-owned, are well represented in China. State-owned firms are directly controlled by local and central bureaucracies (Chang & Wong, 2004; Xia & Walker, 2015); while non-state-owned firms are owned by individuals, often with family support (Cull & Xu, 2005; Xia & Walker, 2015). In general, state-owned firms do not perform as well as non-state-owned firms in terms of normal profitability indicators (Bai, Lu, & Tao, 2009; Xia & Walker, 2015). First, state-owned firms are often organized in pyramid structures to facilitate state control rather than organizational change (Fan, Wong, & Zhang, 2005; Xia & Walker, 2015). As a result, state-owned firms are less likely to develop IT implementation due to internal inertia. Secondly, non-state-owned firms perform more actively in developing external resources network. As a result, non-state-owned firms could achieve competitive advantage by relying on technology spillovers (Xia & Walker, 2015). Finally, state-owned firms often have social objectives as well as financial objectives. For example, state-owned firms may have a goal of employment maximization that must be met concurrently with profitability objectives.

Therefore, the implementation of IT may not have as great an impact on performance in state-owned firms as in private sector firms. Therefore, we posit that firm ownership additionally affects the linkage of IT resources and operating performance (H4) as stated below:

> H4: Firm ownership moderates the relationships between IT resources (operations-focused, decision-focused, service-focused and development capability) and operating performance.

The above discussion leads to development of this theoretical model (Figure 10).

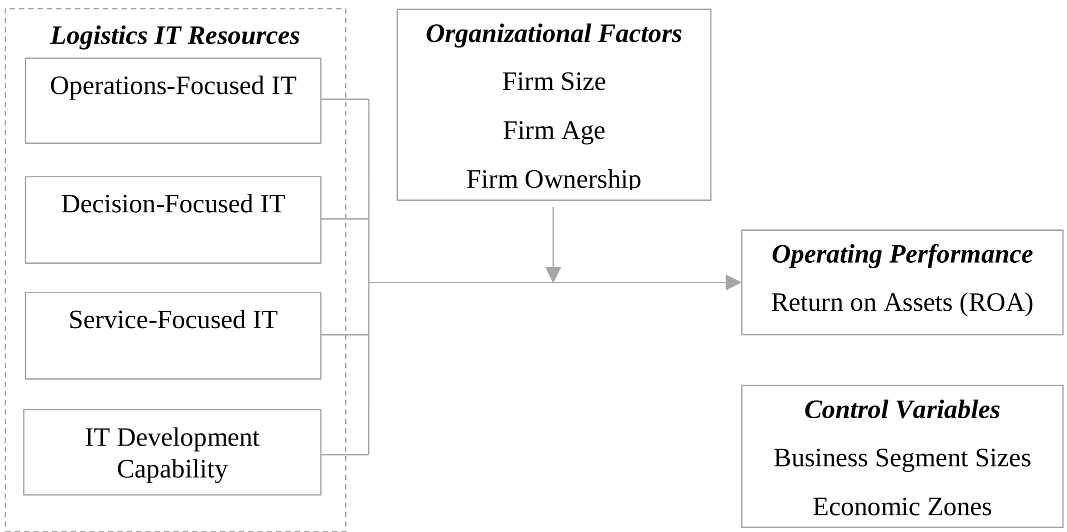

Figure 10: Theoretical model

RESEARCH METHODOLOGY

Sample Description

The empirical questions this study aims to answer are (1) To what extent are logistics IT resources associated with improved operational performance? and (2) To what extent are these relationships contingent on organizational factors? We obtained sample data from the China Communications and Transportation Association (CCTA) based on its “Outstanding Logistics Firms Campaign” conducted in 2012 targeting third party logistics providers (3PLs). A total of 303 firms participated in the campaign, and among them, 244 firms provided all the information as required. The 244 firms were geographically distributed across the seven economic zones of China (as outlined in control variables). We found that six firms reflected negative profits in their financial reports for the year 2011. As there could be various reasons for a firm to reveal negative profit (e.g., tax savings), we excluded these firms from our analysis. We further excluded 19 firms whose business focus on port services, railway transportation, port transportation, and ocean shipping, which gave us a sample of 219 3PLs focusing on traditional warehousing and transportation services.

CCTA validated the financial data for participating firms by checking the financial statements, including balance sheets, income statements, and tax reports. We took two further steps to verify the reliability of the collected information. First, we randomly selected sample firms and compared the gathered information against information on their official websites. We compared the number of employees, headquarters location, the number of overseas subsidiaries, and date of establishment. Second, for publicly listed firms, we compared the collected information with data in published annual reports, such as annual revenue, annual profit, and total assets. In general, the sample data served as a reliable reference to accurately reflect reported firm performance and organizational structure.

As outlined below, we utilize regression analysis to investigate how the relationships between IT resources and organizational factors impact firm performance.

Variable Definitions

Dependent Variables

Return on assets (ROA). This is the ratio of total profit to total assets and is our measure of operational performance. ROA is a relevant variable for measuring performance for asset-based 3PLs since asset utilization is the key to success for these firms (Bowersox & Daugherty, 1995; Bowersox, Closs, & Stank, 2000). We utilize natural logarithm transformed variables for the measure in order to reduce the impact of outliers in the analysis and hypothesize that firms with extensive IT resources are more likely to efficiently manage their property to generate earnings.

Independent variable

Operations-focused IT. This is a standardized count variable consisting of five types of IT applications, including Global Position System (GPS), Geographical Information System (GIS), Electronic Data Interchange (EDI), Radio Frequency Identification System (RFID), and barcoding. In line with Bardhan and colleagues (2007), each operations-focused IT application is measured as a binary variable based on the extent of firm usage (0=not used and 1=some or extensive usage). Note, we do not differentiate between "some use" and "extensive use" given the subjectivity of this distinction.

Decision-focused IT. This is a standardized count variable consisting of three types of IT applications, including transportation management system, warehousing management system, and decision-supporting system. Each application is measured as a binary variable based on the extent of firm usage (0=not used and 1=some or extensive usage).

Service-focused IT. This is a standardized count variable consisting of three types of logistics IT applications, including online transaction, order management system, and cargo tracking system. Similarly, we define each service-focused IT application as a binary variable based on the extent of firm usage (0=not used and 1=some or extensive usage).

IT development capability. We determine whether a firm has received a technology development award to approximate that firm's capability for developing IT applications. These logistics firms typically pursue government- or industry-level technology awards to demonstrate their superior capabilities in technology development. IT development capability is measured as a binary variable (0=not awarded and 1=awarded). Likewise, we use a standardized measure for IT development capability.

Firm size. This variable represents the total number of individuals employed by a logistics firm. A large firm may have the economies of scale to convert logistics IT resources into a competitive advantage. On the other hand, given bureaucratic considerations, the size of the firm could stifle the impact of IT usage on performance.

Firm age. This variable represents the number of years since a firm began operations to the time of this study. Firm age may influence the relationships between IT resources and operating performance either positively or negatively.

Firm ownership. Two types of firm ownership, state-owned and private-owned, are well represented in the Chinese logistics industry (0=private-ownership and 1=state-ownership). In general, state-owned firms in China do not perform as well as privately-owned firms (Bai, Lu, & Tao, 2009; Xia & Walker 2015). The bureaucratic tendency of state-owned firms may suppress the impact of IT usage on performance.

Control Variables

Sizes of business segments. We classify the 3PLs based on the transportation-orientation of the firm (dummy variable is coded 0 if the number of vehicles owned by the firm is less than the sample median number of vehicles and coded 1 otherwise) and the size of their warehousing operations (dummy variable is coded 0 if the size of warehouses is less than the sample median size of warehouses and coded 1 otherwise).

Economic zones. China is a geographically large and regionally diverse emerging market (Xia & Walker, 2015). We classify the economic zones of firms' headquarters as seven binary variables: North China, Northeast China, East China, Central China, South China, Southwest China, and Northwest China to account for differences among the regions regarding IT development and performance.

Table 15 shows descriptive statistics for our variables before data transformation while Table 16 provides correlations between variables after transformation. Among the 219 sample logistics firms, the mean ROA is 0.12 with a standard deviation of 0.22; the mean firm size is 1,543 employees with a standard deviation of 418 employees; the mean firm age is 12.5 years with a standard deviation of 10.2 years; around 41% of the sample logistics firms are state-owned, while the remaining 59% are non-state-owned firms. In addition, there is wide variation among the firms with respect to IT applications, with some of the sample logistics firms having applied a wide range of operations-focused IT, decision-focused IT, and/or service-focused IT with high IT development capability, while others have only limited use of these IT applications with low IT development capability. In general, the sample logistics firms represent significant variation in terms of IT resources (operations-focused IT, decision-focused IT, service-focused IT, and IT development capability) and organizational factors (firm size, firm age, and firm ownership).

Table 15: Data Description

Variables	Definition	Mean	St. Dev	Min	Max
Dependent variable					
Firm performance					
ROA	Variable indicates return on assets	0.120	0.220	0	1.63
Independent variable					
IT resources					
OPERATIONS_IT	Count variable indicates operations-focused IT	3.274	1.400	0	5
DECISION_IT	Count variable indicates decision-focused IT	2.763	0.540	0	3
SERVICE_IT	Count variable indicates service-focused IT	2.703	0.612	0	3
IT_DEVELOPMENT	Dummy variable indicates IT development capability	0.324	0.469	0	1
Organizational factors					
FIRM_SIZE (K · Head)	Number of employees shows firm size	1.543	4.183	0.05	39.98
FIRM_AGE (Year)	Number of years since the firm began operation	12.461	10.207	2	64
STATE_OWNERSHIP	Dummy variable means state-owned firm	0.411	0.493	0	1
Control variables					
Sizes of Business Segments					
TRANSPORTATION_SIZE	Dummy variable indicates size of transportation business segment	0.506	0.501	0	1
WAREHOUSING_SIZE	Dummy variable indicates size of warehousing business segment	0.516	0.501	0	1
Economic Zones					
NORTH_CHINA	Dummy variable indicates firm HQ locates in North China	0.132	0.340	0	1
NORTHEAST_CHINA	Dummy variable indicates firm HQ locates in Northeast China	0.032	0.176	0	1
EAST_CHINA	Dummy variable indicates firm HQ locates in East China	0.557	0.498	0	1
CENTRAL_CHINA	Dummy variable indicates firm HQ locates in Middle China	0.100	0.301	0	1
SOUTH_CHINA	Dummy variable indicates firm HQ locates in South China	0.105	0.307	0	1
SOUTHWEST_CHINA	Dummy variable indicates firm HQ locates in Southeast China	0.023	0.150	0	1
NORTHWEST_CHINA	Dummy variable indicates firm HQ locates in Southwest China	0.050	0.219	0	1
Observations		219	219	219	219

Table 16: Correlation Matrix

	Variable	1	2	3	4	5	6	7	8	9
1	OPERATIONS_ IT	1.000								
2	DECISION_ IT	0.353***	1.000							
3	SERVICE_IT	0.416***	0.438***	1.000						
4	IT_DEVELOPMENT	0.207***	0.106	0.065	1.000					
5	FIRM_SIZE	0.035	-0.010	0.047	0.141**	1.000				
6	FIRM_AGE	-0.003	-0.027	0.010	0.122*	0.274***	1.000			
7	STATE_OWNERSHIP	-0.071	-0.011**	-0.156**	-0.043	0.105	0.224***	1.000		
8	TRANSPORTATION_SIZE	0.069	-0.011*	0.119*	0.000	0.224***	0.021	-0.160**	1.000	
9	WAREHOUSING_SIZE	0.164**	0.082	0.023	0.066	0.016	0.034	0.140**	0.068	1.000

Note: *p<0.1, **p<0.05, ***p<0.01

Estimation Model

The central task of this study is to investigate how IT resources and organizational factors impact operating performance. As noted above, we focus on four types of IT resources: operations-focused IT, decision-focused IT, service-focused IT, and IT development capability. To compare the magnitude of the impact on the performance of different types of IT resources, we utilize standardized measures for the IT constructs. Our empirical model is as follows:

$$
\begin{aligned}
\mathrm{ROA} = {} & \beta_0 + \beta_1 \cdot \mathrm{IT\_RESOURCES} \\
& + \beta_2 \cdot \mathrm{IT\_RESOURCES} \cdot \mathrm{FIRM\_SIZE} \\
& + \beta_3 \cdot \mathrm{IT\_RESOURCES} \cdot \mathrm{FIRM\_AGE} \\
& + \beta_4 \cdot \mathrm{IT\_RESOURCES} \cdot \mathrm{STATE\_OWNERSHIP} \\
& + \beta_5 \cdot \mathrm{FIRM\_SIZE} + \beta_6 \cdot \mathrm{FIRM\_AGE} + \beta_7 \cdot \mathrm{STATE\_OWNERSHIP} \\
& + \beta_8 \cdot \mathrm{TRANSPORTATION\_SIZE} \\
& + \beta_9 \cdot \mathrm{WAREHOUSING\_SIZE} \\
& + \beta_{10} \cdot \mathrm{ECOMONIC\_ZONE} \qquad (1)
\end{aligned}
$$

where

$$\mathrm{IT\_RESOURCES} = \{\mathrm{OPERATIONS\_IT}, \mathrm{DECISION\_IT}, \mathrm{SERVICE\_IT}, \mathrm{IT\_DEVELOPMENT}\}$$

EMPIRICAL RESULTS

Table 17 presents the estimation results. In Table 17, Model 4.1.1 contains just the control variables while Model 4.1.2 adds the direct relationships. Models 4.1.3, 4.1.4 and 4.1.5 add in the interaction terms between specific moderating variables and the four IT variables. Model 4.1.6 includes all of the interaction terms and is, therefore, the most complete model. We, therefore, use Model 4.1.6 to describe our results. Table 18 summarizes the results with respect to the hypotheses.

First, we examine the direct effects of IT resources on operating performance. In Model 4.1.2, the coefficients for operations-focused IT and IT-development capability are positive and significant at 0.162 and 0.192, respectively. Therefore, we find support for H1a and H1d. In Model 4.1.6, we find the coefficients for operations-focused IT and decision-focused IT are significantly positive at 0.431 and 0.439, respectively. Thus we find support for H1a and H1b. While the coefficient for service-focused IT is significantly negative at -0.497, opposite to our hypothesis. Thus we do not find support for H1c. In general, the results indicate that logistics firms can benefit more from the operations-focused IT, decision-focused IT, and IT-development capability than they can from service-focused IT.

Second, we examine the moderating effects of firm size on the relationship between IT resources and operating performance. Firm size, itself, is negatively related to ROA, which indicates that large firms are associated with lower asset efficiency compared to small firms. In Model 4.1.6, the coefficient for the interaction term between IT development capability and firm size is negative and significant, indicating that firm size may suppress the positive relationship between IT development capability and operating performance. However, firm size has no significant impacts on the relationships between the other types of IT resources and ROA. The results imply that firm size may have mixed effects on the relationships between IT resources and operating performance. On the whole, large firms may not necessarily make better use of their IT development capability than smaller firms to improve asset efficiency. Therefore, the results only partially support H2b and do not support H2a.

Third, we explore the moderating effects of firm age on the relationship between IT resources and operating performance. As shown in the models, firm age itself has no significant effect on ROA. In Model 4.1.6, the coefficient for the interaction term for operations-focused IT and firm age is significantly negative at -0.027, indicating that firm age can suppress the positive relationship between operations-focused IT and operating performance. The coefficient for the interaction term for decision-focused IT and firm age is negative and significant at -0.026, indicating that firm age may suppress the positive relationship between decision-focused IT and operating performance. The coefficient for the interaction term between service-focused IT and firm age is significantly positive at 0.027, implying that firm age can mitigate the negative relationship between service-focused IT and operating performance. The coefficient for the interaction term between IT development capability and firm age is significantly positive at 0.016, implying that firm age can enhance the positive relationship between IT development capability and operating performance. Overall, we identify that firm age can complement various types of IT resources to influence operating performance which provides evidence to support H3.

Lastly, we examine the moderating effects of firm ownership on the relationship between IT resources and operating performance. As presented in Model 4.1.6, we find that state ownership is negatively related to ROA, indicating that state-owned firms may not be using logistics assets efficiently compared to non-state-owned firms. The coefficient for the interaction term for decision-focused IT and state ownership is significant and negative at -0.374, indicating that state-ownership may suppress the positive relationship between decision-focused IT and operating performance. However, firm ownership has no significant effects on the relationships between the other types of IT resources and ROA. In general, the results indicate that state-owned firms may not take advantage of decision-focused IT resources to improve asset efficiency, at least compared to privately-owned firms. Therefore, the evidence partially supports H4.

Table 17: Estimation Results (ROA and Four IT Constructs)

Variables	Return on Assets (ROA)					
	Model 4.1.1	Model 4.1.2	Model 4.1.3	Model 4.1.4	Model 4.1.5	Model 4.1.6
Independent Variables						
<u>Logistics IT</u>						
OPERATIONS_IT		0.162* (0.096)	0.155 (0.107)	0.405** (0.169)	0.218* (0.119)	0.431** (0.178)
DECISION_IT		0.003 (0.099)	0.048 (0.108)	0.301* (0.172)	0.203* (0.120)	0.439** (0.180)
SERVICE_IT		-0.110 (0.101)	-0.159 (0.111)	-0.307* (0.183)	-0.238 (0.152)	-0.497** (0.203)
IT_DEVELOPMENT		0.192** (0.087)	0.247** (0.096)	0.118 (0.135)	0.223** (0.108)	0.127 (0.147)
<u>Firm Size</u>						
OPERATIONS_IT · SIZE			0.006 (0.054)			0.036 (0.053)
DECISION_IT · SIZE			-0.037 (0.052)			-0.009 (0.052)
SERVICE_IT · SIZE			0.031 (0.045)			-0.019 (0.046)
IT_DEVELOPMENT · SIZE			-0.033 (0.026)			-0.042* (0.025)
<u>Firm Age</u>						
OPERATIONS_IT · AGE				-0.018 (0.012)		-0.027** (0.013)
DECISION_IT · AGE				-0.025* (0.013)		-0.026* (0.015)
SERVICE_IT · AGE				0.016 (0.014)		0.027* (0.016)
IT_DEVELOPMENT · AGE				0.007 (0.009)		0.016* (0.010)
<u>Firm Ownership</u>						
OPERATIONS_IT · STATE_OWNERSHIP					-0.127 (0.200)	0.052 (0.205)
DECISION_IT · STATE_OWNERSHIP					-0.535*** (0.195)	-0.374* (0.210)
SERVICE_IT · STATE_OWNERSHIP					0.318 (0.207)	0.221 (0.220)
IT_DEVELOPMENT · STATE_OWNERSHIP					-0.033 (0.180)	-0.074 (0.183)
Control Variables						
FIRM_SIZE		-0.063*** (0.022)	-0.062* (0.032)	-0.091*** (0.023)	-0.064*** (0.022)	-0.074** (0.032)
FIRM_AGE		-0.009 (0.009)	-0.011 (0.009)	-0.013 (0.010)	-0.012 (0.009)	-0.015 (0.010)
STATE_OWNERSHIP		-0.477*** (0.182)	-0.445** (0.183)	-0.477*** (0.181)	-0.444** (0.180)	-0.418** (0.181)
TRANSPORTATION_SIZE	0.247 (0.178)	0.313* (0.178)	0.343* (0.179)	0.384** (0.176)	0.286 (0.178)	0.374** (0.177)
WAREHOUSING_SIZE	-0.348* (0.179)	-0.345** (0.174)	-0.312* (0.177)	-0.349** (0.171)	-0.342* (0.173)	-0.324* (0.173)
ECONOMIC_ZONE	YES	YES	YES	YES	YES	YES
CONS	-3.411*** (0.396)	-2.671*** (0.416)	-2.689*** (0.421)	-2.979*** (0.416)	-2.649*** (0.414)	-2.865*** (0.421)
N	219	219	219	219	219	219
R-squared	0.080	0.203	0.218	0.258	0.239	0.298
Adj R-squared	0.045	0.144	0.143	0.187	0.167	0.198

Note: Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Table 18: Hypotheses Summary

Hypotheses	Results
The direct effects of logistics IT resources	
H1a: Firms with a broad implementation of operations-focused IT resources are associated with superior operating performance.	(Supported, Positive)
H1b: Firms with a broad implementation of decision-focused IT resources are associated with superior operating performance.	(Supported, Positive)
H1c: Firms with a broad implementation of service-focused IT resources are associated with superior operating performance.	(Not Supported, Negative)
H1d: Firms with higher IT development capability are associated with superior operating performance.	(Supported, Positive)
The moderating effects of organizational factors	
Firm Size	
H2a: Firm size moderates the relationships between operations-focused IT resources and operating performance.	(Not Supported)
H2b: Firm size moderates the relationships between decision-focused IT resources and operating performance.	(Not Supported)
H2c: Firm size moderates the relationships between service-focused IT resources and operating performance.	(Not Supported)
H2d: Firm size moderates the relationships between IT development capability and operating performance.	(Supported, Negative)
Firm Age	
H3a: Firm age moderates the relationships between operations-focused IT resources and operating performance.	(Supported, Negative)
H3b: Firm age moderates the relationships between decision-focused IT resources and operating performance.	(Supported, Negative)
H3c: Firm age moderates the relationships between service-focused IT resources and operating performance.	(Supported, Positive)
H3d: Firm age moderates the relationships between IT development capability and operating performance.	(Supported, Positive)
Firm Ownership	
H4a: Firm ownership moderates the relationships between operations-focused IT resources and operating performance.	(Not Supported)
H4b: Firm ownership moderates the relationships between decision-focused IT resources and operating performance.	(Supported, Negative)
H4c: Firm ownership moderates the relationships between service-focused IT resources and operating performance.	(Not Supported)
H4d: Firm ownership moderates the relationships between IT development capability and operating performance.	(Not Supported)

ROBUSTNESS CHECKS

As a robustness check, the relationships between IT resources and other operational performance measures are examined, an example being labor productivity. In the previous analysis, we utilize ROA as the dependent variable, which represents a firm's asset efficiency. Now the relationships between different types of IT resources and labor efficiency are examined. Labor productivity is evaluated as the ratio of total profit to number of employees (Lo, Wiengarten, Humphreys, Yeung, & Cheng, 2013). We utilize natural logarithms to transform this variable. As with the main analysis, the results in the first column in Table 19 present the findings for the control variables only (Model 4.2.1). Model 4.2.2 adds the main effects, while Models 4.2.3, 4.2.4 and 4.2.5 add the effects for firm size, firm age and firm ownership status, respectively. Model 4.2.6 adds all of the effects and is, therefore, the most complete model. The discussion will focus on the results of Models 4.2.2 and 4.2.6.

As presented in Model 4.2.2, operations-focused IT and IT development capability are positively related to labor productivity while decision-focused IT and service-focused IT are not significant. From Model 4.2.6, it is shown that firm age negatively affects the relationship between operations-focused IT and labor productivity; positively affects the relationship between service-focused IT and labor productivity; and positively affects the relationship between IT-development capability and labor productivity. Last, state-ownership may negatively impact the relationship between decision-focused IT and labor productivity but may positively impact the relationship between service-focused IT and labor productivity.

Table 19: Robustness Checks (Labor Productivity and Four IT Constructs)

Variables	Labor Productivity					
	Model 4.2.1	Model 4.2.2	Model 4.2.3	Model 4.2.4	Model 4.2.5	Model 4.2.6
Independent Variables						
Logistics IT						
OPERATIONS_IT		0.210* (0.107)	0.185 (0.118)	0.505*** (0.188)	0.256* (0.134)	0.452** (0.201)
DECISION_IT		-0.070 (0.110)	0.036 (0.119)	0.176 (0.192)	0.066 (0.135)	0.270 (0.203)
SERVICE_IT		-0.136 (0.113)	-0.237* (0.122)	-0.510** (0.203)	-0.332* (0.170)	-0.635*** (0.229)
IT_DEVELOPMENT		0.160* (0.096)	0.165 (0.106)	-0.012 (0.150)	0.139 (0.121)	-0.007 (0.166)
Firm Sizes						
OPERATIONS_IT · SIZE			0.044 (0.059)			0.071 (0.060)
DECISION_IT · SIZE			-0.084 (0.057)			-0.056 (0.058)
SERVICE_IT · SIZE			0.052 (0.050)			0.010 (0.051)
IT_DEVELOPMENT · SIZE			-0.003 (0.028)			-0.013 (0.029)
Firm Age						
OPERATIONS_IT · AGE				-0.024* (0.013)		-0.028* (0.015)
DECISION_IT · AGE				-0.021 (0.015)		-0.019 (0.017)
SERVICE_IT · AGE				0.032** (0.015)		0.033* (0.018)
IT_DEVELOPMENT · AGE				0.015 (0.010)		0.018* (0.011)
Firm Ownership						
OPERATIONS_IT · STATE_OWNERSHIP					-0.138 (0.224)	0.067 (0.232)
DECISION_IT · STATE_OWNERSHIP					-0.362* (0.219)	-0.177 (0.237)
SERVICE_IT · STATE_OWNERSHIP					0.410* (0.233)	0.176 (0.248)
IT_DEVELOPMENT · STATE_OWNERSHIP					0.093 (0.202)	-0.028 (0.206)
Control Variables						
FIRM_SIZE	-0.104*** (0.024)	-0.111*** (0.024)	-0.153*** (0.035)	-0.146*** (0.026)	-0.114*** (0.025)	-0.166*** (0.036)
FIRM_AGE	-0.017* (0.010)	-0.018* (0.010)	-0.023** (0.010)	-0.024** (0.011)	-0.019* (0.010)	-0.025** (0.012)
STATE_OWNERSHIP	-0.122 (0.200)	-0.097 (0.202)	-0.050 (0.201)	-0.062 (0.202)	-0.068 (0.202)	-0.017 (0.205)
TRANSPORTATION_SIZE	-0.334* (0.199)	-0.310 (0.198)	-0.270 (0.197)	-0.261 (0.196)	-0.323 (0.200)	-0.246 (0.200)
WAREHOUSING_SIZE	0.026 (0.193)	-0.049 (0.194)	0.000 (0.194)	-0.030 (0.190)	-0.069 (0.195)	-0.007 (0.196)
ECONOMIC_ZONE	(YES)	(YES)	(YES)	(YES)	(YES)	(YES)
CONS	1.937*** (0.458)	2.031*** (0.463)	1.915*** (0.463)	1.781*** (0.463)	1.993*** (0.466)	1.783***(0.476)
Observations	219	219	219	219	219	219
R-squared	0.232	0.264	0.293	0.311	0.281	0.330
Adj R-squared	0.192	0.210	0.225	0.245	0.212	0.236

Note: Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01.

For a second robustness check, the relationship between integrated IT capability and operating performance is examined. In the previous analysis, the focus was on the four types of mid-level IT constructs. It was found that operations-focused IT, decision-focused IT, and IT development capability are positively related to ROA while service-focused IT is negatively related to ROA. However, the relationship between integrated IT capability and operational performance is not known. We measure integrated IT capability as the standardized count variable taking into account all the IT resources implemented by a logistics firm. In Table 20, integrated IT capability is positively related to ROA, but firm age and state-ownership suppress the relationship between integrated IT resources and ROA. On the other hand, firm size has no significant effect on the relationship between integrated IT resources and operational performance.

Table 20: Robustness Checks (ROA and Integrated IT Capability)

Variables	Return on Assets (ROA)					
	Model 4.3.1	Model 4.3.2	Model 4.3.3	Model 4.3.4	Model 4.3.5	Model 4.3.6
INTEGRATED_IT_CAPABILITY		0.146* (0.086)	0.153* (0.092)	0.385*** (0.131)	0.312** (0.126)	0.462*** (0.149)
INTEGRATED_IT_CAPABILITY · SIZE			-0.006 (0.027)			0.002 (0.027)
INTEGRATED_IT_CAPABILITY · AGE				-0.018** (0.007)		-0.015** (0.008)
INTEGRATED_IT_CAPABILITY · STATE_OWNERSHIP					-0.312* (0.173)	-0.212 (0.180)
FIRM_SIZE	-0.055*** (0.022)	-0.058*** (0.022)	-0.056*** (0.023)	-0.062*** (0.022)	-0.057*** (0.022)	-0.062*** (0.022)
FIRM_AGE	-0.007 (0.009)	-0.008 (0.009)	-0.008 (0.009)	-0.004 (0.009)	-0.011 (0.009)	-0.006 (0.009)
STATE_OWNERSHIP	-0.507*** (0.181)	-0.469*** (0.181)	-0.470*** (0.182)	-0.517*** (0.180)	-0.470*** (0.180)	-0.511*** (0.181)
TRANSPORTATION_SIZE	0.281 (0.179)	0.270 (0.179)	0.271 (0.179)	0.322* (0.178)	0.273 (0.178)	0.318* (0.178)
WAREHOUSING_SIZE	-0.267 (0.174)	-0.312* (0.175)	-0.310* (0.176)	-0.332* (0.173)	-0.289* (0.175)	-0.314* (0.175)
ECONOMIC_ZONE	YES	YES	YES	YES	YES	YES
CONS	-2.827*** (0.413)	-2.740*** (0.414)	-2.750*** (0.418)	-2.952*** (0.419)	-2.648*** (0.415)	-2.856*** (0.428)
N	219	219	219	219	219	219
R-squared	0.165	0.176	0.176	0.198	0.189	0.204
Adj R-squared	0.120	0.128	0.124	0.148	0.137	0.145

Note: Bootstrap standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01

MANAGERIAL IMPLICATIONS

These findings are valuable to logistics firms in emerging markets as managing logistics IT resources is necessary to achieve competitive advantage. These findings are also valuable to buyer firms in emerging markets as logistics IT resources may affect service costs, effectiveness, and quality. For example, domestic logistics firms in China are encouraged to pursue a broad implementation of IT resources. The national standard, Classification and Evaluation Index for Logistics Enterprise (GB/T 19680-2013), has utilized logistics IT resources as one essential criteria to classify logistics firms and evaluate logistics service. As a result, more and more buyer firms in China have considered the implementation of logistics IT resources as one critical criterion when purchasing logistics services and evaluating logistics providers.

In general, integrated IT capability can help logistics firm improve their operating efficiency. However, firm ownership and firm age may affect the benefits from the implementation of logistics IT resources. Logistics firms should carefully manage different types of logistics IT resources since not all types of logistics IT resources are as beneficial to operating performance. Logistics firms should implement extensive operations- and decision-focused IT and pursue high IT-development capabilities, all of which may help improve operation effectiveness and cost reduction. However, logistics firms should carefully apply service-focused IT which may add operational complexities and decrease employee autonomy, resulting in lower operating performance. In addition, organizational factors, such as firm age and firm ownership status, may affect the relationships between various types of IT resources and operating performance. Older firms should pay close attention to effectively implement operations- and decision-focused IT while younger firms should pay close attention to customer relationships in the implementation of service-focused IT. State-owned logistics firms should be aware of the effectiveness in the implementation of decision-focused IT, which may, if not implemented properly, lead to lower asset efficiency.

Buyer firms are encouraged to select logistics service providers with broad implementation of logistics IT resources. This analysis indicates that higher integrated IT capabilities help logistics providers realize greater operating efficiency. It is suggested that buyer firms to carefully consider the types of logistics IT resources owned by logistics service providers. Logistics service providers with broad applications of service-focused IT resources but narrow applications of operation-focused IT and decision-focused IT may lead to lower operating efficiency. Moreover, buyer firms should be aware of organizational factors when purchasing logistics services in emerging markets. Older firms may not realize effectiveness in the implementation of operation-focused IT and decision-focused IT. State-owned logistics firms typically could not utilize their IT resources as efficiently as those private-owned logistics firms.

CONCLUSIONS

Many successful logistics firms in emerging markets have undergone dramatic changes to their internal and external operations due to the implementation of IT resources. However, IT resources are only one element of a firm’s resources that must be managed carefully to drive competitive advantage (Barney, 1991). We propose that the complementary effects of logistics IT resources and organizational factors on operating performance deserve greater attention from both practitioners and researchers. Drawing on resource complementarity theory, two research questions are explored: (1) To what degree are different types of logistics IT resources related to operating performance? (2) To what degree are these relationships contingent on organizational factors, such as firm size, firm age, and firm ownership?

This study contributes to previous research in three significant ways. Firstly, to help group various logistics activities (Wade & Hulland, 2004), we generalize the previous logistics IT typology into four mid-level IT constructs: operations-focused IT, decision-focused IT, service-focused IT, and IT development capability. Secondly, the direct relationship between the four types of logistics IT resources and operating performance is explored. Operations-focused IT, decision-focused IT, and IT development capability are identified as positively related to ROA, but service-focused IT is negatively related to ROA. Thirdly, the complementary effects of logistics IT resources and organizational factors on operating performance are explored. Findings show that firm age adversely influences the relationships between the operations- and decision-focused IT and operating performance, but positively influences the relationships between service-focused IT and IT development capability and operating performance. Moreover, firm size negatively affects the relationship between IT development capability and operating performance, while state ownership adversely affects the relationship between decision-focused IT and operating performance.

This study is developed based on sample data, and thus, the results are subject to limitations. First, we explore logistics IT resources, organizational factors, and operating performance by focusing on a convenient sample of Chinese logistics firms in the traditional transportation and warehousing segments. It would be valuable for future research to examine a similar research question through the collection of data from broad sectors of logistics firms. Second, we explore the research questions using a sample of Chinese logistics firms. Future research could compare these findings to results from other emerging market context, for example, logistics firms in India or Mexico, could be compared to our findings. It is expected that the effects of logistics IT resources vary across different countries. These additional findings would be valuable to multinational logistics firms, especially if they operate in multiple global markets. Lastly, a cross-sectional approach is used to examine the relationships between logistics IT resources and operating performance by collecting sample data from a single year. Future research could consider a longitudinal study to compare operating performance prior to, and after, the implementation of various types of logistics IT resources in order to get a better understanding of causal relationships.

Chapter 5: Future Extensions

This dissertation has highlighted numerous opportunities for future study. The impact of consumer stockpiling on retail operations is likely to be far-reaching and could dramatically change how firms make stock decisions. The impact of logistics IT resources on a logistics firm's performance is likely to be contingent on various logistics sectors across markets. Toward the continued study of the dissertation, three specific areas are identified to explore.

The first line of work would explore how environmental stress originating from financial and economic events affects consumer stockpiling from the perspective of product package sizes. Increasing product variety through alternative package sizes is a common mechanism in the grocery industry. In practice, some retailers, including Wal-Mart, have pressured manufacturers to pack their products in smaller sizes to make them more affordable to consumers with a tight budget. Thus, package sizes play a critical role in distinguishing consumers as non-stockpilers or stockpilers. The consumption of toilet tissues could be used as a case study to provide further implications for retail assortment management in the face of consumers stockpiling when impacted by environmental stress due to financial and economic events, but specifically, consumers on tight budgets.

The second line of work could follow up how environmental stress originating from natural disasters affects consumer stockpiling from the perspective of product substitution behavior. The pursuit of product substitution has been explained by psychology-based, stockout-based, and budget-based motivations. Using the consumption of bottled water as a case study, this work explains how supply-side characteristics (retail network and product variety), demand-side characteristics (hurricane experience and household income), and disaster-side characteristics (hazard proximity and hazard intensity) impact product substitution behavior. In particular, this work focuses on how product substitution behavior affects consumer surplus during hurricane disasters.

The third line of work would explore the complementary effects of organizational factors on the effectiveness of logistics IT resources focusing on warehousing and trucking industries in emerging and developed markets. The theory of swift, even flow is utilized to guide this work. The theory highlights how productivity rises with the speed by which materials or information flow through the process and falls with the variability associated with the flow (Schmenner, 2004, 2015). The implementation of logistics IT resources reduces the variation in quality, quantity, and time and throughput time of material or information. However, the productivity gain may be contingent on types of logistics IT resources (productivity-focused, decision-focused, service-focused, and IT capability), organizational factors (firm size, firm age, and firm ownership), and market contexts (emerging and developed markets). The findings would be valuable to logistics service providers and buyers, especially when they operate in multiple global markets.

Appendices

Table A1: Promotion Pattern (Sample Retailer)

Variables	PROMOTION_INTERVAL		PROMOTION_FREQUENCY	
	Model A2.1.1 (Negative Binomial)	Model A2.1.2 (Negative Binomial)	Model A2.1.3 (Negative Binomial)	Model A2.1.4 (Negative Binomial)
Intercept	2.02*** (0.62)	2.14*** (0.63)	1.52 (1.18)	1.55 (1.22)
$STRESS\_CCIP_q$	-0.01 (0.41)	0.01 (0.42)	-0.59 (0.78)	-0.59 (0.81)
QUARTER_1		-0.33 (0.34)		-0.02 (0.65)
QUARTER_2		-0.00 (0.35)		-0.23 (0.71)
QUARTER_3		-0.37 (0.35)		0.09 (0.66)
Observations	17	17	9	9
LR chi2	0.00	1.84	0.55	0.74
Pseudo R^2	0.00	0.02	0.02	0.03

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

Table A2: Correlation Matrix (Sample Retailer)

Variables	$D_{t,s}$	$STOCKING\_PERIOD^{s}_{t,s}$	$STRESS\_CCIP_{t}$	NY	CA	MI	OH	NJ	PA
$D_{t,s}$	1.000								
$STOCKING\_PERIOD^{s}_{t,s}$	0.707	1.000							
$STRESS\_CCIP_{t}$	-0.100	-0.037	1.000						
NY	0.404	0.007	0.000	1.000					
CA	0.273	0.014	0.000	-0.200	1.000				
MI	-0.188	-0.008	0.000	-0.200	-0.200	1.000			
OH	-0.225	-0.008	0.000	-0.200	-0.200	-0.200	1.000		
NJ	-0.237	-0.009	0.000	-0.200	-0.200	-0.200	-0.200	1.000	
PA	-0.026	0.004	0.000	-0.200	-0.200	-0.200	-0.200	-0.200	1.000

Table A3: Segment Consumption Rates and Stockpiling Propensity (NY, CA, and PA)

MTH	$STRESS\_CCIP_m$	NY			CA			PA		
		$C^{s}_{m,s}$	$C^{ns}_{m,s}$	$\rho_{m,s}$	$C^{s}_{m,s}$	$C^{ns}_{m,s}$	$\rho_{m,s}$	$C^{s}_{m,s}$	$C^{ns}_{m,s}$	$\rho_{m,s}$
2007M10	1.00	49,839.63	47,768.62	1.04	41,803.11	40,367.07	1.04	24,506.95	25,049.99	0.98
2007M11	1.02	49,801.68	47,617.21	1.05	41,765.16	40,215.66	1.04	24,469.00	24,898.58	0.98
2007M12	1.04	49,755.48	47,432.88	1.05	41,718.96	40,031.33	1.04	24,422.80	24,714.25	0.99
2008M01	1.03	49,778.58	47,525.04	1.05	41,742.06	40,123.49	1.04	24,445.90	24,806.41	0.99
2008M02	1.12	49,608.62	46,846.98	1.06	41,572.10	39,445.43	1.05	24,275.94	24,128.35	1.01
2008M03	1.23	49,387.52	45,964.83	1.07	41,351.00	38,563.28	1.07	24,054.84	23,246.20	1.03
2008M04	1.31	49,243.96	45,392.10	1.08	41,207.44	37,990.55	1.08	23,911.28	22,673.47	1.05
2008M05	1.37	49,116.91	44,885.19	1.09	41,080.39	37,483.64	1.10	23,784.23	22,166.56	1.07
2008M06	1.45	48,971.70	44,305.87	1.11	40,935.18	36,904.32	1.11	23,639.02	21,587.24	1.10
2008M07	1.44	48,978.30	44,332.21	1.10	40,941.78	36,930.66	1.11	23,645.62	21,613.58	1.09
2008M08	1.45	48,965.10	44,279.54	1.11	40,928.58	36,877.99	1.11	23,632.42	21,560.91	1.10
2008M09	1.48	48,900.75	44,022.80	1.11	40,864.23	36,621.25	1.12	23,568.07	21,304.17	1.11
2008M10	1.63	48,610.34	42,864.16	1.13	40,573.82	35,462.61	1.14	23,277.66	20,145.53	1.16
2008M11	1.64	48,590.54	42,785.16	1.14	40,554.02	35,383.61	1.15	23,257.86	20,066.53	1.16
2008M12	1.74	48,390.89	41,988.60	1.15	40,354.37	34,587.05	1.17	23,058.21	19,269.97	1.20
2009M01	1.75	48,382.64	41,955.69	1.15	40,346.12	34,554.14	1.17	23,049.96	19,237.06	1.20
2009M02	1.81	48,260.53	41,468.53	1.16	40,224.01	34,066.98	1.18	22,927.85	18,749.90	1.22
2009M03	1.81	48,253.93	41,442.20	1.16	40,217.41	34,040.65	1.18	22,921.25	18,723.57	1.22
2009M04	1.78	48,313.33	41,679.19	1.16	40,276.81	34,277.64	1.18	22,980.65	18,960.56	1.21
2009M05	1.75	48,382.64	41,955.69	1.15	40,346.12	34,554.14	1.17	23,049.96	19,237.06	1.20
2009M06	1.79	48,305.08	41,646.28	1.16	40,268.56	34,244.73	1.18	22,972.40	18,927.65	1.21
2009M07	1.80	48,277.03	41,534.36	1.16	40,240.51	34,132.81	1.18	22,944.35	18,815.73	1.22
2009M08	1.78	48,311.68	41,672.61	1.16	40,275.16	34,271.06	1.18	22,979.00	18,953.98	1.21
2009M09	1.81	48,272.08	41,514.61	1.16	40,235.56	34,113.06	1.18	22,939.40	18,795.98	1.22
2009M10	1.82	48,240.73	41,389.53	1.17	40,204.21	33,987.98	1.18	22,908.05	18,670.90	1.23
2009M11	1.82	48,242.38	41,396.12	1.17	40,205.86	33,994.57	1.18	22,909.70	18,677.49	1.23
2009M12	1.83	48,225.88	41,330.28	1.17	40,189.36	33,928.73	1.18	22,893.20	18,611.65	1.23

Table A4: Segment Consumption Rates and Stockpiling Propensity (MI, OH, and NJ)

MTH	$STRESS\_CCIP_m$	MI			OH			NJ		
		$C^{s}_{m,s}$	$C^{ns}_{m,s}$	$\rho_{m,s}$	$C^{s}_{m,s}$	$C^{ns}_{m,s}$	$\rho_{m,s}$	$C^{s}_{m,s}$	$C^{ns}_{m,s}$	$\rho_{m,s}$
2007M10	1.00	16,647.75	16,224.88	1.03	13,457.87	14,488.01	0.93	12,109.41	14,086.96	0.86
2007M11	1.02	16,609.80	16,073.47	1.03	13,419.92	14,336.60	0.94	12,071.46	13,935.55	0.87
2007M12	1.04	16,563.60	15,889.14	1.04	13,373.72	14,152.27	0.94	12,025.26	13,751.22	0.87
2008M01	1.03	16,586.70	15,981.31	1.04	13,396.82	14,244.43	0.94	12,048.36	13,843.38	0.87
2008M02	1.12	16,416.75	15,303.24	1.07	13,226.86	13,566.37	0.97	11,878.40	13,165.32	0.90
2008M03	1.23	16,195.64	14,421.10	1.12	13,005.76	12,684.22	1.03	11,657.30	12,283.17	0.95
2008M04	1.31	16,052.09	13,848.36	1.16	12,862.20	12,111.49	1.06	11,513.74	11,710.44	0.98
2008M05	1.37	15,925.03	13,341.46	1.19	12,735.15	11,604.58	1.10	11,386.69	11,203.53	1.02
2008M06	1.45	15,779.83	12,762.14	1.24	12,589.94	11,025.26	1.14	11,241.48	10,624.21	1.06
2008M07	1.44	15,786.43	12,788.47	1.23	12,596.54	11,051.60	1.14	11,248.08	10,650.55	1.06
2008M08	1.45	15,773.23	12,735.81	1.24	12,583.34	10,998.93	1.14	11,234.88	10,597.88	1.06
2008M09	1.48	15,708.88	12,479.06	1.26	12,518.99	10,742.19	1.17	11,170.53	10,341.14	1.08
2008M10	1.63	15,418.47	11,320.43	1.36	12,228.58	9,583.55	1.28	10,880.12	9,182.50	1.18
2008M11	1.64	15,398.67	11,241.43	1.37	12,208.78	9,504.55	1.28	10,860.32	9,103.50	1.19
2008M12	1.74	15,199.01	10,444.87	1.46	12,009.13	8,707.99	1.38	10,660.67	8,306.94	1.28
2009M01	1.75	15,190.76	10,411.95	1.46	12,000.88	8,675.08	1.38	10,652.42	8,274.03	1.29
2009M02	1.81	15,068.66	9,924.80	1.52	11,878.77	8,187.92	1.45	10,530.31	7,786.87	1.35
2009M03	1.81	15,062.06	9,898.46	1.52	11,872.17	8,161.59	1.45	10,523.71	7,760.54	1.36
2009M04	1.78	15,121.46	10,135.46	1.49	11,931.57	8,398.58	1.42	10,583.11	7,997.53	1.32
2009M05	1.75	15,190.76	10,411.95	1.46	12,000.88	8,675.08	1.38	10,652.42	8,274.03	1.29
2009M06	1.79	15,113.21	10,102.54	1.50	11,923.32	8,365.67	1.43	10,574.86	7,964.62	1.33
2009M07	1.80	15,085.16	9,990.63	1.51	11,895.27	8,253.75	1.44	10,546.81	7,852.70	1.34
2009M08	1.78	15,119.81	10,128.87	1.49	11,929.92	8,392.00	1.42	10,581.46	7,990.95	1.32
2009M09	1.81	15,080.21	9,970.88	1.51	11,890.32	8,234.00	1.44	10,541.86	7,832.95	1.35
2009M10	1.82	15,048.85	9,845.80	1.53	11,858.97	8,108.92	1.46	10,510.51	7,707.87	1.36
2009M11	1.82	15,050.50	9,852.38	1.53	11,860.62	8,115.51	1.46	10,512.16	7,714.46	1.36
2009M12	1.83	15,034.00	9,786.55	1.54	11,844.12	8,049.67	1.47	10,495.66	7,648.62	1.37

Table A5: Longitudinal Distribution (Sample Households)

Age Group	2,932 Sample Households					
	2007		2008		2009	
	obs	percent	obs	percent	obs	percent
One year old	310	26.52%	288	30.41%	254	31.13%
Two years old	859	73.48%	659	69.59%	562	68.87%
Sub Total	1,169	100%	947	100%	816	100%
Total			2,932			

Table A6: Geographic Distribution (Sample Households)

Region	2,932 Sample Households					
	2007		2008		2009	
	Obs	Percent	Obs	Percent	Obs	Percent
New England	46	3.93%	40	4.22%	40	4.90%
Middle Atlantic	146	12.49%	102	10.77%	110	13.48%
East North Central	249	21.30%	197	20.80%	163	19.98%
West North Central	103	8.81%	90	9.50%	73	8.95%
South Atlantic	194	16.60%	162	17.11%	140	17.16%
East South Central	78	6.67%	59	6.23%	44	5.39%
West South Central	142	12.15%	118	12.46%	103	12.62%
Mountain	79	6.76%	61	6.44%	45	5.51%
Pacific	132	11.29%	118	12.46%	98	12.01%
Sub Total	1,169	100%	947	100%	816	100%
Total			2,932			

Table A7: Correlation Matrix (Sample Households)

Variables	c_q	ρ_q	HOUSEHOLD_SIZE	AVG_INCOME	ONE_YEAR_OLD	$STRESS\_CCIP_q$
c_q	1.000					
ρ_q	0.052	1.000				
HOUSEHOLD_SIZE	-0.131	-0.096	1.000			
INCOME_HEAD	0.133	0.110	-0.436	1.000		
ONE_YEAR_OLD	0.050	0.042	0.003	0.037	1.000	
$STRESS\_CCIP_q$	-0.006	0.045	0.014	0.015	0.027	1.000

Table A8: Robustness Checks (Weekly Sales Volume at the Retailer Level)

Variables	Weekly Sales Volume (DV: $D_{t,s}$)			
	Model A2.2.1 (OLS Regression)	Model A2.2.2 (OLS Regression)	Model A2.2.3 (OLS Regression)	Model A2.2.4 (OLS Regression)
Intercept	28,947.01*** (2,523.93)	20,821.10*** (724.01)	37,031.77*** (3,516.34)	25,734.41*** (952.07)
NY	31,652.00*** (3,569.38)	22,719.58*** (1023.52)	31,652.00*** (3,544.65)	22,720.47*** (954.96)
CA	22,033.32*** (3,569.38)	15,361.24*** (1,024.04)	22,033.32*** (3,544.65)	15,332.12*** (955.45)
MI	-11,917.03*** (3,569.38)	-8,781.03*** (1,021.31)	-11,917.03*** (3,544.65)	-8,814.82*** (952.90)
OH	-14,640.32*** (3,569.38)	-10,533.25*** (1,021.38)	-14,640.32*** (3,544.65)	-10,548.60*** (952.96)
NJ	-15,494.53*** (3,569.38)	-10,960.66*** (1,022.83)	-15,494.53*** (3,544.65)	-10,960.44*** (954.31)
STRESS_SHOCK_t			-3,643.61** (1,111.48)	-2,194.75*** (299.23)
$\text{STOCKING\_PERIOD}^s_{t,s}$		23,714.91*** (772.66)		26,238.41*** (985.59)
$\text{STOCKING\_PERIOD}^s_{t,s} \cdot \text{NY}$		25,322.54*** (1,081.62)		25,331.93*** (1,009.17)
$\text{STOCKING\_PERIOD}^s_{t,s} \cdot \text{CA}$		17,090.26*** (1,064.02)		17,306.82*** (993.10)
$\text{STOCKING\_PERIOD}^s_{t,s} \cdot \text{MI}$		-8,050.31*** (1,111.60)		-7,847.79*** (1,037.51)
$\text{STOCKING\_PERIOD}^s_{t,s} \cdot \text{OH}$		-11,166.14*** (1,109.13)		-11,075.31*** (1,034.89)
$\text{STOCKING\_PERIOD}^s_{t,s} \cdot \text{NJ}$		-12,396.08*** (1,127.51)		-12,391.93*** (1,051.98)
$\text{STOCKING\_PERIOD}^s_{t,s} \cdot \text{STRESS\_SHOCK}_t$				-1,275.82*** (318.50)
Observations	702	702	702	702
R^2	0.317	0.952	0.328	0.958
Adjusted R^2	0.312	0.951	0.322	0.957

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

Table A9: Robustness Checks (Periodic Consumption Rate at the Household Level)

Variables	Periodic Consumption Rate (DV: c_q)	
	Model A2.3.1 (Fixed Effects)	Model A2.3.2 (Fixed Effects)
Intercept	182.92** (66.47)	224.88*** (67.11)
HOUSEHOLD_SIZE	11.02 (13.94)	10.69 (13.91)
AVG_INCOME_HEAD	2.04* (1.22)	1.98 (1.22)
ONE_YEAR_OLD	40.49*** (6.82)	21.55** (8.18)
$STRESS\_SHOCK_q$		-16.00*** (3.83)
Observations	7,158	7,158
F test	12.37	13.67

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

Table A10: Correlation Matrix

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	STOCKPILING_PROP_EARLY	1.000														
2	PROD_AVAIL_EARLY	0.363	1.000													
3	PROD_AVAIL_LATE	-0.147	0.133	1.000												
4	PROD_AVAIL_POST_W1	-0.163	0.105	0.306	1.000											
5	PROD_AVAIL_POST_W2	-0.083	0.148	0.276	0.429	1.000										
6	PROD_AVAIL_POST_W3	-0.046	0.158	0.249	0.374	0.447	1.000									
7	PROD_AVAIL_POST_W4	0.017	0.189	0.241	0.339	0.403	0.458	1.000								
8	NTW_COUNTY	-0.053	-0.035	0.021	0.073	0.048	0.057	0.040	1.000							
9	NTW_COUNTRY	0.103	0.027	-0.002	-0.026	-0.044	-0.028	0.012	0.219	1.000						
10	PROD_VAR_SKU	-0.112	-0.034	0.063	0.096	0.097	0.091	0.035	0.029	-0.615	1.000					
11	HUR_EXP_STATE	-0.238	-0.091	0.007	0.117	0.083	0.071	0.069	0.035	0.107	-0.059	1.000				
12	PER_CAPITA_INC	0.175	0.093	0.007	-0.004	0.041	0.044	0.066	0.355	-0.047	0.212	-0.218	1.000			
13	HUR_LANDFALL_DIST	-0.446	-0.230	0.050	0.173	0.078	0.069	0.016	0.203	0.131	-0.009	0.340	-0.208	1.000		
14	HUR_TRACK_DIST	-0.411	-0.181	0.079	0.112	0.050	0.017	0.008	-0.102	0.049	-0.059	0.360	-0.235	0.416	1.000	
15	HUR_WIND_SPEED	0.010	-0.030	0.011	0.014	0.044	0.017	0.034	-0.044	0.020	0.018	0.186	0.047	-0.201	0.175	1.000

Table A11: Robustness Checks (Step 1: Consumer Stockpiling Propensity)

Dependent Variable LN(STOCKPILING_PROP) × 1000	Model A3.1.1 Quantile (.25)	Model A3.1.2 Quantile (.50)	Model A3.1.3 Quantile (.75)
Independent Variable			
Supply-Side Characteristics			
NTW_COUNTY	-89.360*** (27.194)	-199.634*** (21.805)	-254.932*** (29.537)
$(\text{NTW\_COUNTY})^2$	21.592* (10.264)	40.331*** (8.298)	31.098** (10.480)
NTW_COUNTRY	15.125*** (2.352)	17.946*** (1.821)	20.220*** (2.436)
$(\text{NTW\_COUNTRY})^2$	-0.114*** (0.017)	-0.156*** (0.011)	-0.178*** (0.020)
PROD_VAR_SKU	1.827*** (0.383)	1.501*** (0.321)	1.016*** (0.264)
$(\text{PROD\_VAR\_SKU})^2$	-0.005*** (0.001)	-0.005*** (0.001)	-0.003*** (0.001)
Demand-Side Characteristics			
HUR_EXP_STATE	7.154* (4.107)	2.305 (3.962)	-1.531 (5.620)
$(\text{HUR\_EXP\_STATE})^2$	-0.259 (0.358)	0.143 (0.315)	0.756* (0.425)
PER_CAPITA_INC	78.107*** (6.781)	78.959*** (7.578)	76.948*** (5.620)
$(\text{PER\_CAPITA\_INC})^2$	-4.634*** (0.476)	-4.654*** (0.505)	-4.547*** (0.386)
Disaster-Side Characteristics			
HUR_LANDFALL_DIST	-141.565*** (4.375)	-145.628*** (4.950)	-138.407*** (7.071)
$(\text{HUR\_LANDFALL\_DIST})^2$	6.382*** (0.395)	7.174*** (0.454)	7.384*** (0.591)
HUR_TRACK_DIST	-134.162*** (9.822)	-163.078*** (11.404)	-188.881*** (12.214)
$(\text{HUR\_TRACK\_DIST})^2$	15.668*** (2.351)	20.630*** (2.385)	24.399*** (2.607)
HUR_TRACK_WIND	17.685*** (1.093)	16.724*** (1.272)	20.285*** (1.616)
$(\text{HUR\_TRACK\_WIND})^2$	-0.158*** (0.008)	-0.149*** (0.010)	-0.173*** (0.013)
Control Variable			
Retail Format			
CHAIN_GROC	-293.381*** (58.406)	-415.879*** (44.111)	-529.305*** (45.027)
CHAIN_WHS	134.411*** (38.310)	122.938*** (19.468)	154.310*** (32.348)
CHAIN_DISC	97.523 (80.470)	99.655 (111.990)	228.054* (93.496)
CHAIN_DOLLAR	-82.076 (98.183)	2.648 (77.554)	99.629 (71.447)
CHAIN_DRUG	233.025*** (42.730)	300.801*** (47.061)	470.170*** (52.711)
CHAIN_LIQ	51.642 (122.744)	178.070** (86.549)	333.887*** (75.772)
Retail Chain			
RETAIL_CHAIN	Included	Included	Included
Hurricane Events			
TRACK_DAY_AFT_LANDFALL	-41.232*** (3.246)	-29.500*** (3.502)	-13.000*** (3.382)
SALES_DAY_BEF_LANDFALL	40.725*** (4.953)	49.775*** (5.165)	62.396*** (5.303)
Category Volume			
VOL_COUNTY	2.694 (1.773)	5.480*** (1.264)	7.912*** (1.697)
VOL_STATE	4.967*** (0.312)	2.717*** (0.204)	0.943* (0.386)
Category Competition			
HHI_COUNTY	-31.254* (15.193)	-14.209 (15.939)	0.336 (21.268)
HHI_STATE	3,099.605***(241.239)	2,810.689***(257.650)	2,460.445*** (273.985)
Geodemographic Feature			
POP_DENSITY_COUNTY	-0.053 (0.053)	-0.084* (0.044)	-0.154*** (0.042)
LAND_AREA_COUNTY	1.319** (0.500)	2.468** (0.779)	2.001* (0.914)
WATER_AREA_COUNTY	4.549*** (1.189)	5.961*** (0.991)	8.028*** (1.496)
POP_DENSITY_STATE	-3.139*** (0.374)	-4.022*** (0.427)	-4.200*** (0.546)
LAND_AREA_STATE	-0.581*** (0.041)	-0.594*** (0.038)	-0.622*** (0.046)
WATER_AREA_STATE	0.968*** (0.199)	1.038*** (0.172)	0.202 (0.174)
CONSTANT	-620.447*** (68.289)	-437.719*** (42.418)	-460.804*** (71.778)
Observations	38,418	38,418	38,418
Pseudo R2	0.2391	0.3151	0.3740

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

Table A12: Robustness Checks (Step 2: In-Store Product Availability)

Dependent Variable LN(PRODUCT_AVAIL) × 1000	Model A3.2.1 EARLY Week	Model A3.2.2 LATE Week	Model A3.2.3 POST Week 1
Mediating Variable			
STOCKPILING_PROP	0.101*** (0.013)	-0.251*** (0.016)	-0.103*** (0.014)
Independent Variable			
Supply-Side Characteristics			
NTW_COUNTY	18.938* (8.136)	-28.678** (9.851)	18.522* (8.544)
$(\text{NTW\_COUNTY})^2$	-5.816* (2.863)	5.429 (3.466)	-6.953* (3.006)
NTW_COUNTRY	1.487* (0.652)	17.355*** (0.790)	11.360*** (0.685)
$(\text{NTW\_COUNTRY})^2$	-0.016** (0.005)	-0.121*** (0.006)	-0.094*** (0.006)
PROD_VAR_SKU	-0.585*** (0.089)	-0.041 (0.108)	0.235* (0.094)
$(\text{PROD\_VAR\_SKU})^2$	0.002*** (0.000)	-0.000 (0.000)	-0.001** (0.000)
Demand-Side Characteristics			
HUR_EXP_STATE	-3.250** (1.115)	-5.679*** (1.351)	5.379*** (1.171)
$(\text{HUR\_EXP\_STATE})^2$	0.330*** (0.087)	0.355*** (0.106)	-0.375*** (0.092)
PER_CAPITA_INC	1.112 (2.373)	18.821*** (2.873)	6.538** (2.492)
$(\text{PER\_CAPITA\_INC})^2$	0.065 (0.151)	-1.173*** (0.183)	-0.327* (0.158)
Disaster-Side Characteristics			
HUR_LANDFALL_DIST	4.441* (2.369)	-7.198* (2.869)	-10.187*** (2.488)
$(\text{HUR\_LANDFALL\_DIST})^2$	-0.866*** (0.169)	-0.754*** (0.204)	0.840*** (0.177)
HUR_TRACK_DIST	-4.549 (3.636)	-14.267** (4.403)	-9.949** (3.818)
$(\text{HUR\_TRACK\_DIST})^2$	-0.244 (0.653)	-2.605*** (0.790)	2.402*** (0.685)
HUR_TRACK_WIND	1.043* (0.521)	4.341*** (0.631)	-1.210* (0.547)
$(\text{HUR\_TRACK\_WIND})^2$	-0.010* (0.004)	-0.037*** (0.005)	0.008* (0.004)
Control Variable			
Retail Format			
CHAIN_GROC	91.223** (31.053)	21.057 (37.599)	7.295 (32.608)
CHAIN_WHS	-53.072*** (9.403)	80.571*** (11.385)	64.764*** (9.874)
CHAIN_DISC	-36.271* (20.673)	-33.011 (25.030)	-24.586 (21.708)
CHAIN_DOLLAR	-33.241* (18.786)	-489.162*** (22.746)	-261.804*** (19.727)
CHAIN_DRUG	-64.099*** (12.288)	123.957*** (14.878)	62.981*** (12.904)
CHAIN_LIQ	-30.482* (16.847)	69.352*** (20.398)	83.078*** (17.690)
Retail Chain			
RETAIL_CHAIN	Included	Included	Included
Hurricane Events			
TRACK_DAY_AFT_LANDFALL	1.294 (1.010)	-6.840*** (1.222)	-6.530*** (1.060)
SALES_DAY_BEF_LANDFALL	13.118*** (1.303)	12.316*** (1.578)	-15.508*** (1.369)
Category Volume			
VOL_COUNTY	1.161* (0.677)	1.022 (0.819)	-0.790 (0.710)
VOL_STATE	0.181* (0.096)	0.285* (0.116)	-0.053 (0.101)
Category Competition			
HHI_COUNTY	1.506 (4.840)	7.384 (5.861)	-12.895* (5.083)
HHI_STATE	-29.724 (87.311)	500.936*** (105.715)	190.803* (91.683)
CONSTANT	-83.973*** (21.401)	-247.550*** (25.912)	1073.491*** (22.472)
Observations	38,418	38,418	38,418
F	50.98***	42.26***	46.67***

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

Table A12 (Continued): Robustness Check II (Mediating Effects on Product SKU Availability)

Dependent Variable LN(PRODUCT_AVAIL) × 1000	Model A3.2.4 POST Week 2	Model A3.2.5 POST Week 3	Model A3.2.6 POST Week 4
Mediating Variable			
STOCKPILING_PROP	-0.057*** (0.015)	-0.079*** (0.016)	-0.037* (0.016)
Independent Variable			
Supply-Side Characteristics			
NTW_COUNTY	36.747*** (9.473)	11.766 (9.777)	4.465 (9.827)
$(\text{NTW\_COUNTY})^2$	-11.103*** (3.333)	-0.855 (3.440)	3.583 (3.457)
NTW_COUNTRY	10.451*** (0.759)	5.320*** (0.784)	7.730*** (0.788)
$(\text{NTW\_COUNTRY})^2$	-0.084*** (0.006)	-0.047*** (0.006)	-0.055*** (0.006)
PROD_VAR_SKU	0.262* (0.104)	0.526*** (0.107)	0.020 (0.108)
$(\text{PROD\_VAR\_SKU})^2$	-0.001* (0.000)	-0.001*** (0.000)	0.000 (0.000)
Demand-Side Characteristics			
HUR_EXP_STATE	-2.027 (1.299)	-4.890*** (1.340)	-1.044 (1.347)
$(\text{HUR\_EXP\_STATE})^2$	0.265** (0.102)	0.494*** (0.105)	0.215* (0.105)
PER_CAPITA_INC	5.586* (2.763)	14.534*** (2.852)	11.530*** (2.866)
$(\text{PER\_CAPITA\_INC})^2$	-0.125 (0.176)	-0.658*** (0.181)	-0.399* (0.182)
Disaster-Side Characteristics			
HUR_LANDFALL_DIST	3.452 (2.759)	-3.707 (2.847)	0.252 (2.862)
$(\text{HUR\_LANDFALL\_DIST})^2$	-0.609** (0.197)	-0.139 (0.203)	-0.576** (0.204)
HUR_TRACK_DIST	-4.592 (4.234)	-24.918*** (4.370)	-8.934* (4.392)
$(\text{HUR\_TRACK\_DIST})^2$	-0.093 (0.760)	4.495*** (0.784)	1.943* (0.788)
HUR_TRACK_WIND	1.155* (0.607)	0.611 (0.626)	0.318 (0.629)
$(\text{HUR\_TRACK\_WIND})^2$	-0.010* (0.005)	-0.007 (0.005)	-0.005 (0.005)
Control Variable			
Retail Format			
CHAIN_GROC	38.980 (36.154)	-15.955 (37.316)	15.882 (37.504)
CHAIN_WHS	45.664*** (10.947)	36.748** (11.299)	23.875* (11.356)
CHAIN_DISC	-146.811*** (24.069)	-109.031*** (24.842)	-171.162*** (24.967)
CHAIN_DOLLAR	-283.968*** (21.872)	-125.125*** (22.575)	-276.705*** (22.689)
CHAIN_DRUG	16.646 (14.307)	-9.607 (14.767)	-61.396*** (14.841)
CHAIN_LIQ	-31.343 (19.614)	-20.196 (20.245)	-83.245*** (20.347)
Retail Chain			
RETAIL_CHAIN	Included	Included	Included
Hurricane Events			
TRACK_DAY_AFT_LANDFALL	-5.045*** (1.175)	-4.875*** (1.213)	-6.206*** (1.219)
SALES_DAY_BEF_LANDFALL	-19.405*** (1.518)	-13.950*** (1.566)	-14.288*** (1.574)
Category Volume			
VOL_COUNTY	-1.309* (0.788)	-0.971 (0.813)	0.597 (0.817)
VOL_STATE	-0.072 (0.112)	0.254* (0.115)	0.061 (0.116)
Category Competition			
HHI_COUNTY	-17.734** (5.635)	-7.266 (5.817)	-24.542*** (5.846)
HHI_STATE	127.456 (101.653)	172.303 (104.921)	199.616* (105.449)
CONSTANT	5.863 (24.916)	3.854 (25.717)	27.882 (25.846)
Observations	38,418	38,418	38,418
F	36.41***	28.18***	27.03***

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

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