Consumer Food Stockpiling and Retail Recovery Heterogeneity Before, During, and After Hurricane Sandy 2012

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1. INTRODUCTION

Managing responses to increasingly unpredictable natural disasters requires a deeper understanding of short-term market reaction to unfamiliar situations, especially with regards to human basic needs such as food. When faced with imminent disaster and potential threat towards future food supply, consumers may exhibit an anomaly in food retail purchase behavior – sudden stockpiling – resulting in sales surge within a short period of time (King & Devasagayam, 2017; McKinnon et al., 1985; Stiff et al., 1975; Su, 2010). Retailers' ability to promptly resupply its market with essential items is crucial to the post-disaster recovery process, such as for communities hit by Hurricane Katrina in 2005 (Horwitz, 2009; Hu et al., 2013; Lodree & Taskin, 2009; Münzberg et al., 2016; Taskin & Lodree, 2016). This concern is increasingly urgent as climate change exacerbates the hazards and potential economic costs of extreme weather, even on areas already familiar to the risk (Dinan, 2017; Lim et at., 2018; Marsooli et al., 2019; Pant & Cha, 2019).

After arriving on US soil late October 2012, Hurricane Sandy (Sandy) became one of the costliest US disasters. To date, Sandy is the fourth costliest tropical cyclone in the US at $78.7 billion – after Katrina 2005 ($178.8 billion), Harvey 2017 ($138.8 billion), and Maria 2017 ($99.9 billion) (NOAA, 2021a). It is among the few billion-dollar weather disasters since 1980 to hit New Jersey and New York state (NOAA, 2021a), while being only the third recorded hurricane recorded to have made landfall in New Jersey (Kunz et al., 2013).

Despite merely a borderline Category 1 on the Saffir-Simpson Hurricane Wind Scale (SSHS) near landfall, Sandy was especially destructive due to its surprising size. Vulnerable residents underestimated Sandy's impact (Anderson et al., 2016; Hernández et al., 2018) and the National Hurricane Center (NHC) no longer issued advisories given the storm was no longer a tropical cyclone (Kantha, 2013). In reality, Sandy's extreme precipitation and storm surge – tidal surge due to storm – across over 1,000 kilometers of coastline combined to produce heavy flooding in New Jersey and New York (Kunz et al., 2013). While the flooding caused huge damages to property and infrastructure, a subsequent nor'easter storm extended power outages during Sandy across 21 states to 13 days, disrupting daily activities. Although shorter in duration than hurricane Katrina (18 days for Louisiana, 23 days for Texas), Rita, Wilma, and Ike, Sandy occurred in a region that was not as heavily hit by those prior hurricanes.

Given the unforeseen cost and severity of Sandy, literature on the superstorm itself remains very limited in scope. Extant studies on Hurricane Sandy can be broadly categorized into studies on post-hurricane impact or recovery and those on the events during or shortly before the storm. Post-hurricane studies cover areas of health impact (Greene et al., 2013; Schwartz et al., 2015; Schwartz et al., 2017; Swerdel et al., 2014), community recovery (Binder et al., 2015; Schmeltz et al., 2013), and physical or institutional infrastructure improvements required to build resilience (Abramson & Redlener, 2012; Rosenzweig & Solecki, 2014). Studies regarding events around the period of the superstorm itself largely focus on the physical evolution of the storm and its direct impact (Casey-Lockyer et al., 2013; Dominianni et al., 2018; Halverson & Rabenhorst, 2013), human movement (Brown et al., 2016; Wang & Taylor, 2014), as well as information through social interaction during the storm (Gupta et al., 2013; Kryvasheyeu et al., 2015; Lachlan et al., 2014; Neppalli et al., 2017; Shelton et al. 2014).

Meanwhile, among studies that attempt to describe human responses right before or during a natural disaster, few investigate the consumer purchase behavior from the perspective of retailers. Earlier studies show that consumers stockpile certain items before hurricanes. Beatty et al. (2019) finds significant increase in sales of emergency supplies – bottled water, batteries, and flashlights – right before the forecasted landfall of 22 US hurricanes between 2002 and 2012. Also merging extensive scanner data on weekly sales with geographic, demographic, and weather data across 4 hurricanes between 2009-2015, Pan et al. (2020) confirms bottled water pre-hurricane stockpiling and finds that it adversely affects retailer' ability to provide pre-hurricane level of product variety of bottled water directly post-hurricane. Meanwhile, Beatty et al. (2021) does not find evidence of widespread price gouging of gasoline by retailers and wholesalers. Even so, none of these studies included Sandy in their hurricane samples.

Using event study approach, this paper contributes to the economic disaster response literature by investigating the heterogeneity of pre-hurricane stockpiling behavior seen from both retailers and consumers during the relatively underestimated arrival of Sandy. By contributing to the literature gap on Sandy, this study simultaneously provides a novel description of a pre-disaster consumer purchase behavior across products in a region historically less exposed to extreme weather events of such magnitude. After establishing the incidence of pre-hurricane consumer stockpiling during Sandy, this study further investigates the heterogeneity of the experience among retailers. We use weekly store-level supermarket scanner data in the US to understand which retail channel – among drug stores, food grocers, and mass merchandizers – faced the highest consumer pre-hurricane stockpiling behavior. Further categorizing stores according to their sizes within the two latter channels, we also investigate how prepared stores were in responding to increased purchase demand around the time of the hurricane. Then, we investigate the heterogeneity among consumer households across demographics. Synthesizing these results allow us to piece together a picture of the consumer's food purchase behavior and retailer responses around the hurricane week for households residing in a region not often beset by hurricanes.

2. EVENT STUDY METHODS

While our study applies event study methods in investigating both retailer and consumer heterogeneity, we adjust for differences in the nature of data between the retail scanner and consumer panel data.

2.1 An Empirical Difference-in-Differences Model for Retail Sales

To compare the product sales anomalies attributable to Sandy, we use event study approach that uses a difference-in-differences method whereby sales at individual food retailers are compared (a) inside versus outside a hurricane threat radius and (b) weekly, during the hurricane versus the same week one year earlier. The main variable of interest comes from a three-way interaction of weekly indicator variables with two other binary variables, one indicating store sales during the hurricane year and another indicating store sales inside the hurricane radius. For each product category j, we estimate the same basic model for two outcome variables, the logged weekly sales volume, and the logged weekly number of UPCs sold:

$$lnVolume_{i,t,j} = \alpha_j + \sum_{t=-11}^{8} \delta_{t,j}(ThreatRadius\ x\ HurricaneYear\ x\ RelativeWeek_t) + \gamma_{1,j}ThreatRadius + \gamma_{2,j}HurricaneYear + \gamma_{3,j}(ThreatRadius\ x\ HurricaneYear) + \boldsymbol{\mu}_j \sum_a Irene_a + \varepsilon_{i,t,j} \quad (1)$$

$$lnUPCcount_{i,t,j} = \alpha_j + \sum_{t=-11}^{8} \delta_{t,j}(ThreatRadius\ x\ HurricaneYear\ x\ RelativeWeek_t) + \gamma_{1,j}ThreatRadius + \gamma_{2,j}HurricaneYear + \gamma_{3,j}(ThreatRadius\ x\ HurricaneYear) + \boldsymbol{\mu}_j \sum_a Irene_a + \varepsilon_{i,t,j} \quad (2)$$

where *i* indexes individual stores, *j* indexes the product categories, and *t* indexes a particular sales week relative to the hurricane week. ***ThreatRadius*** is an indicator variable taking on the value of 1 if a store's nearest distance to the hurricane path is within 100 miles or 0 otherwise, with its coefficient γ_1 capturing location fixed effects. *HurricaneYear* is an indicator variable that takes on the value of either 1 for hurricane year (2012) or 0 for control year (2011) and its coefficient γ_2 captures year fixed effects. By including interaction between *ThreatRadius* and *HurricaneYear*, the coefficient γ_3 captures location-year fixed effects. To control for the effects of hurricane Irene that also hit New Jersey and its surroundings in 2011, the vector of dummy variable *Irene* is included so that the vector of coefficients $\boldsymbol{\mu}$ absorbs purchasing shocks during each of the two weeks – the week of Irene and the prior week – and takes on the value of 1 when both the store's sales is during one those two weeks in 2011 and the store's county centroid is within 100 miles of Irene's historical path or 0 otherwise.

In both equations (1) and (2) for each product category *j*, the coefficients δ_t on the three-way interaction terms between *ThreatRadius*, *HurricaneYear*, and *RelativeWeek* capture the average impact of Sandy on the weekly sales from the store during that week. We label the hurricane week's coefficient as δ_0, and investigate sales 11 weeks prior and 8 weeks after, and δ_{-2} will serve as the coefficient of the reference week. Hence, the estimated coefficients δ_t will capture the week-specific impact for store sales in counties within the 100-mile vicinity of the hurricane path for each of the relative weeks relative to week t = -2, to the prior year, and to stores outside the vicinity. Thus, in equation (1), the coefficients δ_{-1} or δ_0 capture sales volume anomalies for the week directly before the Sandy week and the Sandy week itself for affected stores. Due to overwhelming purchases for stockpiling, we expect both coefficients to be positive and significant for all product categories. Meanwhile, the coefficients δ_1 and δ_2 in equation (2) capture reduction of UPCs sold in the two weeks after Sandy and are not expected to be significantly positive due to shopping disruption and consumers drawing down their stockpiles. The dependent variables in equations (1) and (2) are logged so that the δ_t's can be interpreted as percentage changes in sales volume or UPCs sold.

As the temporal reference for the event study approach, we determine the period of impact for each county. Due to the weekly frequency of the scanner data, the analyses in this study are done at week level. This study follows Pan et al. (2020) by first defining the influence date as the date at which the hurricane is at shortest distance from the store's county's centroid. Consequently, all stores located within the same county have an identical influence date. The week of the influence date is selected as the hurricane week if there are at least 4 days between the influence date and the prior Saturday. Else, the preceding week is considered to be the hurricane week instead. As the scanner data was compiled as Sunday-to-Saturday week cycles, this adjustment by Pan et al. (2020) attempts to allow more comparability when including more than one hurricane occurring on different days of the week.

We also include several measures as controls. The relative week of t = -2 is selected as the reference week because NHC's "cone of uncertainty" forecasts are for a maximum of 5 days, and potentially affected consumers are not expected to show stockpiling behavior beyond two weeks before the hurricane arrives. To account for seasonal fluctuations, we make use of sales volume and count of UPCs sold from both 2011 and 2012. Specifically, we include data from only 20 weeks of 2012 for each store – the hurricane week itself, the 11 weeks prior, and the 8 weeks after – and then include the corresponding 2011 data for the same week-of-the-year. Standard errors are clustered at county level to account for unobserved county-level variations.

2.2 An Empirical Difference-in-Differences Model for Consumer Purchases

To investigate heterogeneity of consumer response to Sandy's impending arrival across demographics, we conduct a similar event study analysis using household weekly-aggregated shopping data. Using household-week observations of volume purchased per member across the same period as in Section 2.1, we estimate the following equation:

$$VolumePerMember_{i,t,j} = \alpha_j + \sum_{t=-11}^{8} \rho_{t,j}(ThreatRadius\ x\ HurricaneYear\ x\ RelativeWeek_t\ x\ DemogDum_t) + \sum_{t=-11}^{8} \delta_{t,j}(ThreatRadius\ x\ HurricaneYear\ x\ RelativeWeek_t) + \gamma_{1,j}ThreatRadius + \gamma_{2,j}HurricaneYear + \gamma_{3,j}(ThreatRadius\ x\ HurricaneYear) + \boldsymbol{\mu}_j \sum_a Irene_a + \varepsilon_{i,t,j} \quad (3)$$

where *i* indexes individual households, *j* indexes the product categories, and *t* indexes a particular purchase week relative to the hurricane week. All components are identical to Equation (1) and (2), except for the inclusion of *DemogDum* – a variable indicating the demographic group the household belongs to – and its respective four-way interaction with *ThreatRadius*, *HurricaneYear*, and *RelativeWeek*. To simplify the analysis, we investigate this heterogeneity one demographic feature at a time, unconditional on all other demographic variables. Thus, our coefficient of interest is now ρ_t which represents the average gap in per member weekly purchased volume change by households in Sandy-affected counties relative to those in non-affected counties, to the reference week, and to the same week in the previous year, for each product category. Similar to regressions in Section 2.1, we cluster standard errors at county level.

If there is no heterogeneity across consumers, we expect to see the coefficient of ρ_{-1} not to be statistically different from zero. Considering the relatively small sample of affected households in the panel data, we expect considerable fluctuations when households shop less frequently. Therefore, if the absolute magnitude of the coefficient of ρ_{-1} has been attained at other weeks, the gap is not specific to Sandy and we consider it to be evidence that the pre-hurricane stockpiling has no observed heterogeneity across consumer demographics.

3. DATA

To explore the heterogeneity in sales of various food categories across retail stores in the US shortly prior to Sandy, this study combines hurricane path data with store-level and household-level scanner data from The Nielsen Company (US), LLC. While the storm data is obtained from the same source as data used in earlier pre-hurricane stockpiling studies (Beatty et al., 2019; Pan et al.,2020), we extend the investigation beyond purchases of battery, flashlight, and bottled water. Furthermore, unlike them, this study does not include hurricane-specific control variables as we only investigate a single major hurricane event. However, similar to them, we merge the hurricane data and the store-level sales data at the county level.

To provide a broader picture of the consumer purchase basket shortly before Sandy hit, this study includes data for 4 food categories and 1 personal hygiene product. Following empty supermarket shelves in the US due to panic buying during the Covid pandemic, we include product categories included as part of a hurricane preparedness checklist designed by Direct Energy (2016) which included zero-preparation foods (peanut butter, canned beans), minimal-preparation foods (dry pasta), and sanitation supplies (toilet paper). We still include bottled water because Sandy was not included in the data for either Beatty et al. (2019) or Pan et al. (2020). All the above food categories are non-perishable foods and had also seen significantly increased purchases in United Kingdom during the recent pandemic in 2020 (NFS, 2020).

3.1 Hurricane Sandy 2012

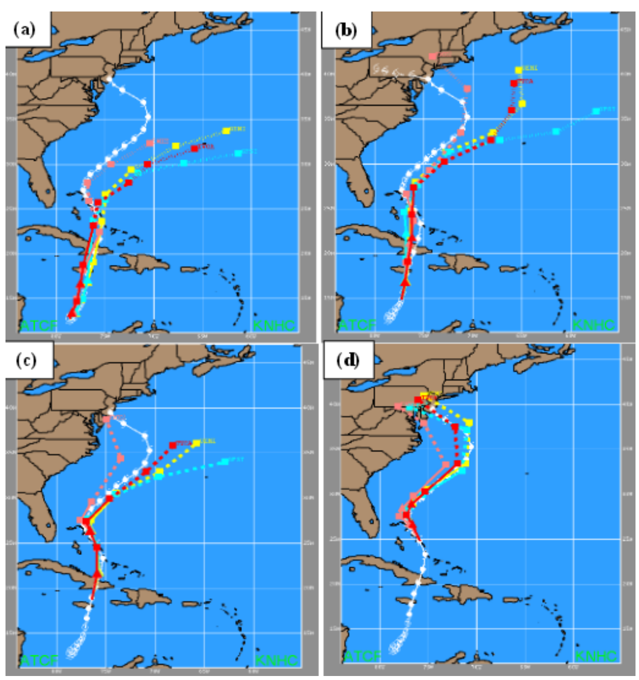
While Sandy peaked at a Category 3 and made landfall on October 29, 2012 as a Category 1 hurricane, it left a devastating impact on New Jersey and New York. As its storm force winds covered over 1,000 miles and disrupted infrastructure services, Sandy's tremendous size was largely responsible for the 72 direct and 87 indirect fatalities in the mid-Atlantic and northeastern United States (Blake et al., 2013). Satellite imagery from both NOAA Office of Satellite and Product Operations (OSPO) and NASA Earth Observatory captured images of Sandy covering over a million square miles shortly after its landfall on US coast.

Sandy's arrival came at an enormous cost. New Jersey's damage assessment reports 346,000 homes damaged, 1,400 vessels sunken or abandoned, and its entire coastline affected by significant erosion (NJDEP, 2015), making Sandy the most destructive disaster in the state. The same document reports that the power loss caused by Sandy affected 70 drinking water systems and 80 wastewater treatment plants. Meanwhile, even as a Coastal Storm Plan was activated in New York state with mandatory evacuations for 375,000 residents of low-lying coastal zones, Sandy's floods extended to the evacuation zones in Bronx, Kings (Brooklyn), New York (Manhattan), Queens, and Richmond (Staten Island) counties, such that nearby hurricane storm surge zones were overwhelmed. With Sandy having caused power outages for 94.4% of Nassau, 77.8% of Suffolk, 69.5% of Richmond, and 40.5% of New York counties (Lin et al., 2016), disrupted power supplies and inundation placed the population at risk of food and waterborne disease (FWBD) as sewage and water treatment facilities were crippled (Rose et al.,2001; McMichael, 2015). Since 1888's major winter storm, it was the first time the New York Stock Exchange closed for two consecutive business days.

In terms of storm path, Sandy was most similar to Irene in 2011. Moving on a northward trajectory, both storms skirted the US eastern coast before unleashing their destructive power on the northeastern states (see Appendix Figure A2). For many households in New Jersey, Sandy was the second hurricane to have hit in 14 months. However, a day before Sandy's landfall in New Jersey, an article exclusively compared the incoming Sandy with Irene and highlighted the far fewer evacuations underway given how much more severe Sandy turned out to be (Holthaus, 2012). Indeed, up until October 23, 16 of 17 forecasting models predicted that Sandy would move out seawards instead of making a left turn towards the coast (Sowers, 2015). The bottom left quadrant in **Figure 3-1** shows how only the European Centre for Medium Range Weather Forecasts (ECMWF) – in coral – came closest to the official track – in white – even at a mere four days before Sandy made landfall in New Jersey on October 29.

To determine Sandy-affected stores, we obtain both the timing and coordinates of Sandy's historical track from Extended Best Tracks (EBT) dataset by Demuth et al. (2006). Unlike Beatty et al. (2019), this paper does not make use of distance-to-landfall as the spatial treatment determinant in the main approach. Instead, similar to Pan et al. (2020)'s method, spatial proximity to the hurricane is measured by calculating the straight-line distances between all county centroids in 40 US states and Sandy's position at every six hours until its dissipation. Only one value – the shortest distance – is taken for each county to represent its proximity to the hurricane.

Figure 3-1 Model forecast tracks at 0000 UTC 23 October 2012 (a), 0000 UTC 24 October 2012 (b), 0000 UTC October 25 2012 (c), and 0000 UTC 26 October 2012 (d). (Source: Blake et al., 2013)



3.2 Retail Scanner Data

We obtain the retail scanner data for this study from the Nielsen ScanTrack database. Tracking weekly store-level sales across the continental US for nearly all metropolitan statistical areas (MSAs) and major urban areas, this dataset provides a more accurate look into consumer purchases without the problems of recall bias and observer bias often found in diary collection or surveys. The consistency of reporting across time for each store and retailer allows for store- or retailer-level controls on unobserved characteristics using fixed effects in regression analyses. The week-level dataset includes quantity sold from participating stores for every Universal Product Code (UPC) sold that week. While individual stores cannot be identified, the granular level of product detail allows investigation into the variety and brands purchased by consumers across a wide spectrum of products during the week. Identifiable at Saturday-ending weeks, the scanner data provides a way to control for seasonal patterns or other identifiable events during the year.

We obtain product volume and number of unique UPCs sold for 5 product categories (including bottled water). This builds upon both Pan et al. (2020)'s bottled water investigation and Beatty et al. (2019)'s use of dollar-value sales as dependent variable. Since previous works did not include Sandy, this study includes bottled water to test the hypothesis that pre-hurricane consumer stockpiling behavior also occurred during the 2012 extreme weather event. We expect our results to show bottled water being overpurchased shortly before Sandy, thus consistent with the results of the aforementioned studies. At the same time, four other product categories appear in the hurricane preparedness grocery checklist by Direct Energy (2016)

In conducting a deeper analyses of hurricane preparedness behavior from a narrower hurricane sample, we take advantage of the different retail formats or channels indicated as store characteristic in the scanner data. Stores can be either mass merchandiser stores, food grocery stores, drug stores, liquor stores, convenience stores, or gas station stores. In this study, we drop liquor stores, convenience stores, and gas stations from our sample to focus on the three channels which contribute the largest volume of grocery data. Since the scanner data records actual weekly in-store purchases instead of inventory, not all five categories may be sold in each week for each store. For example, weeks in which the store does not sell a single item in canned beans category will be missing from the sample for analysis of the canned beans category. We assume such occurrence is random and rarely occurs in medium or large stores. We observe that, for example, at any sample week, less than 17.1% of food grocer and less than 19.1% of mass merchandizer stores sold zero bottled water. Meanwhile, a store that does not sell peanut butter at all during the sample period will not be included in the store sample when analyzing peanut butter purchases. Therefore, we expect different total sample of stores when making regression analyses for each of the five product categories.

To compare store experiences within a channel, we choose to group stores according to their size. However, without any information on store size or floor area, we then make use of the full year's scanner data to bin stores into a size category – large, medium, or small – based on annual bottled water purchases. With bottled water being the grocery category with the highest volume, a store's annual volume of bottled water sold is a rough indicator of store size. Since the scale of grocery purchases at food grocers is much higher than at mass merchandizer stores, we define the size categories differently for the two channels.

3.3 Household Scanner Data

We also use Nielsen household-level daily scanner, which tracks purchases from a panel of around 60,000 households from 2007 onwards. From this full panel, we only include 41,451 households who are within 1,000 miles of Sandy's path (see **Table 3-1**). Recording purchase details of each shopping trip made – such as product codes purchased, total dollars spent, store code, and retailer code – by households, the data allows a granular look into the consumer purchase basket. Aside from covering most of the MSAs and major cities, the panel data includes geographic residence up to county level and demographic information, such as household size, income, race, presence and age of children, education, marital status, employment, and type of residence.

Table 3-1 Summary of household sample

Weekly purchases 2011-2012	Volume per household member		
	Mean	Standard deviation	Median
Bottled water (oz)			
Within radius	22.43	47.38	5.40
Outside radius	21.99	48.07	5.07
Combined	22.06	47.96	5.07
Peanut butter (oz)			
Within radius	1.01	1.80	0.45
Outside radius	1.05	1.64	0.50
Combined	1.04	1.66	0.50
Canned beans (oz)			
Within radius	1.74	3.66	0.80
Outside radius	2.35	3.57	1.31
Combined	2.26	3.59	1.21
Dry pasta (oz)			
Within radius	1.87	2.30	1.26
Outside radius	1.40	1.82	0.88
Combined	1.48	1.92	0.94
Toilet paper (rolls)			
Within radius	0.86	1.21	0.61
Outside radius	0.95	0.91	0.75
Combined	0.86	1.21	0.61
Household	# households	Average size	
Within radius	6,591	2.34	
Outside radius	34,860	2.27	
Combined	41,451	2.28	

To match the data frequency with the weekly store-level data, we aggregate the volume of household purchases – within each of the included product categories – from daily to weekly level. As households are more likely to schedule shopping trips for the same grocery category weekly than daily, we believe that the aggregation does not impair our analysis.

4. RESULTS

4.1 Between-channel retailer heterogeneity

To analyze heterogeneity between retailer channels, we separate our store sample into subsamples by retailer channel type – food grocers, mass merchandizers, drug stores. Since not all stores sell all the product categories during the sample period, the total sample of stores is expected to vary across product categories but remain consistent within each product category. We regress weekly store volume or count of UPC sold – using equations (1) or (2), respectively – for each subsample and plot the estimated coefficients (δ_t estimates) – and 95% confidence intervals – into event study graphs. For comparison, we overlay the results for each subsample in one graph.

4.1.1 Volume sold around the hurricane week

As shown in **Figure 4-1**, affected stores of all channel types share consumer pre-hurricane stockpiling purchase patterns in all product groups except dry pasta, showing positive week coefficients at t=-1. On average, bottled water volume rose by 60.5% at mass merchandizers, 59.4% at food grocers, and 40.1% at drug stores, while peanut butter rose by 38.5%, 21.6%, and 45.0%, respectively. Canned beans volume sold rose by 14.8% at mass merchandizers, 7.8% at food grocers, and 20.2% at drug stores. The coefficient signs are also positive at t=0 across channels for bottled water, peanut butter, and canned beans, thereby suggesting that stockpiling continued until Sandy's arrival.

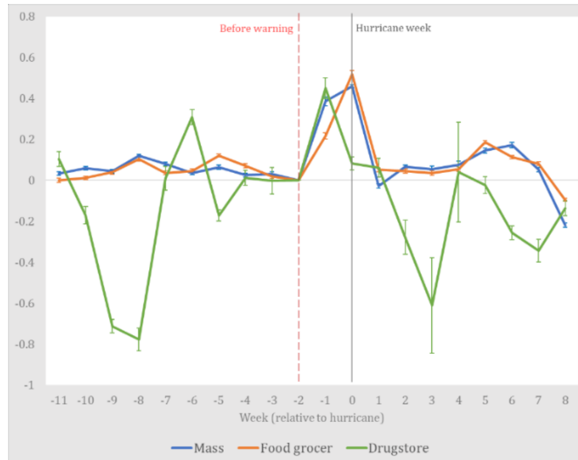
While all channels evidently experienced hurricane-induced purchases in bottled water and peanut butter around Sandy, on average, drug stores show the largest changes in volume sold during the same period for canned beans and dry pasta. On average, Sandy-affected drug stores experienced pre-hurricane purchase spikes in all product groups except dry pasta. While their purchases showed little fluctuation in the weeks before Sandy, on average, bottled water rose by 59.4% a week before the hurricane and canned beans by 29.2% during the Sandy week. Although purchases of peanut butter and toilet paper also rose on average by 45.0% and 21.8%, respectively, a week before Sandy, fluctuations in other weeks also reached 30.9% and 15.3% for the two products, respectively. Since we do not expect dry pasta to be purchased at large volumes from drug stores, the large fluctuations of its weekly purchases shown in **Figure 4-1** are expected. However, given the generally smaller scale of grocery sales, an average drug store sells less volume for any of the five product groups, than a food grocer or a mass merchandizer store (see Appendix **Table A 1**).

Post hurricane-week, on average, purchase volumes fell significantly, except for canned beans. As bottled water volumes fell across channel types a week after Sandy, canned bean purchases at drug stores continued at higher-than-normal levels up to 2 weeks after Sandy, on average, suggesting continued strong demand and available supply for canned beans at drug stores directly after Sandy.

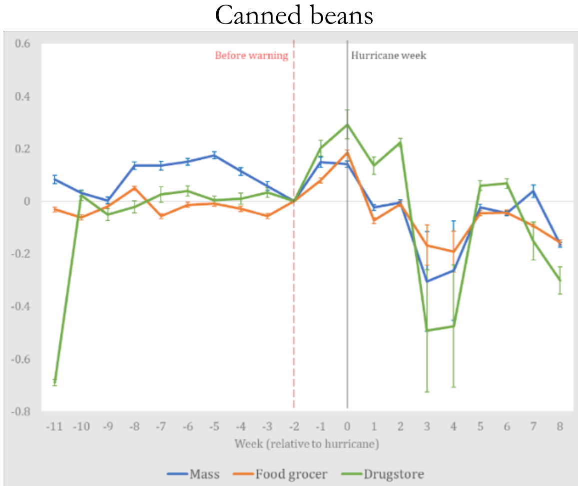
Figure 4-1 Event study plot of volume sold between retailer channel types

Bottled water

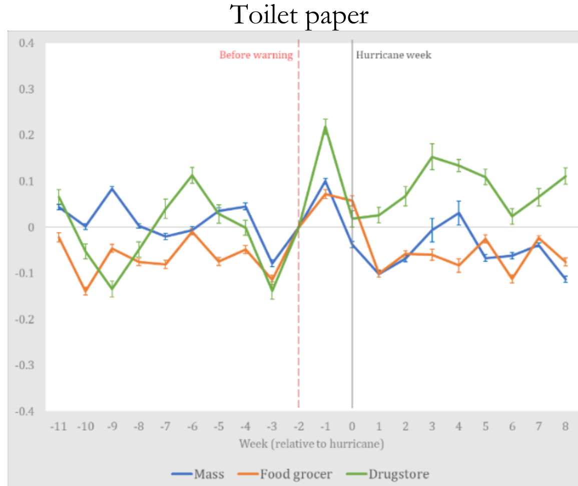
Peanut butter



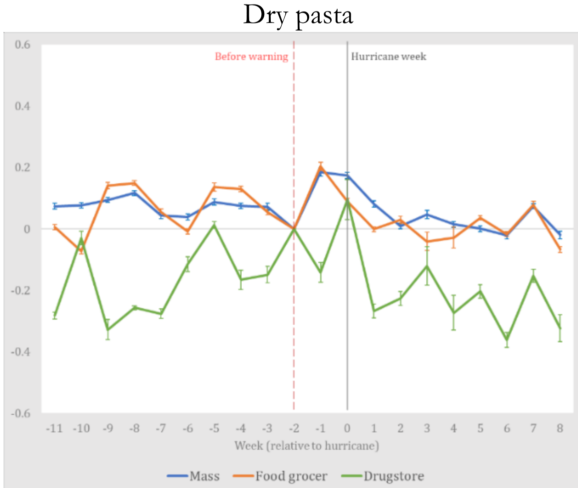
Canned beans



Toilet paper



Dry pasta



Note: Standard errors are clustered at county level. The regressions for each channel are run separately. The base week is set at t=-1 (a week before the hurricane) so the week coefficient at t=-1 is zero when interactions between proximity to hurricane (ThreatRadius) and year of hurricane (Huryear) is included.

4.1.2 Variety of products sold around the hurricane week

As we observe count UPCs sold, we expect a rise when consumers purchase more varied packaging or additional within-brand variants of the same product when stockpiling for Sandy. We also expect a fall when consumers reduce their purchases and return to their preferred product packaging size and variety.

Figure 4-2 shows, across the channel types, food grocers have the most stable while drug stores have the most fluctuating product variety sold across the five product categories. The likely explanation for this pattern is that food grocers are more likely to be the primary grocery shopping destination for most consumers. Meanwhile, outside of the weeks surrounding Sandy, mass merchandizers show stable product variety sold only for bottled water and peanut butter.

After Sandy, affected food grocers experienced a variety drop in bottled water sold as its count of UPCs sold fell by 3.4% and 1.0% at t=1 and t=2, respectively. Meanwhile, peanut butter variety sold at food grocers at t=1 remained 1.4% above average and canned beans variety sold returned to normal levels. During the same time, dry pasta variety sold fell slightly below average weekly levels as toilet paper variety fell by at least 3.9%. These results suggest that, on average, product variety sold after Sandy at affected food grocers shrunk only for bottled water and toilet paper.

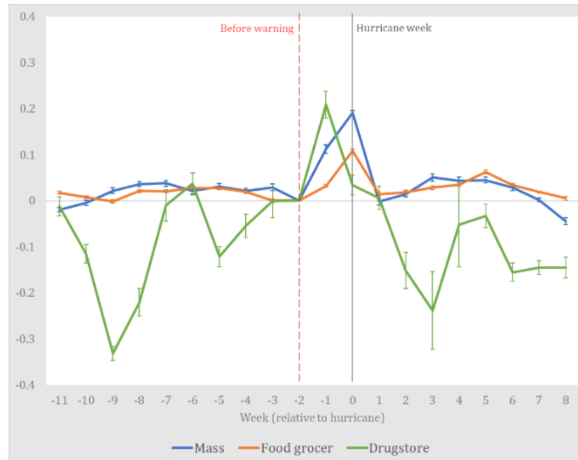
Unlike the volume patterns, the patterns of count of UPCs sold vary between affected mass merchandizers and food grocers in most product categories. Similar to food grocers, mass merchandizers experienced a 6.2% fall in bottled water variety sold at t=1 and a return to normal levels at t=3. Meanwhile, count of UPCs sold for peanut butter recovered by t=1 and consumers continued purchasing higher-than-average variety of dry pasta. Unlike at food grocers, variety of canned beans sold at mass merchandizers fell significantly for 7 consecutive weeks after the hurricane week, dropping by 6.8% below pre-hurricane levels at t=1 and even by 20.0% at t=3. While toilet paper variety sold at mass merchandizers dipped by a mere 1.6% at t=1, it was back within 1% of pre-hurricane levels in the following weeks. These results suggest that, on average, product variety sold at affected mass merchandizers shrunk for bottled water and canned beans.

Other than for bottled water, product variety sold at affected drug stores directly after Sandy are more varied across product categories. Similar to the other channels, count of UPCs sold for bottled water at drug stores fell by 8.7% at t=1 but only returned to pre-hurricane levels after another 5 weeks. Concurrently, count of UPCs sold for canned beans and toilet paper remained above normal levels. However, post-Sandy product varieties sold for peanut butter and dry pasta show patterns which are indistinguishable from pre-hurricane patterns. These results suggest that affected drug stores experienced shrinkage of product variety sold only for bottle water.

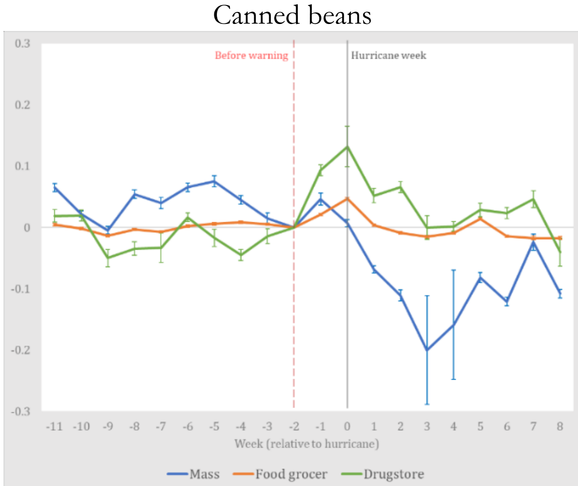
Figure 4-2 Event study plot of count of UPCs sold between retailer channels

Bottled water

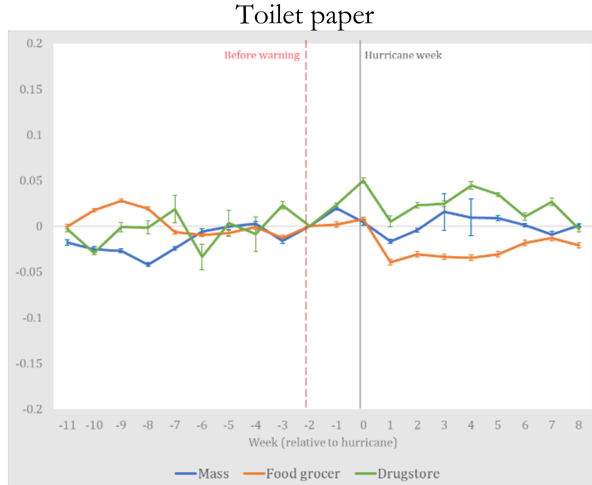
Peanut butter



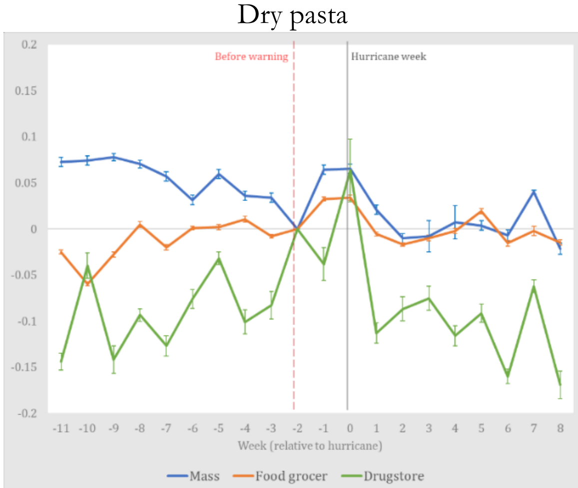
Canned beans



Toilet paper



Dry pasta



Note: Standard errors are clustered at county level. The regressions for each channel are run separately. The base week is set at t=-1 (a week before the hurricane) so the week coefficient at t=-1 is zero when interactions between proximity to hurricane (ThreatRadius) and year of hurricane (Huryear) is included.

4.2 Within-channel heterogeneity

We classify food grocer and mass merchandizer stores into small, medium, and large stores using 2011 bottled water sales as an indicator of size. The classification cutoffs and the number of stores included are tabulated in **Table 4-1**.. One channel type at a time, we separate our store sample into subsamples according to their sizes and regress weekly store volume or count of UPC sold – using equations (1) or (2), respectively – for each subsample before plotting the estimated coefficients (δ_t estimates) and overlaying the results like in Section 4.1.

Table 4-1 Size classification of stores according to annual bottled water volume sold

Food grocer stores			
Category	*Annual bottled water 2011 volume sold*	*Store sample*	*# stores*
Small	volume <= 3 million oz	28%	2,014
Medium	3 million oz < volume <= 9million oz	55%	3,983
Large	volume > 9 million oz	17%	1,269
Mass merchandizer stores			
Category	*Annual bottled water 2011 volume sold*	*Store sample*	*# stores*
Small	volume <= 500k oz	73%	6,326
Medium	500k oz < volume <= 3 million oz	19%	1,628
Large	volume > 3 million oz	8%	695

4.2.1 Volume sold at food grocer stores

In **Figure 4-3**, evidence of pre-hurricane stockpiling is most prominent in large food grocers. The highest rise in volume sold for all five product groups occur a week before Sandy. Except for dry pasta, the peaks of consumer purchases at large food grocers occur earlier than at medium or small food grocers, although smaller in magnitude. Nevertheless, contributing the largest weekly volume of these five products in their respective counties, on average, large food grocers faced a significant brunt of the consumers stockpiling for Sandy. Bottled water increased by 61.1% a week before Sandy and remained 15.5% higher than average during the hurricane week. In the same period, peanut butter volume rose by 40.2% and then by 38.9% the following week. Canned beans volume increased by 19.2% at t=-1 but returned within 1.4% of average by t=0. Volumes of dry pasta and toilet paper, however, also increased a week before Sandy – by 26.1% and 14.4%, respectively – but plunged 11.3% and 14.0% below normal levels, respectively, during the hurricane week. These results suggests that, while stockpiling of toilet paper and canned beans at large food grocers stopped during the hurricane week, consumers continued to stock up on bottled water and peanut butter.

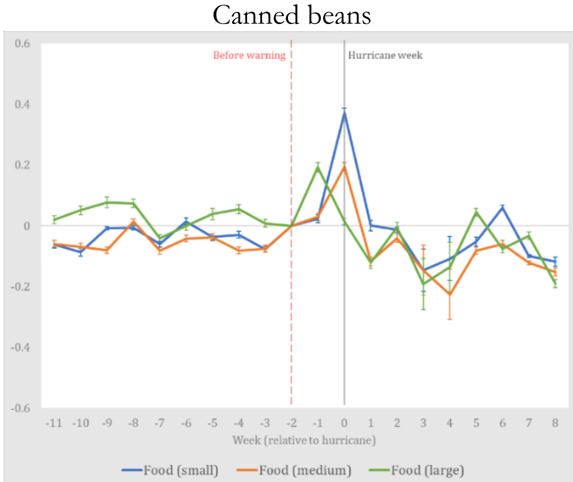
In all product categories except dry pasta, as shown in **Figure 4-3,** small food grocers experienced the highest volume "shock" due to hurricane-related stockpiling, compared to medium and large food grocers. In all product categories, the peak of the purchases occurred during the Sandy week itself instead of the prior week. On average, bottled water volume at small food grocers rose by 19.4% at t=-1 and even by 110% during the Sandy week. Peanut butter volume sold rose by 4.2% at t=-1 and spiked to 71.1% the following week. The same pattern is repeated in volume sold for

Figure 4-3 Event study plot of volume sold among food grocer stores

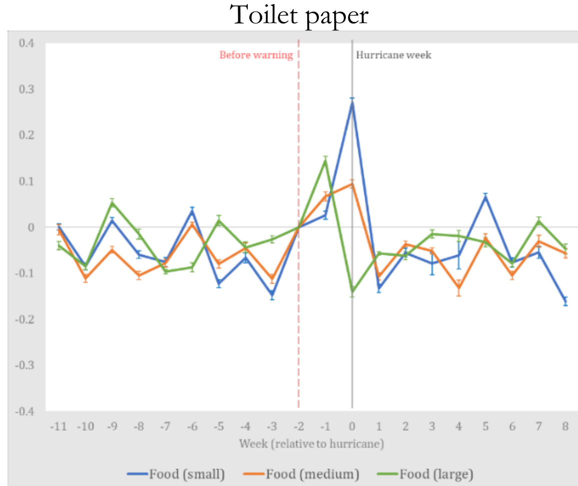
Bottled water

Peanut butter

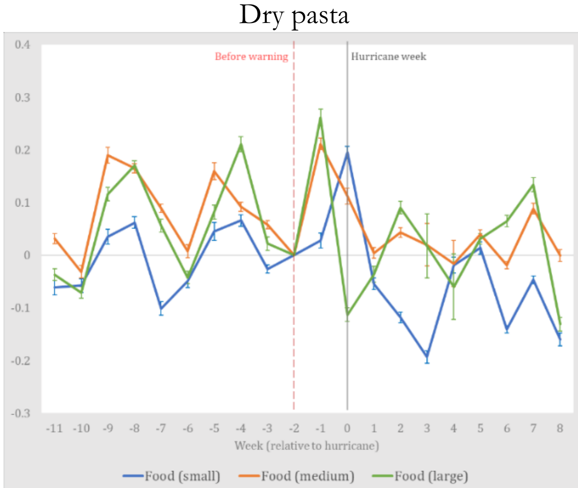
Canned beans



Toilet paper



Dry pasta



Note: Standard errors are clustered at county level. The regressions for each channel are run separately. The base week is set at t=-1 (a week before the hurricane) so the week coefficient at t=-1 is zero when interactions between proximity to hurricane (ThreatRadius) and year of hurricane (Huryear) is included.

canned beans, dry pasta, and toilet paper: rising slightly a week before the hurricane and spiking during the hurricane week itself. These results suggest that, on average, small food grocers experienced pre-hurricane stockpiling by its consumers a week later than other food grocers.

Medium food grocers, on the other hand, experience a mix of consumer stockpiling patterns. In all product categories but dry pasta, similar to small food grocers, the peak of volume sold occurred during the hurricane week itself, albeit at a smaller magnitude. That week, bottled water volume sold rose by 65.0%, peanut butter by 51.4%, canned beans by 19.4%, and dry pasta by 11.2%. However, in all product categories, the positive volume changes a week before Sandy are larger than for small food grocers, suggesting that consumers were also purchasing hurricane stockpiles from medium food grocers early.

4.2.2 Variety of products sold at food grocer stores

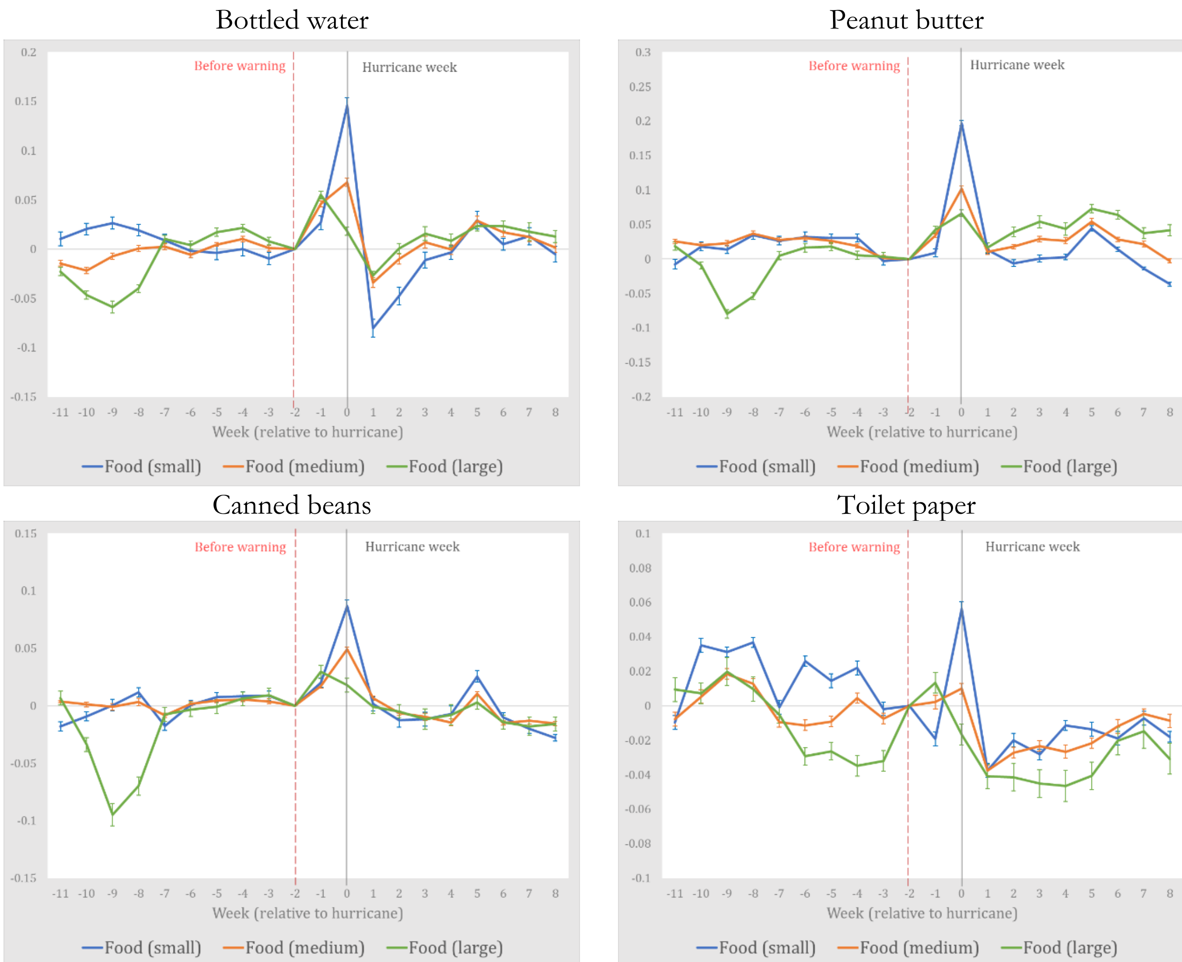
As shown in **Figure 4-4**, for each of the product categories, small food grocer stores on average experienced the largest change in product variety sold, occurring during the Sandy week itself – thus coinciding with the results in **Figure 4-3**. Bottled water count of UPCs sold rose by 14.6%, peanut butter by 19.7%, canned beans by 8.7%, dry pasta by 7.7%, and toilet paper by 5.6%. The coefficients at t=0 are unsurpassed – in absolute terms – in any other week, supporting the notion that consumers were purchasing a wider variety of product packaging, flavor, or variation within each product category for hurricane stockpiling. Following the hurricane week, however, the count of UPCs sold for bottled water fell by 8.0% while its volume in **Figure 4-3** only dipped by 1.1%. In the same week, toilet paper variety sold fell by 3.8% and dry pasta by 1.2%

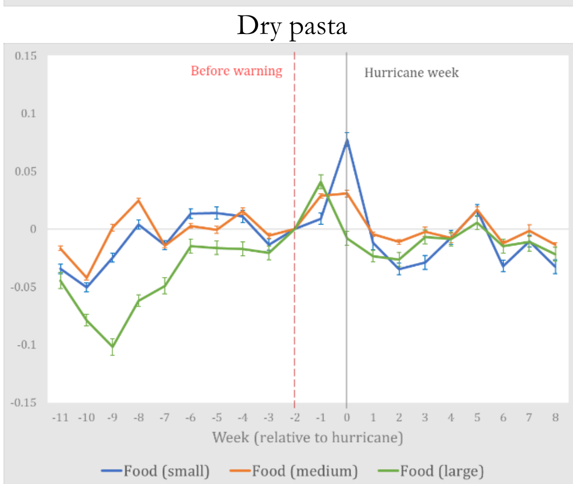
Although similar for in pattern to small food grocers, count of UPCs sold at medium food grocers moved by a small magnitude during the consumer stockpiling for Sandy. On average, bottled water UPCs sold rose by 3.4%, peanut butter by 10.2%, canned beans by 4.9%, dry pasta by 3.1%, and toilet paper by 1.0%. Directly after Sandy, only bottled water and toilet paper variety sold dipped by 3.4% and 3.8%, respectively.

Large food grocer stores, meanwhile, experienced surges in count of UPCs sold mostly a week before Sandy, except for peanut butter. Consistent with timing of volume surges in **Figure 4-3**, on average, variety sold a week prior to Sandy rose by 4.5%, canned beans by 3.0%, dry pasta by 4.1%, and toilet paper by 1.4%. Count of UPCs sold for peanut butter, however, increased the most – by 6.6% – during Sandy week, a week after its volume rose by 40.2%. The difference in timing implies that the rate at which consumers are buying more varied peanut butter during the hurricane week is higher than their purchasing volume. While small, this gap is possible if consumers were considering variety when stockpiling peanut butter or if popular peanut butter UPCs are temporarily out of stock some day during the week.

Meanwhile, we observe a large deviation from the horizontal axis during week t=-10 until t=-8. While we attempted to control for hurricane Irene in 2011, it is highly possible that the spatial impact of Irene was not fully captured by our control variables, thus resulting in the large and significant relative drops of product variety sold in food product categories – bottled water, peanut butter, canned beans, and dry pasta – during the corresponding weeks.

Figure 4-4 Event study plot of count of UPCs sold among food grocer stores





Note: Standard errors are clustered at county level. The regressions for each channel are run separately. The base week is set at t=-1 (a week before the hurricane) so the week coefficient at t=-1 is zero when interactions between proximity to hurricane (ThreatRadius) and year of hurricane (Huryear) is included.

4.2.3 Volume sold at mass merchandizer stores

Among mass merchandizer stores, large stores faced the highest increase in volume sold in all product categories a week before Sandy (see **Figure 4-5**). While bottled water volume rose by 66.0%, peanut butter volume rose by 54.9% but remained at 35.7% higher than average. Canned beans and dry pasta also rose by 40.7% and 26.5% one week before Sandy, respectively. Both products continued to be purchased lower increments during the Sandy week. Toilet paper, meanwhile, rose 25.3% a week before Sandy and then fell by 14.1%. These results suggests that, on average, large mass merchandizer stores experienced Sandy-induced stockpiling by consumers for all products at one week before Sandy and for four product categories during the hurricane week.

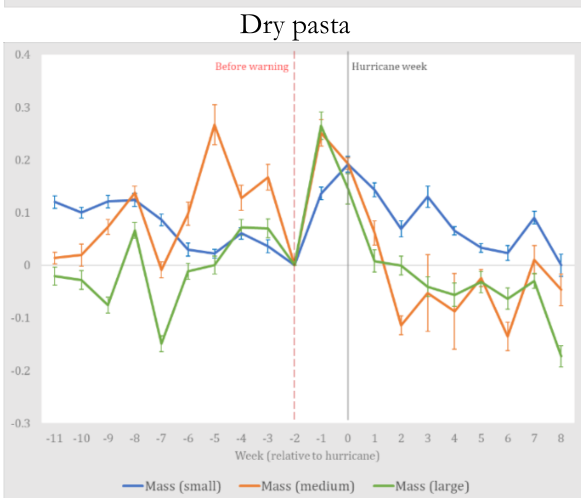
On average, Sandy-affected medium mass merchandizer stores experienced increases in volume sold in only bottled water and peanut butter. Bottled water and peanut butter volumes rose 67.5% and 49.5%, respectively, one week before Sandy, followed by 37.0% and 30.6% during Sandy week itself, respectively. The pattern is not as obvious in the other three product categories. Although toilet paper volume rose 17.4% one week before Sandy, volume sold at medium stores greatly fluctuated throughout the 20-week period. While canned beans and dry pasta volume rose by 26.0% and 25.1% a week before Sandy, respectively, their volumes have also risen by greater magnitudes in other weeks, suggesting that the volume surges may not be solely attributed to Sandy-related stockpiling. These results suggest that consumers preparing for Sandy purchased mostly bottled water and peanut butter from medium-sized mass merchandizers.

Meanwhile, **Figure 4-5** shows that hurricane-induced purchases at affected small mass merchandizer stores occurred most visibly for bottled water and peanut butter. On average, bottled water volume sold rose by 54.4% a week before Sandy and by 42.9% during the hurricane week. Peanut butter volume sold also rose by 30.6% a week prior to Sandy and then by 53.0% during Sandy. While fluctuating across weeks, dry pasta volume sold rose by 13.6% and 19.2% at a week before and during the Sandy week itself, respectively. However, consumers did not seem to stockpile canned beans and toilet paper from small mass merchandizers stores during the two weeks. These results suggest that, similar to medium-sized ones, affected small mass merchandizer stores sold substantial volumes of bottled water and peanut butter to consumers stockpiling for Sandy.

4.2.4 Variety of products sold at mass merchandizer stores

We observe that the product varieties sold across five product categories greatly fluctuate among mass merchandizers, especially small stores. **Figure 4-6** shows that the higher product variety sold from Sandy-induced stockpiling is largely observable for bottled water and peanut butter: their count of UPCs sold rose 6.6% and 8.9% a week before Sandy, respectively. These results are consistent in timing with the positive volume surge in **Figure 4-5**. However, the count of UPCs sold for dry pasta in small mass merchandizers did not increase as fast as its volume. The 6.5% increase in count of UPCs sold and the 19.3% increase in volume sold for dry pasta on the week of Sandy suggests that consumers purchased much more dry pasta from small mass merchandizer stores without buying as much variety. This can occur due to taste or if there is limited variety of

Figure 4-5 Event study plot of volume sold among mass merchandizer stores



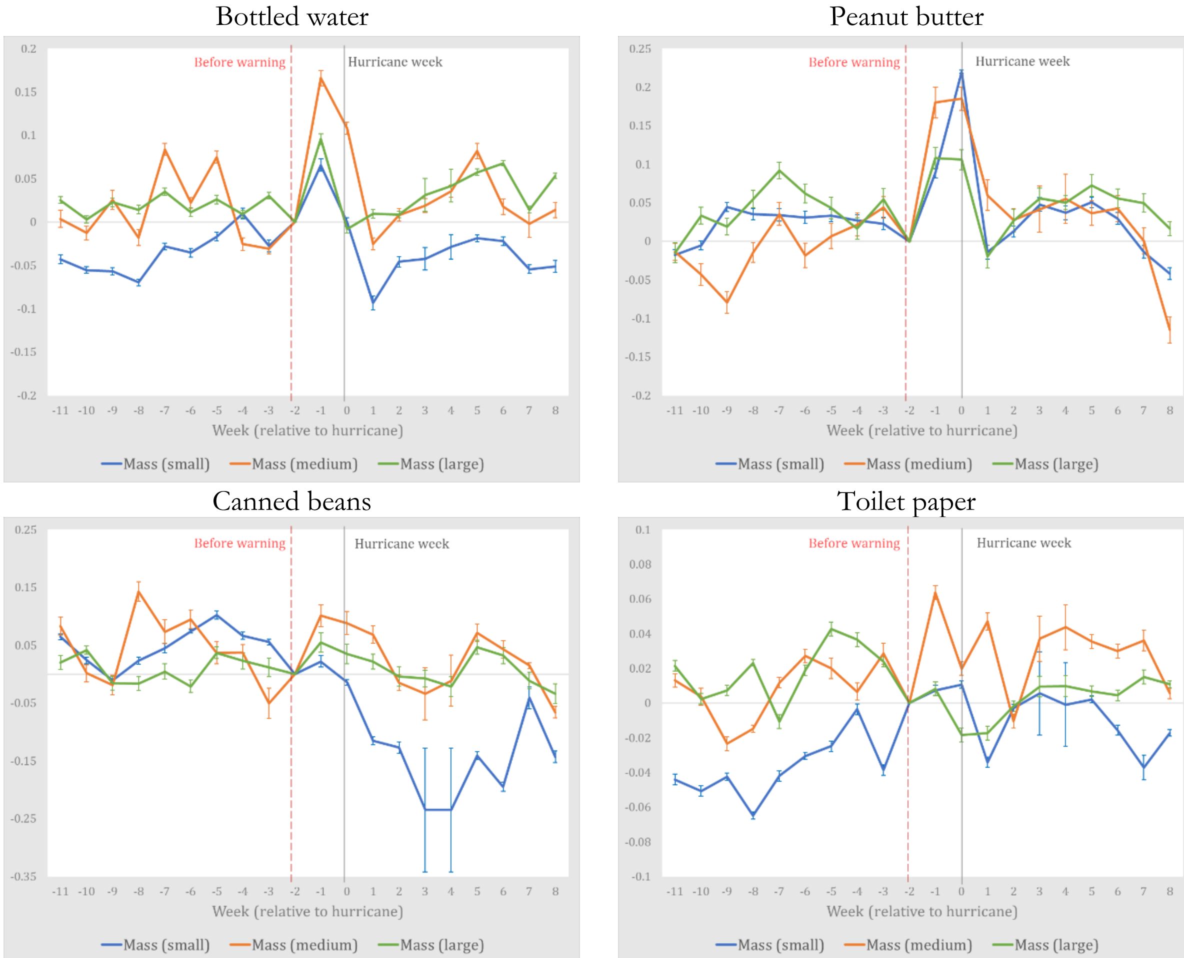
Note: Standard errors are clustered at county level. The regressions for each channel are run separately. The base week is set at t=-1 (a week before the hurricane) so the week coefficient at t=-1 is zero when interactions between proximity to hurricane (ThreatRadius) and year of hurricane (Huryear) is included.

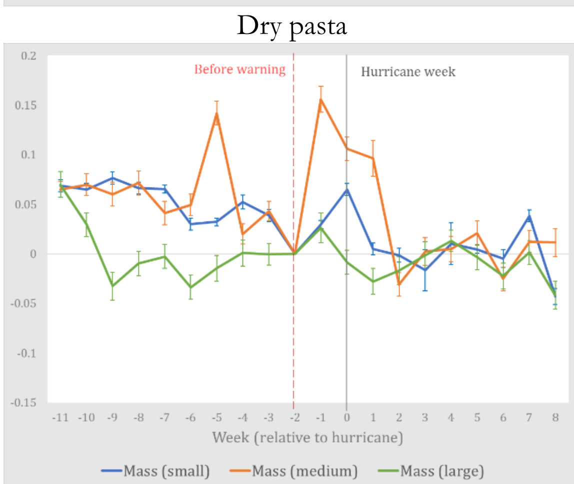
product offerings on the store shelves. More importantly, product variety sold for bottled water, canned beans, and toilet paper a week after Sandy. While consistent with the movements of volume changes in **Figure 4-5**, the 9.3% drop of bottled water count of UPCs sold is the largest drop in magnitude throughout our sample period, suggesting possible shrinkage of store offerings in some stores.

Consequently, **Figure 4-6** depicts medium-sized mass merchandizer stores, on average, to have experienced increased variety of UPCs sold during pre-Sandy consumer stockpiling, most clearly for bottled water and peanut butter. Bottled water count of UPCs sold rose by 16.6% and 10.8% at a week before Sandy and during the hurricane week itself, respectively. During the same period, peanut butter count of UPCs sold rose by 18.0% and 18.5%, respectively. The two-week surge in product variety sold corresponds in timing to the two-week surge in volume sold for the two product categories in **Figure 4-5**. Despite highly fluctuating, count of UPCs sold for the other three product categories experienced their peaks – highest among mass merchandizers – a week before Sandy: canned beans by 10.1%, dry pasta by 15.6%, and toilet paper by 6.4%. Meanwhile, the post-Sandy product variety dip at t=1 – a mere 2.5% – only occurred for bottled water.

The pattern of product variety sold at large mass merchandizers, as shown in **Figure 4-6**, is more mixed. Count of UPCs sold for bottled water rose by 9.6% a week before Sandy before recovering swiftly. Peanut butter count of UPCs sold rose by 10.8% the same week and by 10.6% during the hurricane week. While volume sold for canned beans, toilet paper, and dry pasta clearly spiked a week before Sandy, as depicted in **Figure 4-5**, their respective counts of UPCs sold do not show patterns around t=0 that are observably unique to hurricane Sandy. However, we note that product variety sold for peanut butter, toilet paper, and dry pasta fell by 2.0%, 1.7%, and 2.8%, respectively, a week after Sandy, even as counts of UPCs sold for bottled water and canned beans recovered to at least by 1% above average.

Figure 4-6 Event study plot of count of UPCs sold among mass merchandizer stores





Note: Standard errors are clustered at county level. The regressions for each channel are run separately. The base week is set at t=-1 (a week before the hurricane) so the week coefficient at t=-1 is zero when interactions between proximity to hurricane (threat) and year of hurricane (huryear) is included.

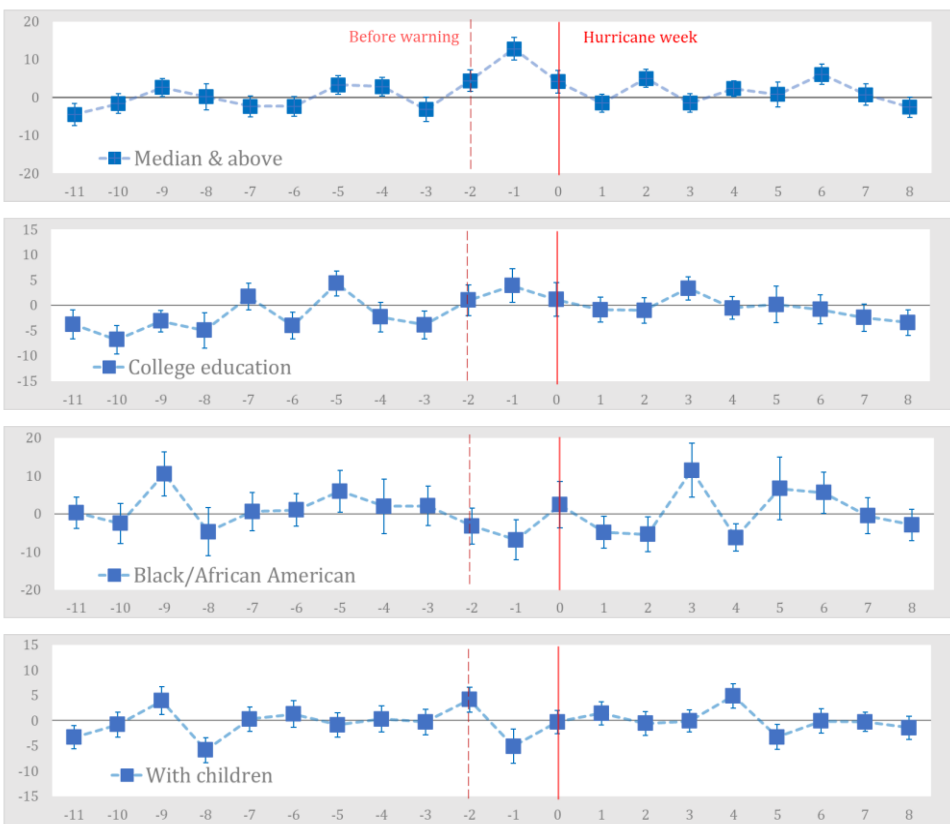
4.3 Consumer heterogeneity

To analyze consumer heterogeneity, we run regressions on weekly household purchase volumes using equation (3) with the full household panel and the demographic indicator for each product category *j*. We then plot the estimated coefficients (and 95% confidence intervals) of the four-way interaction terms (ρ_t estimates) into event study graphs. If there is stockpiling heterogeneity between consumers, we expect the estimated coefficients at t=-1 or t=0 to be significantly different than zero and distinct from the pattern throughout our 20-week sample period.

4.3.1 Bottled water

Figure 4-7 shows clear heterogeneity in hurricane-induced stockpiling around Sandy across annual household income. On average, affected households with higher-than-median income purchased 12.84 oz – equivalent to three quarters of a 16-oz bottle – more per household member than those with lower-than-median income at one week before Sandy. Statistically significant at 5% level and with the largest absolute magnitude throughout the 20-week period, this coefficient indicates heterogeneity in bottled water stockpiling.

Figure 4-7 Average difference in affected households' weekly purchase volumes of bottled water (in oz per member) by demographics

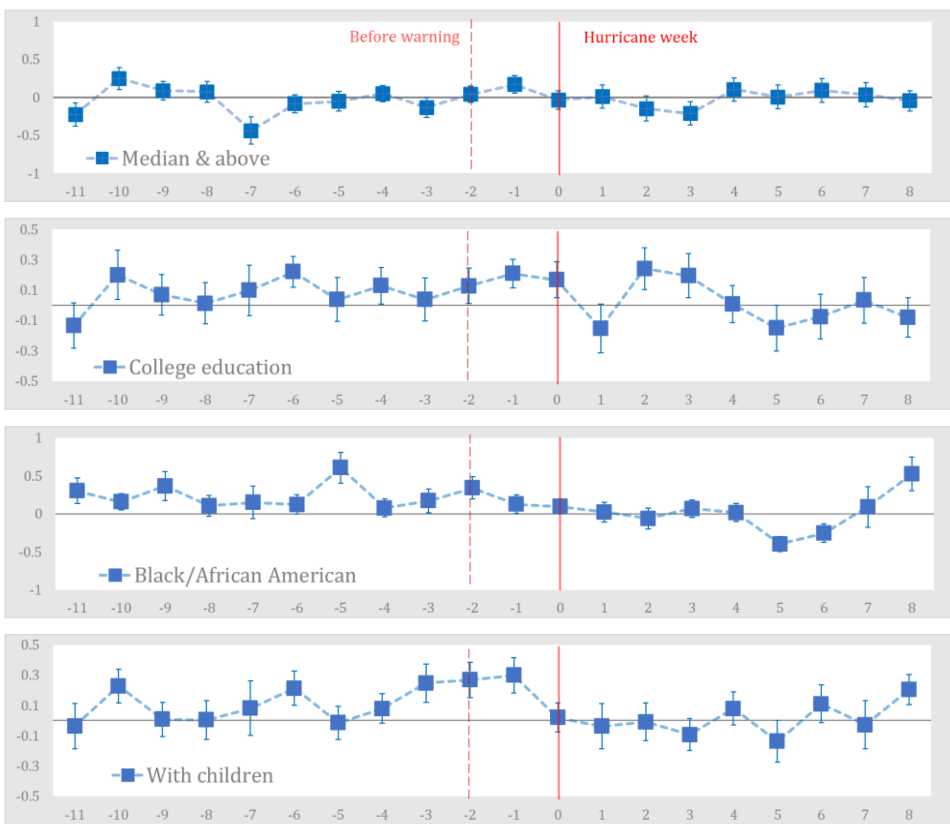


As shown in **Figure 4-7**, other demographics, however, do not show clear heterogeneity specific to the response to Sandy. Unconditionally, on average, affected households with college-educated household heads stockpiled 3.86 oz more per household member than those without. Black/African American households purchase 6.85 oz lower per household member than other households. Households with children on average purchase 5.09 oz less per member than households without children. Although statistically significant at 5%, all three coefficients above have magnitudes which are indistinguishable from other fluctuations during the sample period. Meanwhile, purchase volumes for households living alone are not statistically significantly different from those who are not.

4.3.2 Results: Peanut butter

Shown in **Figure 4-8**, households with children are, on average, purchasing 0.30 oz more peanut butter per household member a week before Sandy than households without children. Statistically significant at 5%, this is also the largest absolute magnitude during the sample period. Given the pattern before the hurricane week, this result suggests that households with children continued to stockpile peanut butter although they have already been purchasing more peanut butter per member in prior weeks.

Figure 4-8 Average difference in affected households' weekly purchase volumes of peanut butter (in oz per member) by demographics

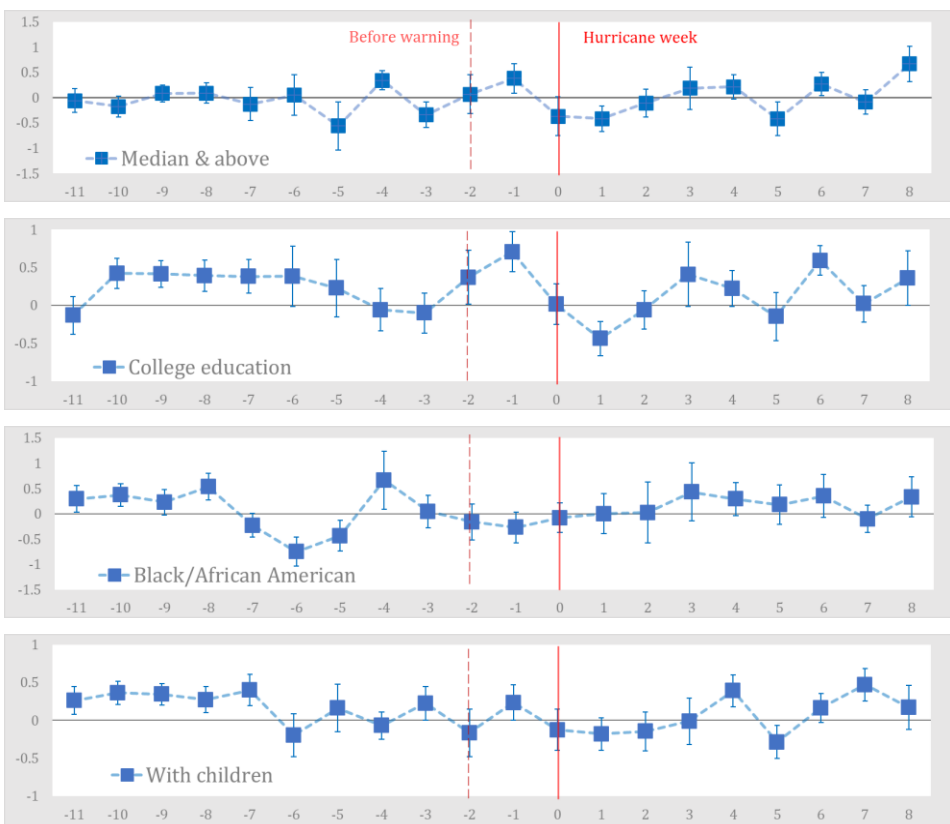


Other demographics show less distinguishable heterogeneity in purchases around the Sandy week. Despite being statistically significant at 5%, the absolute magnitude of coefficients at t=-1 when comparing households binarily across annual household income, college-educated household heads, and race are smaller than other coefficients during the sample period. These results suggest that higher peanut butter stockpiling per person during Sandy is only unconditionally correlated with households with children.

4.3.3 Results: Canned beans

In **Figure 4-9**, unconditionally, households with college-educated household heads are, on average, purchasing 0.70 oz more canned beans per member right before Sandy week. Aside from statistically significant at 5%, the absolute magnitude compared to pre- and post-hurricane patterns suggests that this difference was likely part of the stockpiling behavior in preparation for Sandy. While race or presence of children were not statistically correlated with canned beans purchase volumes at t=-1, annual household income is statistically correlated albeit with a coefficient (absolute) magnitude unnoticeably different than fluctuations throughout the 20-week period.

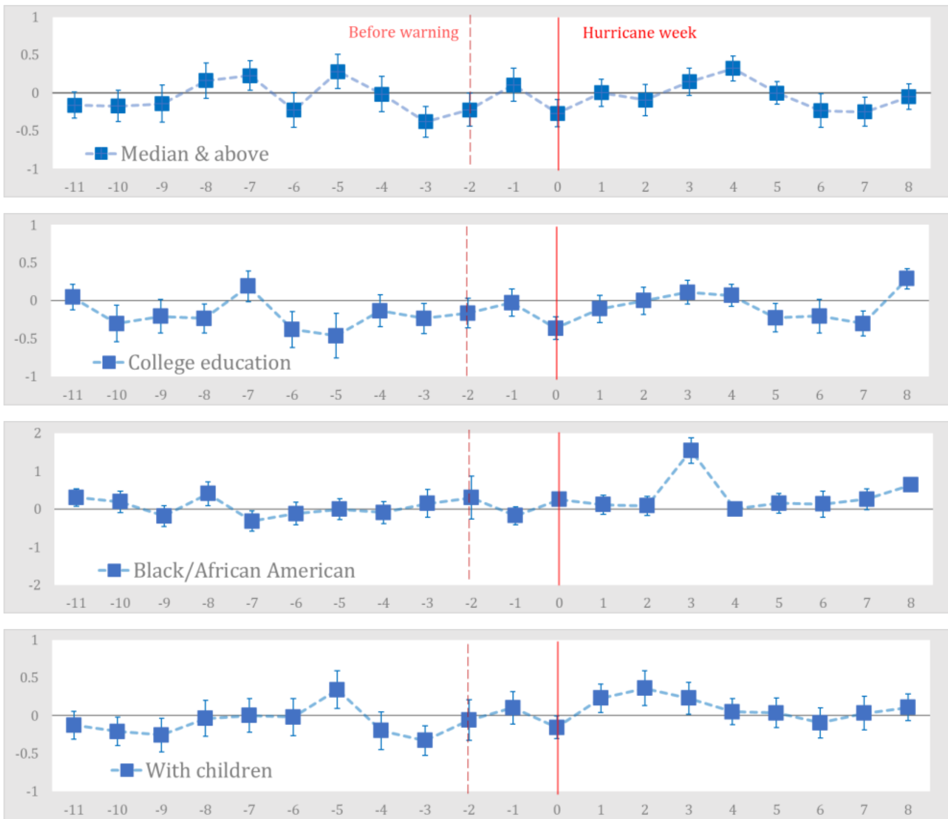
Figure 4-9 Average difference in affected households' weekly purchase volumes of canned beans (in oz per member) by demographics



4.3.4 Results: Dry pasta

We do not observe in **Figure 4-10** statistically significant relationship between household demographics and dry pasta purchase volume a week prior to Sandy. However, we observe that on average, during the hurricane week itself, households with median income (or above) or college-educated household heads unconditionally purchase less dry pasta per member than their counterparts, albeit in very small absolute magnitudes compared to other weeks.

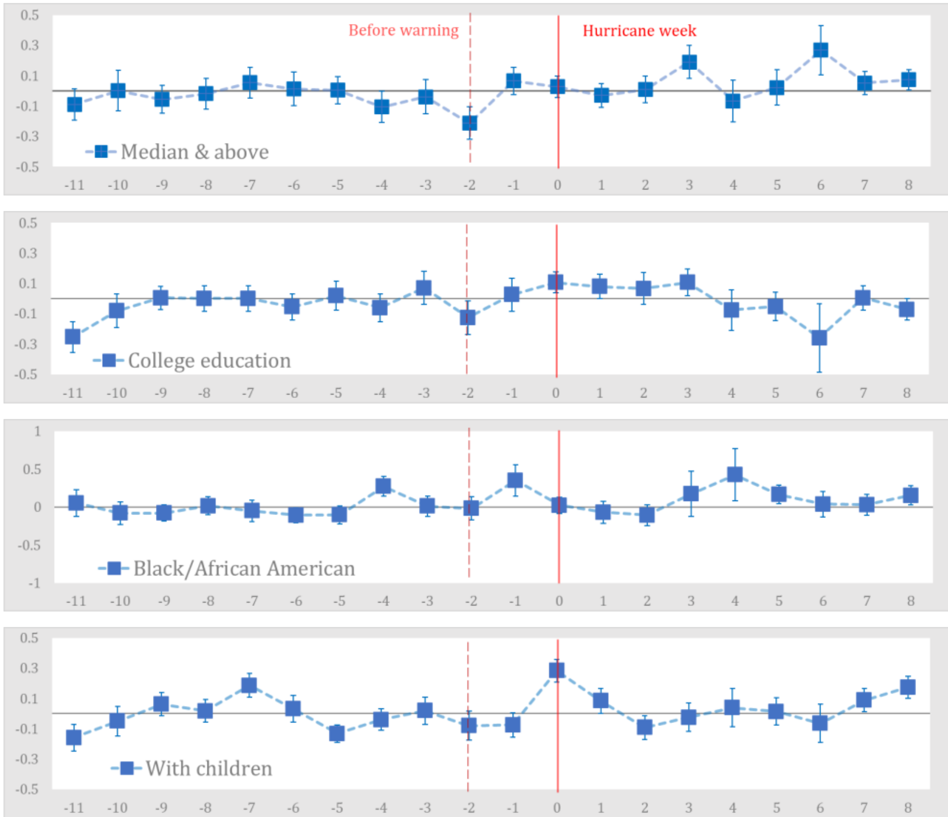
Figure 4-10 Average difference in affected households' weekly purchase volumes of dry pasta (in oz per member) by demographics



4.3.5 Results: Toilet paper

Unconditionally, Black/African American households on average purchased 0.35 more toilet paper rolls per member than other households a week before Sandy (see **Figure 4-11**). Statistically significant at 5% level, households with children on average purchased 0.28 more toilet paper rolls per member than those without children, unconditionally. Household median income and college-educated households heads, however, are not significantly correlated with heterogeneity in toilet paper stockpiling before Sandy.

Figure 4-11 Average difference in affected households' weekly purchase volumes of toilet paper (in rolls per member) by demographics



5. LIMITATIONS AND DISCUSSION

While the retail scanner and consumer panel data provide a large scope of investigation, some features limit our ability to analyze precise market responses disaster events which occur in days. Although the weekly frequency of store-level data is reliable, we are unable to observe the change in consumer behavior every day before the hurricane's date of landfall or arrival at the county. Since hurricane warnings are issued earliest 5 days by the NHC before the landfall, we expect to see a clearer relationship between Sandy warnings and purchases on a daily basis. Meanwhile, although the consumer panel data provides daily shopping items for the household panel, there is a possibility that households did not scan their purchases amidst a disaster as major as Sandy, especially with power outage and other more urgent concerns. We find that the consumer panel data shows a large drop in number of trips and volumes purchased by households during the hurricane week although the retailer scanner data suggests otherwise. These features are specifically challenging in the investigation of major disasters for which the population has only days to prepare.

We also realize that a hurricane is a multifaceted and dynamic object, causing destruction along its path in time and space. With county-level store data, we were unable to precisely match store locations with other weather censors as indicators for the hurricane's impact. As such, we treated hurricane Sandy as a static disaster and computed the week at which its historical position was nearest to the county centroid. While we were fortunate that Sandy's nearest distance occurred in the same calendar week for all the counties included, extra caution – as Pan et al (2021) has attempted – may be needed when including hurricanes which stretch across weekends – and hence, sales reporting weeks – across counties. This is an additional challenge when we do not know, a priori, the timing of consumers' reaction towards an impending disaster. While granular data on flooding can be obtained from FEMA, the geographical information in the store-level data is not sufficient for us to match the locations, and hence treatment.

Furthermore, we realize that our categorization of store sizes is arbitrary and may itself be causing bias in the analysis of heterogeneity. Future research can consider the store's parent chain while also taking into account the mix of stores in the county. Such analysis may allow policymakers understand how different stores of various sizes and channel types within a county play different roles in emergency times. Since our study did not specifically identify or measure the behavior of consumers who only purchased goods during the hurricane, our store-level estimates may also have been caused by new consumers.

While we opted to investigate a single hurricane at depth, we realize that more disaster types should be included in future analysis. To maintain the focus on populations with less familiarity with the disaster, however, it may be advisable to first expand the same approach to the event of hurricane Irene in 2011 whose path shared certain geographical overlaps with Sandy in 2012. Future inclusion of other hurricanes – to control for similar flood-related disaster – and other disaster types will enrich our understanding of how consumers adjust their shopping baskets to prepare for uncertainty amidst perceived impending disruption to food access.

6. CONCLUSION AND FUTURE RESEARCH

After employing a combination of event study and regression analyses on store-level weekly purchases surrounding hurricane Sandy in 2012, we find evidence of heterogeneity of pre-hurricane stockpiling purchases across retailers. Among retail channel types, drug stores on average experienced the largest percentage of consumer purchase surge for canned beans and toilet paper. However, all three channel types – food grocers, mass merchandizers, and drug stores – experienced an increase in volume sold within a narrow range of 58.9%-60.5% for bottled water as well as 45.0%-51.9% for peanut butter at either the week of Sandy or the prior week. These estimates suggest that, on average, population in Sandy-affected areas stockpiled around an extra half-a-week supply of bottled water and peanut butter, consistent with advised 3-day hurricane stockpile.

In terms of timing, mass merchandizers on average peaked in purchase volumes a week before the hurricane for all products and food grocers peaked later (during Sandy week) for bottled water, peanut butter, and canned beans. As expected, the variety of products sold with each category directly after the hurricane was significantly reduced for bottled water in all channels, for toilet paper in food grocers, and for pasta in drug stores. The latter two incidences suggest that, due to the incoming hurricane, consumers were purchasing more of a good they usually did not purchase in that type of retail store.

However, on closer look at the within-channel heterogeneity, we find that consumers first rushed towards larger stores during the week before Sandy's arrival. Among food grocers, large stores on average experienced stockpiling purchases for all products peak at one week before Sandy but purchases for small and medium stores mostly peaked during the hurricane week itself. Within the mass merchandizer channel, we also observe heterogeneity across stores of different sizes. Large and medium stores experienced pre-hurricane stockpiling purchases a week before the hurricane for all 5 product categories, but small mass merchandisers only saw stockpiling purchases for peanut butter and dry pasta – and they peaked later (during the hurricane week itself) instead.

We also find that the pre-Sandy stockpiling behavior is only heterogenous across household demographics for certain product categories. Affected households with higher-than-median income unconditionally, on average, purchased more bottled water per household member than those with lower-than-median income at one week before Sandy. On average, households with children unconditionally purchased more peanut butter per member than those without children. Also, household with college-educated household head unconditionally purchased more canned beans than other households, on average. Black/African American households unconditionally purchased more toilet paper per member than households of other race, on average. Meanwhile, we do not observe heterogeneity in dry pasta stockpiling before Sandy across annual income, college education, presence of children, and race.

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Disclaimer

Researcher(s) own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher 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.

APPENDIX

Figure A 1. Best track positions for Hurricane Sandy, 22 – 29 October 2012 (Blake et al., 2009)

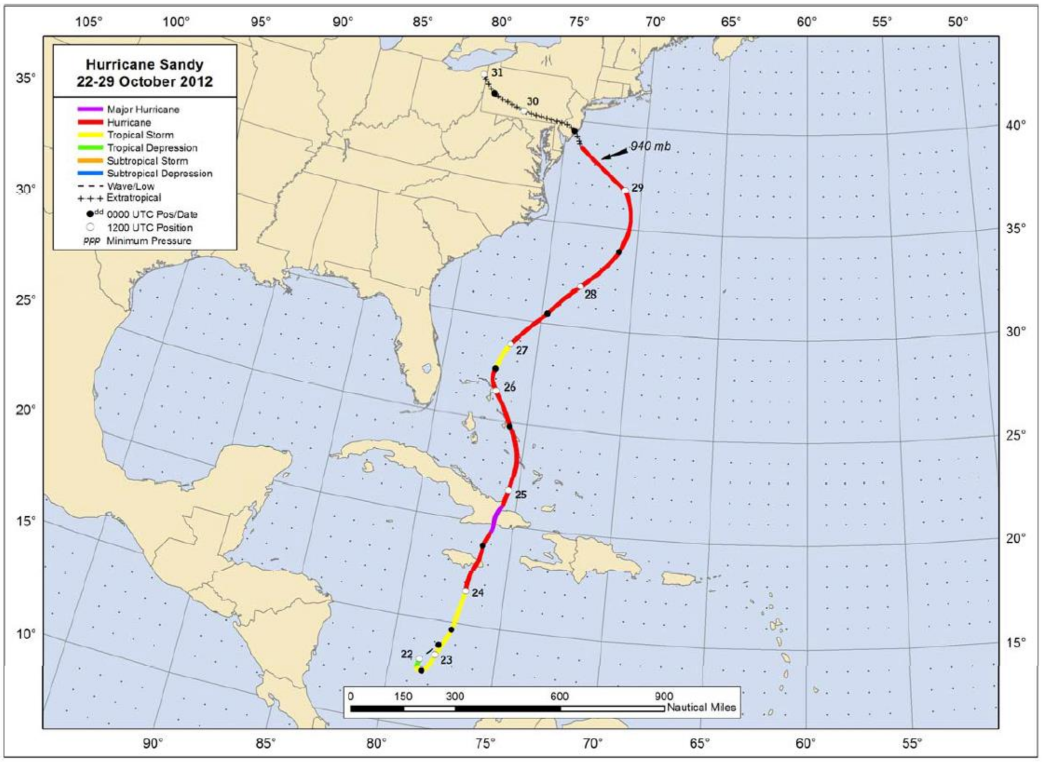

Figure A 2 Path of Hurricane Sandy 2012 and Irene 2011 (Source: NOAA, 2021a)

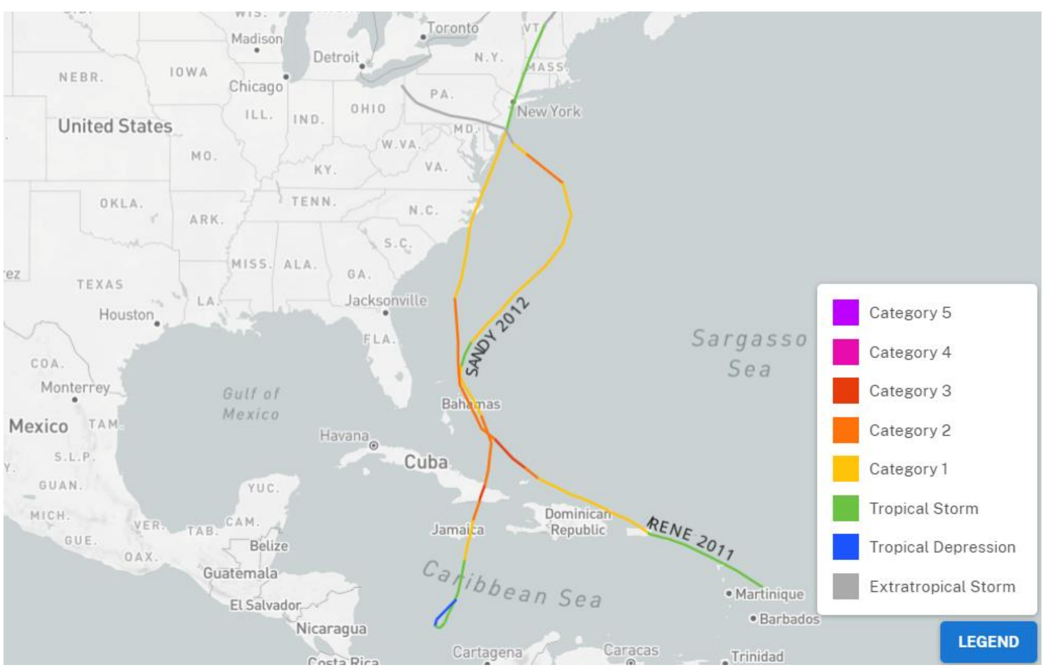

Table A 1 Full sample of store for various product categories

Bottled water

2011-2012	# stores	Weekly volume ('000 oz) Mean	Standard deviation	Median	Weekly UPC count Mean	Standard deviation	Median	% within radius
Food grocer stores								
Large	1,269	2281.7	2385.1	1540.3	275.0	133.5	264.0	15.8%
Medium	3,983	786.3	354.1	726.0	272.3	95.7	252.5	11.8%
Small	2,014	338.5	162.3	318.0	181.1	61.6	182.4	5.6%
Combined	7,266	923.4	1223.3	661.3	247.5	104.3	233.8	15.8%
Mass merchandizers								
Large	695	800.1	321.2	722.1	256.8	44.3	262.8	12.1%
Medium	1,628	235.3	142.9	198.4	142.2	64.1	126.9	12.3%
Small	6,326	27.6	17.5	24.7	28.9	10.1	30.3	10.6%
Combined	8,649	128.8	241.2	33.1	68.6	77.6	33.4	11.1%
Drug stores	11,383	79.9	71.0	63.1	96.0	41.1	95.2	12.6%

Peanut butter

2011-2012	# stores	Weekly volume ('000 oz) Mean	Standard deviation	Median	Weekly UPC count Mean	Standard deviation	Median	% within radius
Food grocer stores								
Large	1,269	32.9	22.8	26.5	102.2	45.9	104.8	15.8%
Medium	3,983	17.9	9.3	16.1	109.7	37.2	104.3	11.8%
Small	1,974	8.7	4.2	8.0	82.5	26.5	82.4	5.5%
Combined	7,226	18.0	14.4	14.4	101.0	38.2	99.2	10.8%
Mass merchandizers								
Large	695	16.4	9.6	14.2	121.8	41.0	114.9	12.1%
Medium	1,628	2.5	3.4	0.4	32.5	38.3	7.3	12.4%
Small	6,247	0.3	0.2	0.3	7.5	2.7	7.8	10.8%
Combined	8,570	2.0	5.3	0.3	21.5	37.4	8.2	11.2%
Drug stores	11,195	0.2	0.3	0.2	4.9	3.8	4.3	12.7%

Canned beans

2011-2012	# stores	Weekly volume ('000 oz) Mean	Standard deviation	Median	Weekly UPC count Mean	Standard deviation	Median	% within radius
Food grocer stores								
Large	1,269	67.2	32.6	60.1	192.4	92.7	198.6	15.8%
Medium	3,983	44.1	21.3	40.7	203.8	58.2	196.6	11.8%
Small	1,974	26.8	11.4	26.0	177.0	54.7	172.8	5.5%
Combined	7,226	43.4	25.4	38.2	194.5	65.8	192.5	10.8%
Mass merchandizers								
Large	695	17.2	14.7	10.5	100.9	56.7	77.0	12.2%
Medium	1,628	2.2	3.0	0.4	20.5	23.4	7.3	13.1%
Small	6,245	0.5	0.3	0.4	8.8	3.8	9.0	10.7%
Combined	8,568	2.1	6.3	0.4	18.5	31.6	9.4	11.2%
Drug stores	10,441	0.1	0.3	0.0	1.2	2.0	0.7	14.8%

Dry pasta								
		Weekly volume ('000 oz)			Weekly UPC count			% within radius
2011-2012	# stores	Mean	Standard deviation	Median	Mean	Standard deviation	Median	
Food grocer stores								
Large	1,269	71.8	54.2	54.8	356.9	215.2	321.7	15.8%
Medium	3,983	38.5	21.1	32.4	347.2	149.5	305.3	11.8%
Small	1,973	17.4	7.6	16.6	218.8	75.1	214.2	5.5%
Combined	7,225	38.6	33.1	28.7	313.9	159.3	277.4	10.8%
Mass merchandizers								
Large	695	16.3	12.2	12.0	173.2	110.0	119.4	12.1%
Medium	1,628	2.0	2.8	0.5	35.7	41.0	11.8	12.5%
Small	6,248	0.6	0.3	0.5	11.3	4.2	11.4	10.5%
Combined	8,571	2.1	5.6	0.5	29.0	56.9	12.1	11.0%
Drug stores	10,859	0.1	0.2	0.0	2.3	2.8	1.6	12.4%

Toilet paper								
		Weekly volume ('000 rolls)			Weekly UPC count			% within radius
2011-2012	# stores	Mean	Standard deviation	Median	Mean	Standard deviation	Median	
Food grocer stores								
Large	1,269	31.1	29.7	20.4	98.3	46.0	82.3	15.8%
Medium	3,983	12.5	5.5	11.6	107.9	36.1	101.0	11.8%
Small	1,974	6.2	2.5	6.0	101.3	32.6	94.5	5.5%
Combined	7,226	14.0	15.6	10.7	104.4	37.4	96.2	10.8%
Mass merchandizers								
Large	695	31.6	14.2	29.1	132.6	15.9	138.9	12.1%
Medium	1,628	11.6	7.7	9.1	100.6	29.1	96.2	12.3%
Small	6,321	4.6	2.4	4.2	59.5	16.2	64.7	10.6%
Combined	8,644	8.1	9.4	5.0	73.1	30.6	69.2	11.1%
Drug stores	11,374	1.8	1.5	1.4	38.6	15.6	39.3	12.6%