Retail Assortment under Demand Shocks:

Evidence from the U.S. Yogurt Market During the Great Recession

Meilin Ma, Department of Agricultural Economics, Purdue University, mameilin@purdue.edu
Fei Qin, Department of Agricultural Economics, Purdue University, qin132@purdue.edu
Jayson Lusk, Department of Agricultural Economics, Purdue University, jlusk@purdue.edu

Selected Paper prepared for presentation at the 2023 Agricultural & Applied Economics Association Annual Meeting, Washington DC; July 23-25, 2023

Retail Assortment under Demand Shocks:

Evidence from the U.S. Yogurt Market During the Great Recession

Abstract

Despite extensive research on retailers' price responses to demand shocks, much less is known about their non-price adjustments. Using heterogeneity in timing, location, and magnitude of income and wealth shocks associated with the 2008 Great Recession, we explore how U.S. retail stores adjusted product offerings in response to the shocks in local markets. Evidence shows that stores reduce product variety and change product sizes besides lowering prices. Using a structural demand model, we quantify the net welfare impact of the price and assortment adjustments. On average, the consumer welfare losses from variety reduction more than offset the welfare gains from price reductions.

Keywords: Consumer welfare, Demand shocks, Product assortment, Retail stores.

JEL Codes: L15, L19, L81

---

* 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(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

Data Availability Statement: The data that support the findings of this study are available from NielsenIQ. Restrictions apply to the availability of these data, which were used under license for this study. Data are available upon request with the permission of NielsenIQ.

1. INTRODUCTION

How do retailers alter their marketing mix amidst demand shocks? Prior economic inquiries into this question have primarily focused on how retailers alter prices in response to demand shocks caused by social conflicts, income reductions, house value changes, and more. Some studies find that the price adjustments are limited even under large, unanticipated demand shocks (Gagnon and Lopez-Salido 2020), while others find considerable price responses (Stroebel and Vavra 2019). Prices may fall under positive (Chevalier et al. 2003) or negative demand shocks (Coibion et al. 2015) that are anticipated like holidays or that come as surprises.

It is well-documented that retailers adjust both prices and product offerings in response to market conditions to maximize profits (Bayus and Putsis 1999; Richards and Hamilton 2015; Handbury 2021). Yet changes in retailer assortment under demand shocks are rarely studied (see Dekimpe et al. 2011 for a summary of work on private labels as an exception), despite extensive work on the assortment of manufacturers facing demand shocks (Bernard et al. 2010; Copeland et al. 2011; Antoniades et al. 2018). Variety adjustments by retailers are complex and have direct welfare implications for consumers who derive value from larger choice sets. Moreover, product assortment affects price-setting decisions of the retailer by changing retailing costs and altering the intensity of price competition among retailers (Jaravel 2019; Richards et al. 2020).

We aim to determine the assortment adjustments made by retailers under demand shocks and examine the welfare effects. We use scanner data on the U.S. yogurt market to study product portfolios offered by retailers in the period surrounding the sizable shocks to local demand caused by the 2008 Great Recession. We choose to study the yogurt market because yogurt is a widely consumed packaged product in the United States (Villas-Boas 2007) and retailers generally offer large numbers of heterogeneous products, leaving considerable room for assortment adjustments.

The Nielsen retail dataset we utilize contains information on over 45,000 retail stores across the United States and provides millions of observations of store-level product offerings. The average store carries more than 100 unique yogurt products and 10 yogurt brands.

We use a set of income and wealth variables to indicate local demand shocks, including county-month unemployment rates to proxy the income of local consumers and county-month average house values to measure local wealth following Dubé et al. (2018). Temporal and spatial variation in the county-level economic conditions identifies the effects of local demand shocks on the products that stores choose to offer, controlling for supply shocks driven by the Recession (i.e., changes in the availability of yogurt products). Though these demand-shock variables may not be perfect, they identify similar effects on product offerings, confirming strong patterns in assortment adjustments to demand shocks.

We focus on the period of 2006 to 2010, years around the peak of the 2008 Great Recession. Data are aggregated to monthly, quarterly, yearly levels, to match with the income/wealth measure of the same frequency. Unique products are identified by the universal product codes (UPCs). Our data cover transactions in grocery stores and mass merchandisers. The two formats of stores have different assortment strategies. On average, grocery stores carry three times more UPCs than mass merchandisers. We find differential assortment adjustments by store format, but both formats of stores remove UPCs under negative demand shocks. Further, reducing the number of UPCs leads to fewer flavors (e.g., strawberry), styles (e.g., Greek), and types (e.g., low fat) and different sizes of yogurt products on the shelf.

We control for a large set of variables to strengthen the baseline identification, including the total numbers of UPCs available on the national market (accounting for manufacturers' responses to aggregate demand shocks), the pre-Recession products offered by the stores (accounting for path dependence), subsidies from food assistance programs (accounting for another key source of demand shocks), local competition, and retailer, market, and time fixed effects. Importantly, we confirm that the assortment effects are indeed driven by retailers not manufacturers by showing that the baseline outcomes hold, after we 1) exclude the three dominant yogurt manufacturers (i.e., Chobani, Danone, and Yoplait) that might affect store assortment via bargaining, or 2) exclude retailers with high chain-level brand concentration, which likely indicates category captaincy (i.e., assortment controlled) by manufacturers. A large set of other sensitivity tests further confirm the baseline findings.

Controlling for product offerings, price changes due to demand shocks are much smaller. Specifically, a 10% decrease in local wealth in a month only results in a 0.1-0.3% decrease in yogurt prices for grocery and mass merchandisers. As prices fall in response to a recession, consumer surplus increases. Yet, as a store removes varieties, consumer surplus falls. To quantify the net welfare impact of the price and assortment responses to local demand shocks, we estimate a discrete choice demand model for a selected set of differentiated yogurt products during the Recession. The average net impact on consumer surplus is negative and economically significant. For instance, when the local wealth falls by 5% in a month, the negative surplus impact due to the variety reduction outweighs the positive surplus impact of the price reduction; the net yearly surplus loss amounts to $36 million for U.S. yogurt consumers.

The study makes two major contributions to the literature. First, regarding the literature on supply-side responses to the income/wealth shocks (Jaravel 2019; Jaravel and O'Connell 2020), we provide new insights in non-price adjustments of retailers. While several studies have examined product adding and dropping by manufacturers (Bernard et al. 2010; Argente et al. 2018) and the expansion of private labels in retail markets during an economic recession (Dubé et al. 2018), we are one of the first to provide a comprehensive analysis of product offerings of retail stores under local demand shocks. Considering retailer assortment helps reconcile the mixed empirical evidence of price adjustments to demand shocks. As we show here, knowledge of both price- and assortment adjustments by stores are needed to determine welfare impacts of income and wealth shocks. The finding that welfare losses from variety reduction more than offset the consumer welfare gains from price reductions echoes recent evidence that product availability explains more spatial variation in consumer utility than prices do (Handbury 2021).

Second, regarding the literature on demand responses to economic shocks, we highlight the role of retailers in altering consumer behavior. Many studies have explored how economic shocks affect consumers' decision to economize on food shopping by spending more time on price-search (Aguiar et al. 2013; Nevo and Wong 2019) and alter the mix of food expenditures to meet caloric and nutrients needs (Griffith et al. 2016). We show that consumers are likely to face a fairly different choice set during a recession and consumer behavioral changes are jointly driven by more intensive searching and a new choice set.

2. ECONOMIC INTUITIONS

Maintaining optimal product offerings is a critical dimension of store quality in the retail sector (Dekimpe et al. 2011; Hwang et al. 2010; Matsa 2011), especially with growing heterogeneity in consumer preferences over an increasing number of product attributes (Saitone and Sexton 2010). To derive basic economic intuitions for how a retailer would adjust in product offerings under a local demand shock, we construct a simple, static conceptual model in Appendix 1. The key insights are summarized as follows.

Consider a two-stage game for a profit-maximizing retail store and one category of food, say yogurt. Each period is assumed to be independent, so the framework is static. Ignoring crosscategory price and sales effects follows the convention of literature (e.g., Nevo 2001; Villas-Boas 2007). In stage 1, the store decides how many yogurt varieties to offer (V). Given variety offerings, stores compete in prices (p) and realize profits in stage 2.

Adding varieties affects store profits via two channels: volume sales and prices. Firstly, volume sales likely increase in V because more varieties satisfy heterogeneous preferences of more consumers as long as the total demand is not fixed. The sales effect likely enlarges in income/wealth of consumers (Y). Secondly, product offerings affect equilibrium prices because adding varieties draws consumers' attention away from prices (e.g., Bordalo et al. 2013; Richards et al. 2020) and, on the other hand, can intensify price competition by crowding the variety space and press down p in equilibrium. This second price effect tends to be weakened by higher Y.

Given these conflicting effects, it is easy to show that the profit-maximizing V has an ambiguous relationship with Y. In the following sections, we construct a sample of store-level observations of product offerings and measure county-level income as well as wealth variation to identify the average effect of demand shocks on stores' variety decisions.

3. DATA

In this section, we describe the data sources, define key variables used in the econometric models, and present summary statistics of the variables. Several measurements of local market economic conditions, including consumer income and wealth, are constructed. Substantial variation in income and wealth across U.S. counties and over time allows us to identify the variety and price effects of local demand shocks.

3.1 Retail scanner data

Our analysis is primarily based on the Nielsen Retail Scanner data (RMS). RMS covers the period of 2006-2010 and contains information of over 100 retail chains in 49 U.S. states (Nielsen, 2023).

This period covers two years before and three years around the peak of the Great Recession. The dataset includes over 45,000 retail stores that report sales and volumes sold of over 6,000 unique yogurt products on a weekly basis. The product is defined by the UPC and has specific attributes.

We know the location of each store at the county level and the format of a store. Specifically, a store is a convenience store, drug store, grocery store, or a mass merchandiser. Because convenience stores and drug stores are minor sellers of yogurt products, contributing less than 0.3% of yogurt sales during the period of interest, we focus on grocery stores and mass merchandisers in this study. Grocery stores, which compete more intensively in product differentiation, generally offer a much richer product portfolio than mass merchandiser stores that tend to be cost-leaders (see detailed statistics are shown in section 4).

We aggregate original weekly data to the monthly, quarterly, and yearly to match with income measures. We do so also because using the weekly data may over-count the number of products removed from the shelf. If a product happens to have zero sales in a week or experiences a temporary stockout, it is not observed in RMS, yet may still be on the shelf. By aggregating data to the monthly/quarterly/yearly level, a product is counted as long as it is sold for once in a month/quarter/year. Given that yogurt is a perishable product, the aggregation should largely, if not completely, eliminate the problem of missing products due to zero sales in a week.

3.2 Income, wealth, and other data

The Great Recession had drastic impacts on household income and wealth all over the country, but with effects being more severe in some locations than others because of reasons such as different distributions of local consumers' occupations. We have two measures of local demand shocks, namely, changes in income and changes in wealth of local households. Both income and wealth may affect the demand (e.g., Dubé et al. 2018). We define the local market at the county level to match with the county-level information of income and wealth.

Unemployment rates, median income, and wage rates are proxies for local income and are obtained from the U.S. Bureau of Labor Statistics. Unemployment rates are observed for a county on a monthly basis, average wage rates on a quarterly basis, and median household income on a yearly basis. For easier interpretation of the econometric outcomes, we transform the unemployment rate to an "employment rate" which equals 100 minus the unemployment rate. In this way, increases in all these income variables, monthly employment rate, quarterly wage rate, and yearly household income, mean increases in the local demand.

The information on house values is a proxy for local wealth following Dubé et al. (2018) and Mian et al. (2015) and is acquired from Zillow.com. House value is observed on the monthly basis. The deep economic fall during the Recession is highlighted in figure 1; a rapid and large jump in the unemployment rate and a quick fall in the house value from September 2008 to December 2010. The recovery from the recession was quite slow. Even by the end of 2014, for example, the average house value had not quite returned to the pre-Recession level. Considerable spatial variation in county-level income and wealth can be seen in Appendix 2.

[Figure 1 approximately here]

Food subsidies like Supplemental Nutrition Assistance Program (SNAP) have significant impacts on local demand (e.g., Hastings and Shapiro 2018). Given that SNAP dollars tend to be negatively correlated with local income levels and store decisions, we include SNAP issuance as a control variable in the econometric models. Total SNAP dollar issuance is obtained from USDA Food and Nutrition Service (https://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap).

The demographic structure of a county also affects the demand for food products. To control for the demographic structure, we obtain information on county-level population and gender ratio on a yearly basis. Again, there is considerable variation in demographics across counties. Table 1 provides summary statistics of the variables measuring local economic conditions and demographics.

[Table 1 approximately here]

4. ECONOMETRIC MODELS

We consider three measurements of product assortment of retail stores. First, we count the number of UPCs and varieties sold by a retailer. Second, we measure the proximity of brands in the variety space using a uniqueness index following Sweeting (2010). Third, we measure the size of products. The corresponding econometric models and our identification strategy are illustrated.

4.1 Product variety

Given the pool of available products in the market, a retail store decides how many unique products (i.e., UPCs) to put on the shelf. We count the number of UPCs carried by each store in a month, a quarter, and a year, respectively. Beside the number of unique products, the number of varieties matters. In Nielsen data, a yogurt variety can be characterized by the flavor (e.g., peach and vanilla), style (e.g., Greek and French), and type (i.e., low-fat and goat milk) of a product. Such information is only available for national-brand UPCs, but not private-label products which account for some 10% of the market by sales. We classify yogurt into 7 flavors, 18 styles, and 16 types as detailed in Appendix 3 and then use the combination of the three attribute dimensions to define varieties. For example, vanilla, fat-free Greek yogurt represents one variety. In total, we have 206 varieties in the sample.

Let i denote the retail store, m the market (i.e., county), and t the period (e.g., month). The dependent variable is the number of UPCs or varieties. Our baseline regression is:

(1) $$y_{imt} = \alpha_0 + \alpha_1 I_{mt} + \alpha_2 W_{mt} + \theta_1 y_{im}^{2006} + \theta_2 N_t + R_r + M_m + Z_{mt} + X_{imt} + T_t + \epsilon_{imt},$$

where I_{mt} is the income variable and W_{mt} is the wealth variable. The mean of the dependent variable in 2006 or pre-Recession, y_{im}^{2006}, is used as a proxy for unobserved shelf space and some continuing assortment strategy or other fixed conditions of the store.

The total number of UPCs available on the U.S. market in t is denoted by N_t. Controlling for the availability of products is critical, because it helps distinguish the assortment by retailers from manufacturers' production changes under demand shocks. There is evidence, for example, that the number of varieties produced under an economic downturn is jointly affected by decisions of retailers, manufacturers, and stock-outs (IRI 2020). We plot the total number of yogurt UPCs and varieties on the U.S. market in Appendix 3. Figure A3 shows that, though product availability grows over time, the growth rate slows down during the Recession. As long as retail stores are able to pick UPCs from the national pool of available products offered by manufacturers, controlling for N_t isolates the assortment effect of income/wealth shocks on stores.

Vector R_r includes retail chain dummies. Vector M_m contains county fixed effects, Z_{mt} includes the county-year population and gender ratio and county-period SNAP issuance, and X_{imt} is the store-county-period number of competitor stores (i.e., stores belonging to different retail chains in the same local market and period).[1] The Recession made more households eligible for food assistance (i.e., negatively correlated with demand shocks), and product offerings may be

[1] SNAP issuance is reported in January and July each year for each county. We let January to June take SNAP issuance reported in January, and July to December take SNAP issuance reported in July. When using quarterly observations, the first two quarters take the January value, and the other two quarters take the July value. When using yearly observations, the average of January and July values are used for a year. We also ran regression controlling for SNAP participation data and obtained consistent outcomes which are available upon request.

positively correlated with food subsidies. Not controlling for SNAP issuance might hence bias the income and welfare effects toward zero. Vector T_t contains quarter dummies, year dummies, and a trend if using monthly data. It contains quarter and year dummies for quarterly data and year dummies for yearly data. The error term is denoted by ϵ_{imt}. Standard errors are clustered at the state level to account for potential correlation among stores in the same state and store-level autocorrelation.

4.2 Brand proximity

When changing the number of products, a store may effectively reposition a given number of brands in the variety space, narrowing or widening the proximity of brands. Even when the number of products remain unchanged, the proximity of brands can be adjusted by repositioning products. For instance, instead of having three brands selling strawberry flavored yogurt, the store may keep only one brand offering the strawberry flavor and the other two brands offering different flavors. As a result, there would be a greater "distance" among brands in the variety space.

Under negative demand shocks, a retail store may be incentivized to reduce brand proximity in the variety space to help soften within-store price competition facing more price sensitive consumers. On the other hand, the proximity among brands may enlarge, if products removed by a retail store are mostly niche products (e.g., special flavors) and the remaining products are largely mainstream ones (e.g., vanilla) that are close to each other in the variety space. The net change in brand proximity is an empirical question.

To measure the proximity of yogurt brands carried by a store, we follow Sweeting (2010) and construct a uniqueness index. Given a variety space, this index indicates the proportion of unique varieties that a brand carries compared with all other brands in the same store. For example, assume a store carries two brands. Brand 1 offers varieties A and B, and Brand 2 offers varieties

A, B, and C. The uniqueness index for Brand 1 is zero, because all its varieties are offered by the other brand. Brand 2's uniqueness index is $\frac{1}{3}$, because variety C is unique. The index varies from zero to one. When it is zero, it means that the brand carries no unique variety compared with other brands in the store. When it is one, it means that none of the varieties carried by the brand is in common with other brands in the store. Partial uniqueness has a value between 0 and 1. The larger the index, the more differentiated the brand is from other brands. Again, because variety information is only available to national-brand products, this index measures proximity among national brands.

We compute the brand-store-period specific uniqueness value for each period. Taking the simple average of uniqueness values across all brands in a store, we obtain the store-period specific measure of brand proximity. For grocery stores, the mean is 0.25, and the mean is 0.49 for mass merchandisers. It is not surprising that mass merchandisers, which generally sell fewer unique products than grocery stores do, are able to separate brands more in the variety space. We construct a regression on the uniqueness index, U_{imt}, in a similar way as equation (1):

(2) $$U_{imt} = \beta_0 + \beta_1 I_{mt} + \beta_2 W_{mt} + \theta_1 U_{im}^{2006} + \theta_2 N_t + R_r + M_m + Z_{mt} + X_{imt} + T_t + \epsilon_{imt},$$

where the variables are defined as in equation (1) and U_{im}^{2006} is the average index value of the store in 2006. Standard errors are clustered at the state level as before.

4.3 Product sizes

Retailers often adjust UPC sizes of products for various purposes, such as changing the unit price "secretly" through "shrinkflation", where price per unit increases by reducing the UPC size (Yonezawa and Richards 2016). In theory, the store may want to carry more small packaged products because each product becomes cheaper, appealing to consumers who tend to reduce expenditure under income or wealth losses. On the other hand, the store may carry more large packaged products that have relatively low unit prices, facing more price sensitive consumers. Whether more small or large packaged UPCs are removed in a recession is an empirical question.

We measure the average size of yogurt products offered by a store (S_{imt}) by taking a simple average of product sizes. One product (i.e., a UPC) may contain multiple containers, and the product size equals the per-container size (e.g., 8 ounces per bottle) multiplied by the number of containers (i.e., two bottles per UPC) in a product. For example, consider a store selling two yogurt products. One product is a 4-ounce bottle, and the other consists of two 4-ounce bottles. Regardless of the numbers of units sold for the two products, we compute the average product size of the store as $\frac{4+4\times 2}{2}$ = 6 ounces. The regression is specified as:

(3) $$S_{imt} = \gamma_0 + \gamma_1 I_{mt} + \gamma_2 W_{mt} + \theta_1 S_{im}^{2006} + \theta_2 N_t + R_r + M_m + Z_{mt} + X_{imt} + T_t + \epsilon_{imt},$$

where the variables are defined as in equation (1) and S_{im}^{2006} is the average product size of the store in 2006. Table 2 indicates that the simple average UPC size is nearly 13 ounces for grocery stores and about 9 ounces for mass merchandisers.[2]

Summary statistics of the number of UPCs, the number of varieties, the uniqueness index, the average product size, and the number of local competitor stores are displayed in table 2. On average, a grocery store carries three times as many UPCs as a mass merchandiser and twice as many varieties. Given the considerable differences in product offerings, we conduct regressions for grocery stores and mass merchandisers separately throughout section 5.

[Table 2 approximately here]

[2] To see whether changes in the average UPC size is driven by changes in the size of a container or the number of containers, we used the simple average container size and number of containers at the store-period level as the dependent variables in equation (3). We revisit this issue in section 5.1.

4.4 Identification

To identify the impact of demand shocks on the product assortment of retail stores, we take the advantage of rich spatial and temporal variation in household income and wealth driven by the 2008 Great Recession. Our baseline regressions use data from 2006 to 2010, a few years when the heaviest demand shocks occurred. As long as income and wealth shocks on the local market are independent from product offerings of individual stores, controlling for the set of variables and fixed effects specified in section 4.1, our identification strategy is valid.

One factor that could invalidate this assumption is an unobservable that affects the location of a store, and hence demand shocks experienced, and the product offerings; however, in our dataset, no store moved to a different county from 2006 to 2011, suggesting little evidence for the concern of such unobservable factors.

Another possible confounding factor is that stores that carry relatively more or fewer varieties systematically experience more severe economic shocks during the Recession. It could be that stores located in relatively wealthy regions, for example, offer more varieties in general and experience less income/wealth decreases in the Recession. If so, we would see a strong correlation between the varieties offered in a store before the Recession, or 2006 in our context, and their income/wealth decreases in later years. We compute the correlation coefficients of dependent variables in equations (1) to (3) with the annual changes in income and wealth for the years of 2008 to 2010. For grocery and mass merchandiser stores, the correlation coefficients are small with magnitudes less than 0.03 in all instances. There is little evidence that Recession-driven demand shocks were systematically related to retailers' pre-Recession assortment decisions.

5. RESULTS

In this section, we first discuss the baseline estimation outcomes. We run a large set of robustness tests to examine the sensitivity of baseline outcomes. Given evidence of price and assortment adjustments made by stores, we employ a discrete choice demand model to estimate the net welfare impact of the adjustments on U.S. yogurt consumers.

5.1 Variety effects of demand shocks

Table 3 displays the baseline regression outcomes using monthly, quarterly, and yearly data, respectively. All the baseline estimates hold after excluding the three largest yogurt manufacturers' UPCs from the sample (see online appendix table B1), indicating little concern over manufacturers deciding store-level assortment.

[Table 3 approximately here]

High R-squared values suggest good fit of all specifications. The general patterns are consistent across frequencies of observations. Specifically, a negative income shock and/or a negative wealth shock induce retail stores to reduce the number of products offered. Columns (1) and (2) show that, when the local wealth (i.e., house value) falls by 1%, grocery stores drop 4.0 UPCs on average or 2.2% of the mean number of UPCs, and an average mass merchandisers drop 3.4 UPCs or 5.7% of the mean UPC number. Columns (3) and (4) show that, when income (i.e., wage) falls by 1% in a quarter, the number of unique products falls by 11.3 or 17.7% of the mean number for mass merchandisers. When wealth falls by one 1% in a quarter, the number of UPCs falls by 5.6 or 2.9% of the mean number for grocery stores. The magnitudes of impacts continue to increase in columns (5) and (6), suggesting that the assortment adjustments strengthen as negative shocks persist. As the number of UPCs falls, the number of UPC varieties decreases as well, suggesting a less diverse portfolio under negative demand shocks.

Changes in the uniqueness index suggest that the differentiation of brands tends to decrease under negative demand shocks, but the effect is weak. Using monthly data, when the local employment rate decreases by 10 percentage points, the uniqueness index for mass merchandiser stores decreases by 3.7 or 14.4% of its standard deviation. Yearly data reveal a similar effect on the uniqueness index for grocery stores. Brands become relatively close to each other in the variety space, likely because more niche products than the mainstream ones under the brands are removed by the store. The remaining products are hence similar across brands.

Finally, there is evidence that grocery stores tend to offer UPCs in relatively large sizes under negative demand shocks, while mass merchandisers offer smaller ones. For grocery stores, lowering unit prices by offering larger packages seems to outweigh lowering UPC prices by offering smaller packages, and the reverse applies to mass merchandisers. Specifically, if the quarterly wage rate decreases by 5%, the average UPC size of a grocery store would enlarge by 1.2 ounces or 76.9% of the standard deviation.[3]

Many prior studies find that consumers are more likely to buy large-sized products, when their income or wealth falls (e.g., Nevo and Wong 2019), and attribute the behavior to more searching by consumers for lower unit-price products. Our finding cautions this reasoning and suggests that consumers would end up buying more large-sized products on average even without more intensive searching, because their choice set contains more large-sized products due to

[3] We also find that grocery stores tend to offer UPCs with more and larger containers as local income falls. Mass merchandisers offer UPCs with fewer containers as local wealth falls. Outcomes are available upon request.

retailers' assortment adjustments. The distinction between the two drivers of the observed behavioral changes is important.

5.2 Robustness tests

We perform a large set of robustness tests to check the sensitivity of baseline outcomes with details reported in the online appendix. (1) To address the concern that manufacturers may affect the store-level assortment, we conduct two robustness tests. First, we exclude the top three yogurt manufacturers (i.e., Chobani, Dannon, and Yoplait jointly occupying more than 70% of total sales) from the sample. The dominant manufacturers might affect store assortment via bargaining with retailers. For instance, a store might not be able to drop a Chobani UPC if Chobani would not allow so. Second, we calculate the chain-year sales Herfindahl-Hirschman Index (HHI) of brands and exclude observations with HHIs in the upper quartile for each retail format. Specifically, HHI higher than 0.30 suggests that the chain's yogurt sales are occupied by one large manufacturer that may act as the category captain to manage the category (Subramanian et al. 2010; Viswanathan et al. 2021). Table B1 confirms the baseline findings and that we have identified assortment decisions of retailers instead of manufacturers.

(2) Instead of using data from 2007 to 2010, we conduct the estimation using observations from 2008 to 2009 when the Recession was the most severe. Also, instead of defining yogurt varieties by the combination of three attribute dimensions, flavors, styles, and types, we estimate the income and wealth effects on flavors, styles, and types, respectively. Third, we use the number of brands and the number of UPC sizes (i.e., ounces per UPC) in a store to measure the richness of its product offering. Estimates in table B2 confirm the patterns shown in table 3 and ensure that our findings are robust to missing information on private-label UPCs.

(3) One may be concerned that assortment adjustments take a relatively long time to realize because of, for instance, contractual arrangements between manufacturers and a retail store. Such behavior would imply that product offerings in the current month may be determined by local income and wealth in prior months. The fact that baseline estimates are similar using quarterly and yearly data should largely eliminate this concern. Nevertheless, we use the two-month rolling average income/wealth (e.g., $\frac{I_{mt}+I_{mt-1}}{2}$) to replace current month income/wealth in equation (1). The estimates in table B3, again, are highly consistent with table 3.

(4) Another potential concern is the measurement of local competition. Simply counting the number of competitor stores may not precisely measure the competition in yogurt variety faced by a retail store. We hence construct an alternative variable, the average number of UPCs carried by a competitor store in the county, to indicate the intensity of variety competition in the local market. Table B4 displays estimates similar to table 3.

(5) Confirm that local demand shocks drive assortment in a store, we add retailer-chain-level income and wealth as control variables. Controlling for chain-level income and wealth is relevant, because evidence shows that retail chains make assortment decisions at the chain level as well (DellaVigna and Gentzkow 2019). Table B5 shows that, though chain-level income and wealth often have significant impacts on store-level assortment, the effects of local income and wealth remain similar as those in table 3.

5.3 Price effects of demand shocks

To determine the consumer welfare implications of demand shocks, we need to understand how retailers adjusted prices jointly with variety. Product offerings by a store also affect equilibrium prices of products in the store. In order to identify the direct effect of demand shocks on product prices, we need to rule out the indirect price effect that demand shocks impose through changing the store's product portfolio.

We examine UPC prices, controlling for the store's product offerings. Taking monthly observations as an example, the store-level average price of a UPC (subscript j) is measured by real \$cents per ounce and has a mean of 13.09 (11.62) with a standard deviation of 4.72 (3.65) for grocery stores (mass merchandisers). Given that the weighted average size of a UPC is about 11 ounces, the average price per UPC is about \$1.4. We set up the regression for UPC-level price effect as:

(4) $\log(p_{jimt}) = \gamma_0 + \gamma_1 I_{mt} + \gamma_2 W_{mt} + \theta_1 X_{imt} + \theta_2 N_t + J_j + R_r + M_m + Z_{mt} + X_{imt} + T_t + \epsilon_{jimt}$,

where X_{imt} describes the store's product portfolio. The vector contains the number of UPCs, the average size of UPCs, and the index of brand proximity. We use the number of available UPCs on the market and X_{imt} values in 2006 as the instrumental variables (IVs) for X_{imt}. Other variables are defined in equation (1). The UPC fixed effects, J_j, are added to capture unobserved UPC attributes that affect prices.

Table 4 shows that, for a 10% wealth decrease in a month, quarter, or year, grocery stores and mass merchandisers reduce price by 0.1-0.3%. Negative income shocks lead to even smaller and mixed price effects. These estimates show some interesting contrast against the estimated variety effects in table 3. First, price adjustments measured in percentage are small compared with the assortment changes for both formats of stores. Second, while stores make larger assortment changes as a shock persists, their price adjustments do not vary much in the persistence of demand shocks. It is probably because stores generally obtain low profit margins and have limited room for further lowering prices. They hence make larger assortment instead of larger price adjustments if the demand shock lasts.

[Table 4 approximately here]

5.4 Welfare analysis

We have shown that retail stores tend to remove products in an economic recession, which harms consumers, *ceteris paribus*, but stores simultaneously lower prices, which benefits consumers. To quantify the net welfare impact of the price and non-price responses, we estimate demand for yogurt and compute changes in consumer surplus (CS) in various counterfactual settings.

Income and wealth shocks during the Recession exogenously and simultaneously affect consumer demand, retailer assortment, and retail prices. To measure CS under the shocks, we need a demand model that is able to incorporate the three dimensions of impact. The simple logit discrete choice model is adopted for its flexibility. To be clear, this model falls short on considering heterogeneity in the net welfare impact, for instance, across income levels. Our focus is on the average welfare impact. High-income consumers are, plausibly, less price sensitive and value variety more than low-income consumers. Thus, if there is a decrease in CS on average, the decrease for high-income consumers is likely larger and that for low-income consumers is smaller or could even be reserved.[4]

Using the simple logit discrete choice model, calculating CS changes takes four steps. First, we estimate consumer demand during the Recession. Second, the baseline assortment and prices of yogurt products are characterized by the pre-Recession period (i.e., 2007). The baseline CS is

[4] Readers interested in heterogeneity in CS changes may refer to Handbury (2021) for a novel utility model that incorporates income-specific variety tastes and price sensitivities.

computed accordingly. Third, given estimated assortment and price effects of income and wealth shocks (see tables 3 and 4), we vary the baseline choice set and compute counterfactual CSs. Fourth, baseline and counterfactual CSs are compared.

Detailed calculation process, summary statistics, and estimation outcomes are presented in Appendix 4. A brief summary is given below. Using the weekly observations from September 2008 to August 2010, we construct a 104-week long sample of yogurt sales in the 30 most populated U.S. counties (located in 12 states) in the Nielsen data. All brand-retailer-specific UPCs sold in each county each week are considered.

Following Villas-Boas (2007), we define the county-week outside option as the difference of the total yogurt consumption (USDA, 2023) and the yogurt volume from Nielsen. Demographic information is obtained from Nielsen Home Scan Data by random selection of households located in each of the 30 counties. Averaging the demographic information of selected households generates market-level demographic variables.

The logit discrete choice model is employed for estimation (e.g., Nevo 2001):

$$(5) \qquad \ln(s_{jmt}) - \ln(s_{0mt}) = x_{jt}\beta - \alpha p_{jmt} + \xi_j + \tau_t + \epsilon_{jmt},$$

where s_{jmt} is the volume share of UPC j in county m in week t, s_{0mt} representing shares of the outside good, p_{jmt} is the price of j in m in t, x_j is a K-dimensional vector of observed product characteristics (i.e., UPC size), ξ_j captures product characteristics unobserved to researchers (i.e., brand and retailer fixed effects), τ_t includes year and quarter fixed effects and demographic information, and ϵ_{jmt} is the mean-zero error term.

Following Allcott et al. (2020), we construct the price instrument by calculating retail chains' cost advantages relative to the national average for each UPC. The intuition is that retail chains supplying products to different geographic areas have different costs, leading to different comparative advantages even for the same products across areas. It involves three steps to construct the instrument. First, we calculate the average log price of UPC j sold by retailer r in all counties but m in week t, $p_{jrt,-m}$. Second, we compute the national average price of UPC j sold all counties but m in week t, $p_{jt,-m}$. Finally, the instrument is constructed as $\Delta \log(p_{jrt,-m}) = \log(p_{jrt,-m}) - \log(p_{jt,-m})$. The estimated own-price elasticities of yogurt products ranges have a mean of -2.1 with standard deviation of 1.0, confirming that yogurt products are price elastic.

Given the estimation outcomes, we compute CS in each week m (Small and Rosen 1981; Hanemann 1984):

$$CS_{m0} = \frac{1}{\alpha} \ln\left(\sum_{j=1}^{J} e^{V_{jm}}\right) + C,$$

where α is the magnitude of price coefficient in equation (5), V_j is the indirect utility of consuming UPC j and equals $x_{jt}\beta - \alpha p_{jmt} + \xi_j + \tau_t$, and C is Euler's constant.

We are interested in the counterfactual setting where the set of UPCs shrinks and their prices fall. In particular, we consider a grocery store facing a 5.0% reduction in the local wealth. Relying on the first columns of table 3 and table 4, the number of UPCs would reduce by about $\frac{4.05\times 5\%}{177.84}$ ≈11% relative to the mean number of UPCs carried by a grocery store and the prices would fall by about $0.03\% \times 5$ ≈0.2%. To remove UPCs, table A4 indicates that UPCs with relatively small market shares are more likely to be removed. We hence generate a random probability of removal for all UPCs with UPC of relatively small volume shares having higher removal probabilities (see online Appendix 2). For remaining products, we lower their prices by 0.2% to reach p'_{jmt}. We hence obtain V'_{jm} as the indirect utility of consuming UPC j and equals $x_{jt}\beta - \alpha p'_{jmt} + \xi_j + \tau_t$.

With a new set of UPCs and lower prices, we compute the change in CS as:

$$\Delta CS_m = CS_{m1} - CS_{m0} = \frac{1}{\alpha}\ln\left(\sum_{j=1}^{J'} e^{V'_{jm}}\right) - \frac{1}{\alpha}\ln\left(\sum_{j=1}^{J} e^{V_{jm}}\right),$$

where J' indicates the new set of UPCs after removals. We repeat the simulation for 100 times to generate 100 sets of random probabilities and 100 counterfactual sets of UPCs, given alternative total proportions of UPCs removed and the fixed price reduction of 0.2%.

Table 5 reports the statistics of two-year average changes in the CS based on each set of 100 simulations with CS measured in real $cent per ounce. Column (1) suggests that, when the proportion of UPC removed is 11% and the price decrease is 0.2%, the mean decrease in the CS is $0.97 cents and the standard deviation is 0.01. Given the U.S. population and per-capita consumption of yogurt from 2008 to 2010, the decrease in CS upon one purchase translates to a loss in CS of about $36 million per year in the United States.

We also lower the proportion of UPC removed to 8.0%, 4.0%, and 0.2% and re-run the simulations. Columns (2) to (4) suggest that even smaller variety reductions have considerable welfare impacts. Column (3) shows the welfare loss due to a 0.2% UPC removal is canceled out by the 0.2% price reduction, leading to a net increase in the CS of $0.4 million per year for U.S. yogurt consumers.[5] The simulation outcomes highlight the importance of incorporating changes in the choice set facing consumers in addition to price changes, when estimating the welfare impact of an economic recession.

[Table 5 approximately here]

---

[5] As a robustness test, we computed CS using 2006-2007 observations to estimate the demand (i.e., effectively fixing demand at the pre-Recession level) and obtained almost identical outcomes. We also tried alternative samples by selecting the top 50 or 200 UPCs in each of the 30 counties and obtained consistent outcomes.

6. CONCLUDING REMARKS

In contrast with extensive research on retailers' price responses to demand shocks, studies on non-price responses have been scant. We provide empirical evidence for the multidimensional margins in which retailers adjust to demand shocks. We rely on scanner data of the U.S. yogurt market to provide insights into stores' assortment adjustments driven by income and wealth shocks in the local market. Evidence indicates that reductions in local income and wealth result in stores reducing prices and responding in non-price dimensions, including carrying fewer varieties, changing product sizes (i.e., ounces/UPC), and reducing brand proximity. Discontinued products in a year tend to be those with small market shares in the previous year.

This study focused on demand shocks associated with the Great Recession, but the phenomena uncovered are likely relevant beyond the historical period. For example, the U.S. food retailing sector experienced massive disruptions in the wake of shutdowns surrounding COVID-19 in March and April 2020. The grocery sector experienced a dramatic increase in sales as consumers stocked up in anticipation of reduced mobility, among other factors (Lusk and McCluskey 2020), while the demand for food services collapsed. There were additional supply disruptions that reduced productivity (e.g., labor illness) and prevented food from moving easily from food service to food retail sectors. During this period, the total number of UPCs sold by U.S. retail stores reportedly fell by 8.7% relative to the prior year (IRI 2020). While this reduction in retail offerings is a result of both supply and demand shocks, it underscores the fact that retailers respond in both price and non-price dimensions. As we showed, the welfare impacts of variety changes may very well dominate the typically studied price-driven welfare effects.

There are a number of topics worthy of additional research. First, it is of interest to determine demand-shock induced assortment adjustments in a larger number of product categories, including those with fewer varieties than yogurt and less room for variety changes. Second, we explored demand-induced variety changes by looking at the number of varieties, brand uniqueness, and UPC sizes, but there are many more changes that retailers can make. Such changes include a mix of product claims, nutritional profiles, stock-out rates, and in-store services (Cavallo and Kryvtsov 2021), but are not observed in Nielsen data. Finally, changing varieties in a store changes the depth of its product line and the differentiation at the store-level (Hamilton and Richards 2009), too, further influencing consumer behavior. Knowledge of these and other phenomena are needed to help deepen understanding of the non-price strategies of food retailers and the welfare impacts on consumers.

REFERENCES

Allcott, H., Diamond, R., Dubé, J. P., Handbury, J., Rahkovsky, I., & Schnell, M. (2019). Food Deserts and the Causes of Nutritional Inequality. *Quarterly Journal of Economics*, *134*(4), 1793-1844. https://doi.org/10.1093/qje/qjz015

Aguiar, M., Hurst, E., & Karabarbounis, L. (2013). Time Use during the Great Recession. *American Economic Review*, *103*(5), 1664-1696. https://doi.org/10.1257/aer.103.5.1664

Antoniades, A., Clerides, S., & Xu, M. (2018). Micro-Responses to Shocks: Pricing, Promotion, and Entry. CEPR Discussion Paper No. DP13281, Available at SSRN: https://ssrn.com/abstract=3274624

Argente, D., Lee, M., & Moreira, S. (2018). Innovation and Product Reallocation in the Great Recession. *Journal of Monetary Economics*, *93*, 1-20. https://doi.org/10.1016/j.jmoneco.2017.11.003

Bayus, B. L., & Putsis Jr, W. P. (1999). Product Proliferation: An Empirical Analysis of Product Line Determinants and Market Outcomes. *Marketing Science*, *18*(2), 137-153. https://doi.org/10.1287/mksc.18.2.137

Bernard, A. B., Redding, S. J., & Schott, P. K. (2010). Multiple-Product Firms and Product Switching. *American Economic Review*, *100*(1), 70-97. https://doi.org/10.1257/aer.100.1.70

Bordalo, P., Gennaioli, N., & Shleifer, A. (2013). Salience and Consumer Choice. *Journal of Political Economy*, *121*(5), 803-843. https://doi.org/10.1086/673885

Buijs, P., Danhof, H. W., & Wortmann, J. H. C. (2016). Just-in-Time Retail Distribution: A Systems Perspective on Cross-Docking. *Journal of Business Logistics*, *37*(3), 213-230. https://doi.org/10.1111/jbl.12135

Cavallo, A., & Kryvtsov, O. (2021). What Can Stockouts Tell Us About Inflation? Evidence from Online Micro Data. *NBER Working Paper,* No. 29209. https://doi.org/10.3386/w29209

Chevalier, J. A., Kashyap, A. K., & Rossi, P. E. (2003). Why Don't Prices Rise During Periods of Peak Demand? Evidence from Scanner Data. *American Economic Review*, *93*(1), 15-37. https://doi.org/10.1257/000282803321455142

Coibion, O., Gorodnichenko, Y., & Hong, G. H. (2015). The Cyclicality of Sales, Regular and Effective Prices: Business Cycle and Policy Implications. *American Economic Review*, *105*(3), 993-1029. https://doi.org/10.1257/aer.20121546

Copeland, A., Dunn, W., & Hall, G. (2011). Inventories and the Automobile Market. *RAND Journal of Economics*, *42*(1), 121-149. https://doi.org/10.1111/j.1756-2171.2010.00128.x

DellaVigna, S., & Gentzkow, M. (2019). Uniform Pricing in U.S. Retail Chains. *Quarterly Journal of Economics*, *134*(4), 2011-2084. https://doi.org/10.1093/qje/qjz019

Dekimpe, M. G., Gielens, K., Raju, J., & Thomas, J. S. (2011). Strategic Assortment Decisions in Information-Intensive and Turbulent Environments. *Journal of Retailing*, *87*, S17-S28. https://doi.org/10.1016/j.jretai.2011.04.006

Draganska, M., & Jain, D. C. (2005). Product-Line Length as a Competitive Tool. *Journal of Economics & Management Strategy*, *14*(1), 1-28. https://doi.org/10.1111/j.1430-9134.2005.00032.x

Dubé, J. P., Hitsch, G. J., & Rossi, P. E. (2018). Income and Wealth Effects on Private-Label Demand: Evidence from the Great Recession. *Marketing Science*, *37*(1), 22-53. https://doi.org/10.1287/mksc.2017.1047

Gagnon, E., & López-Salido, D. (2020). Small Price Responses to Large Demand Shocks. *Journal of the European Economic Association*, *18*(2), 792-828. https://doi.org/10.1093/jeea/jvz002

Griffith, R., O'Connell, M., & Smith, K. (2016). Shopping around: How Households Adjusted Food Spending over the Great Recession. *Economica*, *83*(330), 247-280. https://doi.org/10.1111/ecca.12166

Hamilton, S. F., & Richards, T. J. (2009). Product Differentiation, Store Differentiation, and Assortment Depth. *Management Science*, *55*(8), 1368-1376. https://doi.org/10.1287/mnsc.1090.1032

Handbury, J. (2021). Are Poor Cities Cheap for Everyone? Non-Homotheticity and the Cost of Living Across U.S. Cities. *Econometrica*, *89*(6), 2679-2715. https://doi.org/10.3982/ECTA11738

Hanemann, W. M. (1984). Discrete/Continuous Models of Consumer Demand. *Econometrica*, *52*(3), 541-561. https://doi.org/10.2307/1913464

Hastings, J., & Shapiro, J. M. (2018). How Are SNAP Benefits Spent? Evidence from a Retail Panel. *American Economic Review*, *108*(12), 3493-3540. https://doi.org/10.1257/aer.20170866

Hwang, M., Bronnenberg, B. J., & Thomadsen, R. (2010). An Empirical Analysis of Assortment Similarities across U.S. Supermarkets. *Marketing Science*, *29*(5), 858-879. https://doi.org/10.1287/mksc.1100.0564

IRI. (2020). *Part 7 – Defending and Recapturing the Shelf.* Special COVID-19 Series: Recession-Proof Your Business. Available online at: https://www.iriworldwide.com/IRI/media/Library/IRI-TL-Recession-Series-Part-7-Defending-and-Recapturing-the-Shelf-7-6-2020-vF.pdf

Jaravel, X. (2019). The Unequal Gains from Product Innovations: Evidence from the U.S. Retail Sector. *Quarterly Journal of Economics*, *134*(2), 715-783. https://doi.org/10.1093/qje/qjy031

Jaravel, X., & O'Connell, M. (2020). Real-Time Price Indices: Inflation Spike and Falling Product Variety during the Great Lockdown. *Journal of Public Economics*, *191*, 104270. https://doi.org/10.1016/j.jpubeco.2020.104270

Lusk, J., & McCluskey, J. (2020). Consumer Behavior during the Pandemic. *Economic Impacts of COVID-19 on Food and Agricultural Markets, Council for Agricultural Science and Technology (CAST): Ames, IA, USA*, 11-13. Available at: https://www.cast-science.org/publication/economic-impacts-of-covid-19-on-food-and-agricultural-markets/

Matsa, D. A. (2011). Competition and Product Quality in the Supermarket Industry. *Quarterly Journal of Economics*, *126*(3), 1539-1591. https://doi.org/10.1093/qje/qjr031

Mian, A., Sufi, A., & Trebbi, F. (2015). Foreclosures, House Prices, and the Real Economy. *Journal of Finance*, *70*(6), 2587-2634. https://doi.org/10.1111/jofi.12310

Nevo, A. (2001). Measuring Market Power in the Ready-to-Eat Cereal Industry. *Econometrica*, *69*(2), 307-342. https://doi.org/10.1111/1468-0262.00194

Nevo, A., & Wong, A. (2019). The Elasticity of Substitution between Time and Market Goods: Evidence from the Great Recession. *International Economic Review*, *60*(1), 25-51. https://doi.org/10.1111/iere.12343

Nielsen, 2023. Access to NielsenIQ data with permission: https://www.chicagobooth.edu/research/kilts

Richards, T. J., & Hamilton, S. F. (2015). Variety Pass-Through: An Examination of the Ready-to-Eat Breakfast Cereal Market. *Review of Economics and Statistics*, *97*(1), 166-180. https://doi.org/10.1162/REST_a_00447

Richards, T. J., Klein, G. J., Bonnet, C., & Bouamra-Mechemache, Z. (2020). Strategic Obfuscation and Retail Pricing. *Review of Industrial Organization*, *57*(4), 859-889. https://doi.org/10.1007/s11151-019-09744-z

Saitone, T. L., & Sexton, R. J. (2010). Product Differentiation and Quality in Food Markets: Industrial Organization Implications. *Annual Review of Resource Economics*, *2*(1), 341-368. https://doi.org/10.1146/annurev.resource.050708.144154

Small, K. A., & Rosen, H. S. (1981). Applied Welfare Economics with Discrete Choice Models. *Econometrica*, *49*(1), 105-130. https://doi.org/10.2307/1911129

Stroebel, J., & Vavra, J. (2019). House Prices, Local Demand, and Retail Prices. *Journal of Political Economy*, *127*(3), 1391-1436. https://doi.org/10.1086/701422

Subramanian, U., Raju, J. S., Dhar, S. K., & Wang, Y. (2010). Competitive Consequences of Using a Category Captain. *Management Science*, *56*(10), 1739-1765. https://doi.org/10.1287/mnsc.1100.1211

Sweeting, A. (2010). The Effects of Mergers on Product Positioning: Evidence from the Music Radio Industry. *RAND Journal of Economics*, *41*(2), 372-397. https://doi.org/10.1111/j.1756-2171.2010.00104.x

USDA. (2023). *Dairy Data.* Economic Research Service, USDA. https://www.ers.usda.gov/data-products/dairy-data/

Villas-Boas, S. B. (2007). Vertical Relationships between Manufacturers and Retailers: Inference with Limited Data. *Review of Economic Studies*, *74*(2), 625-652. https://doi.org/10.1111/j.1467-937X.2007.00433.x

Viswanathan, M., Narasimhan, O., & John, G. (2021). Economic Impact of Category Captaincy: An Examination of Assortments and Prices. *Marketing Science*, *40*(2), 261-282. https://doi.org/10.1287/mksc.2020.1251

Yonezawa, K., & Richards, T. J. (2016). Competitive Package Size Decisions. *Journal of Retailing*, *92*(4), 445-469. https://doi.org/10.1016/j.jretai.2016.06.001

TABLES AND FIGURES

Table 1. Summary Statistics of Economic and Demographic Variables

	Frequency	Mean	Std. Dev.	Min	Max
Employment rate (%)	Monthly	92.65	3.15	68.50	98.60
Wage rate	Quarterly	918.88	220.61	426.03	2115.22
Median HH income	Yearly	60.03	15.91	24.50	129.43
House value	Monthly	271.68	157.26	32.25	1088.29
Population (1,000)	Yearly	12.40	21.28	0.03	98.23
Gender ratio	Yearly	0.97	0.05	0.81	1.85
SNAP issuance ($mil)	Monthly	13.62	26.33	0.003	193.60

Source: Authors' calculation based on Nielsen data.
Note: HH stands for household. Statistics are computed based on county-month/quarter/year specific observations in table 3 and weighted by observations. House value and median HH income are measured in real $1,000 with 2015 as the base year. Gender ratio is measured by the female population divided by the male population. SNAP statistics are reported after merging with monthly observations.

Table 2. Summary Statistics of Dependent Variables for Estimation 2007-2010

		Monthly		Quarterly		Yearly	
		Grocery	Mass	Grocery	Mass	Grocery	Mass
#UPCs	Mean	177.84	59.62	191.64	61.96	235.44	68.97
	SD	59.20	60.80	63.57	63.92	75.82	75.78
# Varieties	Mean	26.50	13.69	27.59	13.91	30.88	14.59
	SD	9.85	8.07	10.22	8.35	11.26	9.76
Uniqueness index	Mean	25.46	49.36	24.81	47.89	22.70	44.92
(0-100)	SD	8.98	25.78	8.62	26.21	7.16	27.81
Average UPC size	Mean	12.90	9.23	12.90	9.20	12.90	8.98
	SD	1.49	2.07	1.47	2.06	1.45	2.09
No. Obs.		331,939	61,691	110,760	20,899	27,868	5,770

Source: Authors' calculation based on Nielsen data.
Note: Statistics are weighted by observations. Due to missing information on private labels, the total numbers of observations of #varieties and uniqueness index for grocery stores and mass merchandisers in monthly data are 331,919 and 61,501, respectively. The numbers in quarterly data are 110,757 and 20,814, respectively. In yearly data, the number of observations for mass merchandizers in the variety regression is 5,712.

Table 3. Store Product Offerings in Response to Demand Shocks

	Monthly		Quarterly		Yearly	
	Grocery	Mass	Grocery	Mass	Grocery	Mass
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. #UPC						
Income variable	0.11	0.10	-2.34	11.30***	3.96	11.06*
	(0.24)	(0.21)	(2.38)	(2.72)	(4.25)	(4.69)
Log house value	4.05**	3.45**	5.58**	1.29	6.61*	4.00
	(1.09)	(1.02)	(1.47)	(1.26)	(2.43)	(2.20)
R^2	0.89	0.90	0.88	0.90	0.87	0.90
Dep. #varieties						
Income variable	0.35***	0.14***	0.01	2.38***	1.23	2.49**
	(0.06)	(0.03)	(0.65)	(0.38)	(1.02)	(0.67)
Log house value	0.43	0.72***	1.37**	0.38*	1.18	0.62*
	(0.25)	(0.14)	(0.36)	(0.19)	(0.61)	(0.30)
R^2	0.74	0.82	0.73	0.82	0.75	0.84
Dep. Uniqueness index (0-100)						
Income variable	0.09	0.37**	-0.12	1.87	2.04*	-2.33
	(0.07)	(0.11)	(0.70)	(1.67)	(0.84)	(1.95)
Log house value	-0.36	-0.29	-0.25	-0.59	-1.13	-0.24
	(0.31)	(0.30)	(0.38)	(0.42)	(0.65)	(1.91)
R^2	0.36	0.73	0.34	0.71	0.28	0.64
Dep. UPC size						
Income variable	0.01	-0.03*	-0.24**	0.12	-0.09	0.38*
	(0.01)	(0.01)	(0.08)	(0.15)	(0.12)	(0.16)
Log house value	-0.05	0.31***	0.04	0.25**	0.04	0.16
	(0.07)	(0.07)	(0.06)	(0.08)	(0.08)	(0.09)
R^2	0.75	0.66	0.77	0.67	0.80	0.73
Controls/FE	Y	Y	Y	Y	Y	Y
No. Obs.	331,939	61,691	110,760	20,899	27,868	5,770

Source: Authors' estimation based on Nielsen data.
Note: *** p<0.001, ** p<0.01, * p<0.05. Standard errors are in the parenthesis and clustered at the state level. The income variable is the employment rate in monthly data, the logged wage rate in quarterly data, and the median household income in the yearly data. Control variables (controls) and fixed effects (FE) are listed in equation (1). The numbers of observations of #varieties and uniqueness index are listed in table 2.

Table 4. Price Effects of Demand Shocks

	Monthly		Quarterly		Yearly	
	Grocery	Mass	Grocery	Mass	Grocery	Mass
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Log price ($cent/ounce)						
Income variable	-0.002*	-0.00002	0.004	0.01	-0.02**	-0.01
	(0.001)	(0.001)	(0.005)	(0.01)	(0.01)	(0.01)
Log house value	0.03**	0.01	0.02***	0.0003	0.03***	0.02*
	(0.01)	(0.01)	(0.004)	(0.01)	(0.004)	(0.01)
Controls/FE	Y	Y	Y	Y	Y	Y
No. Obs.	57,770,031	3,658,496	20,799,392	1,287,593	6,421,351	395,332

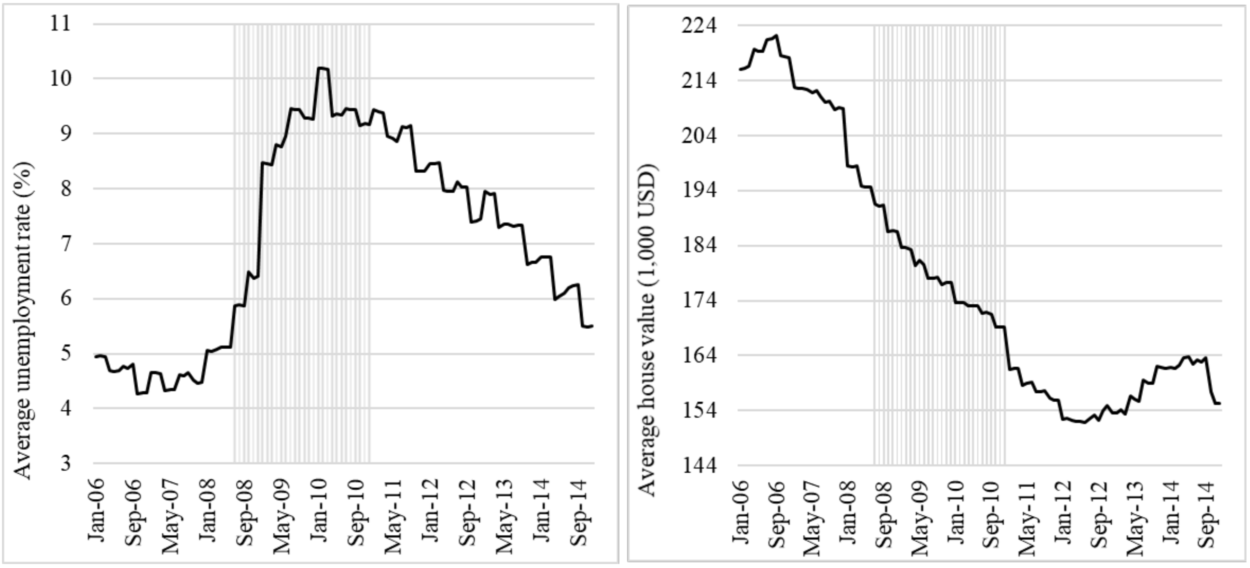
Source: Authors' estimation based on Nielsen data.
Note: Same as table 3.

Table 5. Simulated Welfare Impacts of Demand-Driven Price and Variety Changes

	(1)	(2)	(3)	(4)	(5)
Scenarios					
Assumed price change	-0.2%	-0.2%	-0.2%	-0.2%	-0.2%
Assumed variety change	-11.0%	-8.0%	-4.0%	-0.2%	0.0%
Welfare changes					
Mean ΔCS	-0.97	-0.69	-0.32	0.01	0.02
S.D. ΔCS	0.01	0.01	0.005	0.001	0.003
Min ΔCS	-1.00	-0.70	-0.33	0.003	0.01
Max ΔCS	-0.95	-0.67	-0.31	0.01	0.04
Mean ΔCS/year (mil$)	-36.08	-25.67	-11.90	0.37	0.74

Source: Authors' calculation using Nielsen data. U.S. yogurt consumption data are found at USDA website: https://www.ers.usda.gov/data-products/dairy-data/
Note: The U.S. per capita consumption of yogurt, excluding frozen yogurt, in 2008, 2009, and 2010 are 11.7, 12.5, and 13.5 pounds, respectively. In column (5), only one simulation is needed, because there is no random removal of UPCs but a specific price reduction. We hence report the statistics for 52 simulated weekly CS changes.

Figure 1. Nation-Level Average Monthly Income and Wealth 2006-2014



Source: U.S. Bureau of Labor Statistics and www.Zillow.com.
Note: The gray areas cover September 2008 to December 2010.

Appendix 1. A Simple Conceptual Model

Maintaining optimal product offerings is a critical dimension of store quality in the retail sector (Dekimpe et al. 2011; Hwang et al. 2010; Matsa 2011), especially with growing heterogeneity in consumer preferences over an increasing number of product attributes (Saitone and Sexton 2010). To derive basic economic intuition as to how a retailer would adjust product offerings under a local demand shock, we construct a simple, static conceptual model.

Consider a local retail market with a given number of heterogeneous retail stores. Each multi-category store maximizes one-period profits of the yogurt category separately, instead of across all categories, following most studies on retailer decisions (e.g., Nevo 2001; Villas-Boas 2007). We assume that a store faces a fixed number of consumers who have heterogeneous tastes covering a given variety space (i.e., attribute space). The distribution of consumer mass over the variety space is exogenous to the store. For simplicity, we let consumers match their tastes with varieties exactly. If a consumer does not find the most preferred yogurt product, no purchase takes place. If the consumer finds the preferred product, he/she buys some units depending on his/her income and wealth. Let Y represent demand shifters such as income and wealth of consumers. The number and actions of competitors in the local market are also exogenous to any store in a given period. The intensity of competition in variety is measured by the parameter θ, which is determined by the number and strategies of competitor stores. Increasing the intensity of competition drags down the consumption for a yogurt variety in a given store, everything else the same. Mathematically, therefore, θ may also be viewed as another demand shifter in our model.

Consider a two-stage game. In stage 1, the store decides how many yogurt varieties, V, to offer to maximize profits. The volume sold for each variety carried by the store is determined by demand shifts, including competition, in the local market. Given the exogenous distribution of consumer tastes, each variety can be matched to some consumers. Thus, a larger choice set allows more consumers to match preferences with varieties in the store and increase the total volume sold. Because we assume that consumers only buy yogurt products that exactly match the preferences, the volume sold for each variety is independent of the total number of varieties and determined by Y and θ. In stage 2, the store obtains a market equilibrium price, p^v, for variety v, which depends on varieties offered, local demand, and competition. Product offerings may affect equilibrium prices because adding varieties draws consumers' attention away from prices (e.g., Bordalo et al. 2013; Richards et al. 2019) and, on the other hand, can intensify price competition by crowding the variety space. The two forces have opposite effects on price.

The cost of selling $\boldsymbol{q}$ units of yogurt and carrying V varieties is characterized by the function, $c(V, \boldsymbol{q})$, where vector $\boldsymbol{q}$ consists of q^v for each variety. The cost function contains two parts. The cost of purchasing $\boldsymbol{q}$ units from wholesalers equals $\sum_{v=1}^{V} w^v q^v$ where w^v is the corresponding wholesale price and exogenous to the store. We assume that all units of a variety in the store are sold to consumers within a period. Given that yogurt products are perishable, this assumption is equivalent to imposing just-in-time inventory management in the store, which is widely applied in the retail sector (e.g., Buijs et al. 2016).

Without loss of generality, we do not distinguish retail and wholesale prices among products and denote them by p and w without subscripts. Alternatively, p may be interpreted as the average price achieved by the store in a market, while w is the average wholesale price, given the choice of V varieties. The total volume sold is $q = \sum_{v=1}^{V} q^v$. The objective function of the store is expressed as:

$$\max_{V} \pi = p(V|\theta, Y)q(V|\theta, Y) - c\big(V, q(V|\theta, Y)\big),$$

where $c\big(V, q(V|\theta, Y)\big) = wq(V|\theta, Y) + s(V)$.

To derive the comparative statics, we assume that the volume sold follows an increasing and concave function in V and Y and the equilibrium prices increases in Y but has an ambiguous relationship with V.

$q_V > 0, q_{VV} < 0, q_Y > 0, q_{YY} < 0, p_Y > 0, p_{YY} < 0,$

where the subscript indicates the variable of which the derivative is taken. The variety cost, $s(V)$, is set to be increasing and convex in V, or $s_V > 0$, and $s_{VV} > 0$, because it is exponentially more costly to manage the inventory of an increasingly large number of varieties (Draganska and Jain 2005).

We further assume that positive demand shifters and the varieties offered are complementary to volume sales as well as prices:

$q_{VY} \geq 0$ and $p_{VY} \geq 0$.

Intuitively, this assumption implies that higher income consumers tend to buy more units of each additional variety offered by the store and pay higher for a new variety.

The first order condition for the number of varieties is found by setting $\frac{\partial \pi}{\partial V}$ to zero:

$$\frac{\partial \pi}{\partial V} = (p - w)q_V + p_V q - s_V = 0.$$

As long as the store stays in business, $(p - w)$ is positive to ensure non-negative profits. Relying on the Implicit Function Theorem, we express the optimal V as the local demand increases:

$$\frac{\partial V^*}{\partial Y} = -\frac{(p-w)q_{VY}+p_Y q_V+p_{VY}q+p_V q_Y}{(p-w)q_{VV}+p_{VV}q+p_V q_V-s_{VV}}.$$

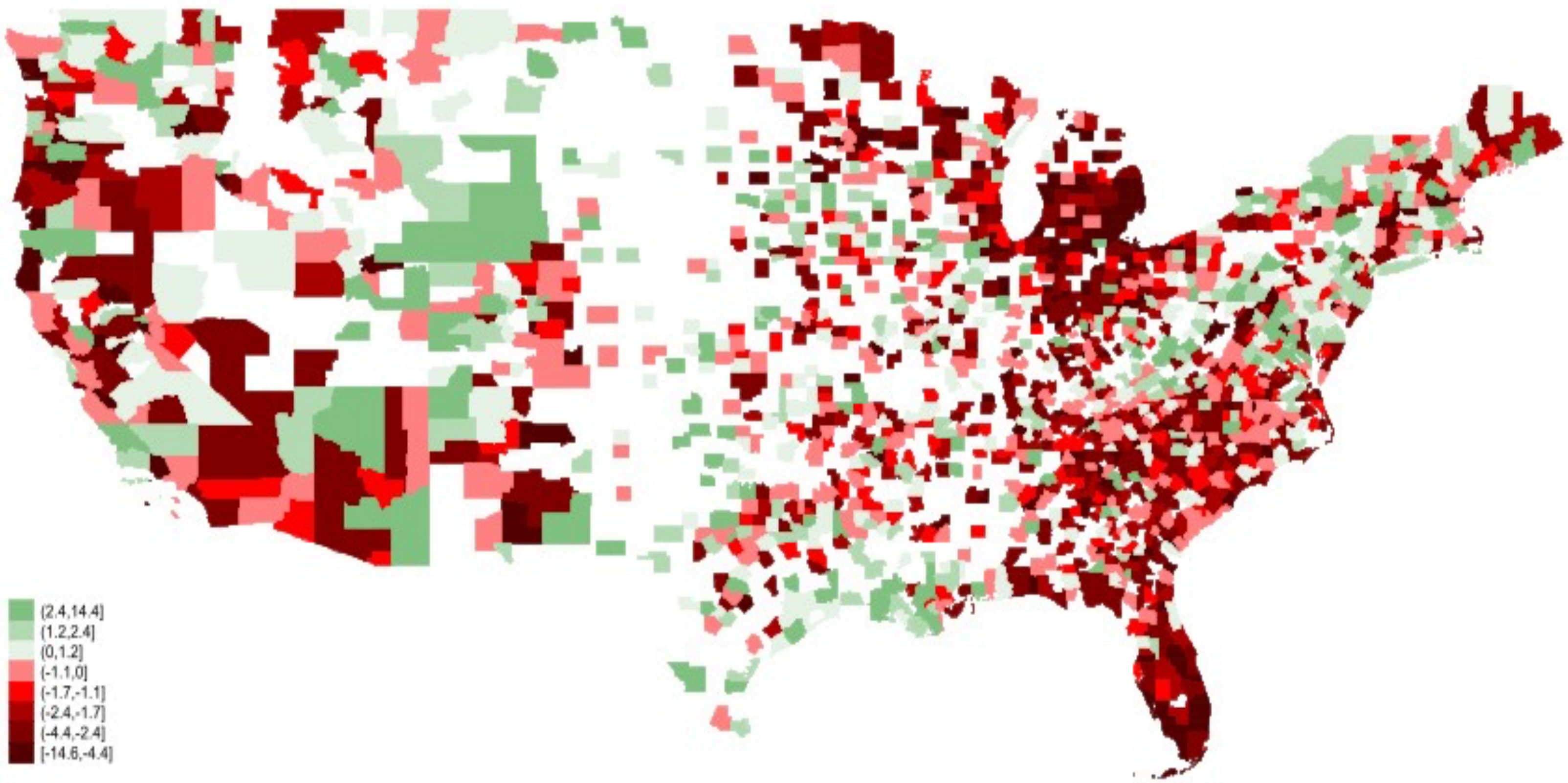
The numerator and denominator have ambiguous signs. If $p_V > 0$, the numerator is positive and means that the marginal increase in store maximized profits from carrying more varieties increases with the local demand. Intuitively, if there is a positive income or wealth shock, the store enjoys larger incremental profits from adding a variety on the shelf, everything else the same. The sign of the denominator depends on the relative magnitudes of marginal price and sales impacts of adding varieties. The rise in volume sales (i.e., q_{VV}) decrease in V, while the marginal cost of adding varieties rises (i.e., s_{VV}). However, $p_V q_V$ and $p_{VV} q$ may be positive. Thus, the optimal number of varieties offered could increase or decrease in demand shocks.

Appendix 2. Spatial Variation in County-Level Income and Wealth

The following figures show the variation in the changes of real-USD county-level income (i.e., household median income) and wealth (i.e., house value) from 2006 to 2009. On average, there were decreases in income and wealth over the period. We set eight value ranges in each figure. Green indicates that a county experienced an increase in income/wealth, while red indicates a decrease. The darker the color is the larger the magnitude of the change. In both figures, the blank spots are counties not included in the Nielsen dataset.

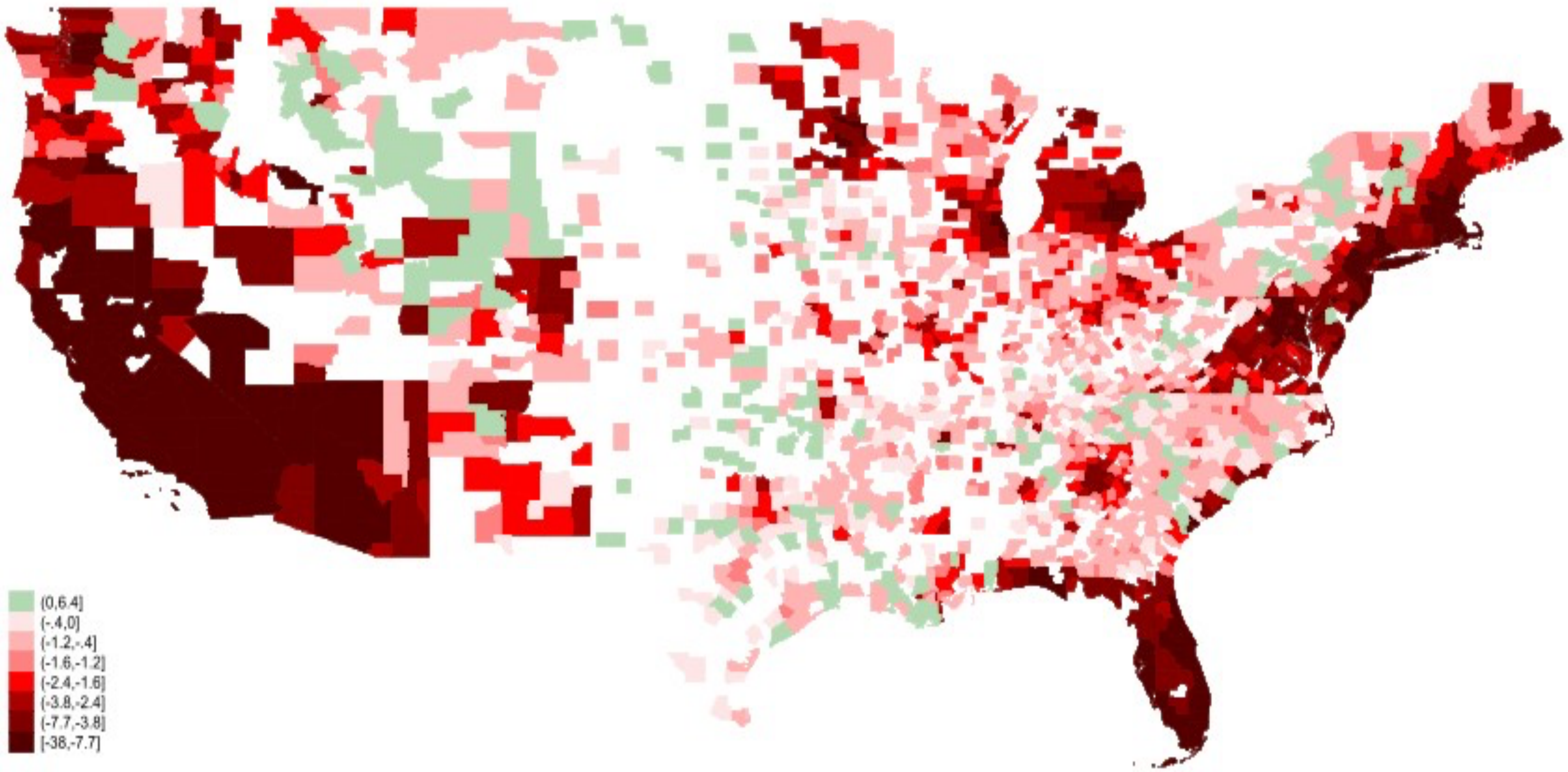
Spatial variation in income and wealth changes is substantial. Figure A1 suggests that a small number of counties experienced income increases from 2006 to 2009, while others experienced income reductions. Some most severely hit counties were in the West Coast, South, and Southeast Coast. Some counties in the Central saw income increases. Figure A2 shows that most counties had reductions in their house values during the Recession. Counties in the West Coast, South, and East Coast were affected most strongly. An even smaller number of counties saw increases in house values.

Figure A1. Changes in U.S. County Median Household Incomes from 2006 to 2009



Source: U.S. Bureau of Labor Statistics.
Note: Measured in 2015 real 1,000 USD.

Figure A2. Changes in U.S. County Average House Values from 2006 to 2009



Source: www.Zillow.com
Note: Measured in 2015 real 10,000 USD.

Appendix 3. List of Product Varieties

There are more than 2,000 flavors, 32 styles, and 43 types of yogurt products observed in the full Nielsen dataset. We classify the three dimensions of product variety into relatively few categories to enable the construction of the uniqueness index. The full list of grouped flavors, styles, and types is presented in table A1. Examples of each group are given, and so are the corresponding shares of UPCs belonging to the group.

Table A1. Flavors, Styles, and Types of Yogurt Products

		Flavor		
Code	Name	Definition	Examples	Share of UPCs (%)
01	Plain	No added flavor	Plain	9.94
02	Vanilla	Pure vanilla flavor	Vanilla	9.54
03	Fruit, single	Containing only one type of fruit flavor	Blackberry	46.16
04	Fruit, multi	Containing two or more types of fruit flavors	Strawberry & Banana	12.65
05	Fruit mixed with other(s)	Fruit flavor(s) mixed with other flavor(s)	Blueberries & Cream	10.18
06	Other, single	Containing one of the following flavors: vegetable-related flavor, nut-related flavor, spice-related flavor, cake-related flavor, and other single flavors	Coffee, honey	10.16
07	Other, mixed	Containing two or more of the following flavors: vegetable-related flavor, nut-related flavor, spice-related flavor, cake-related flavor, and other single flavors	Vanilla parfait & Granola	1.37

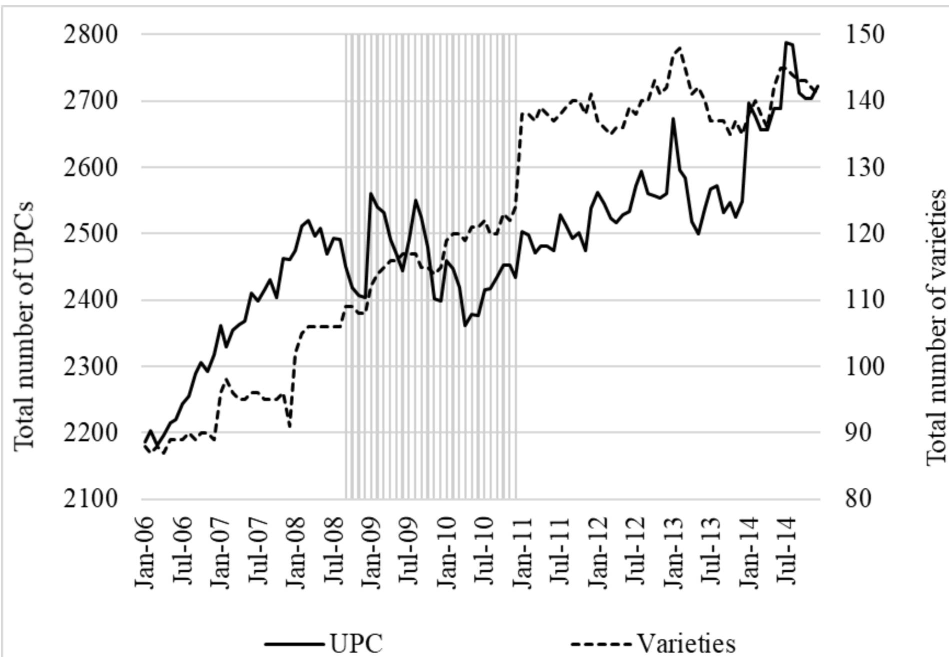
Table A1 (Continued)

Style			Type		
Code	Name	Share of UPCs (%)	Code	Name	Share of UPCs (%)
01	Natural/Premium/Organic	9.33	01	Fat-free	35.98
02	Natural/Organic Greek	2.85	02	Goat milk	0.50
03	Bulgarian	0.12	03	Goat milk low-fat	0.09
04	Custard	0.38	04	Goat milk non-fat	0.07
05	Gelatin	0.05	05	Imitation	0.03
06	Greek	21.92	06	Lactose-free	0.47
07	Greek kefir	0.03	07	Low-fat	39.17
08	Israeli Leben/Leben	0.14	08	Low-fat lactose-free	1.11
09	Kefir	0.52	09	Natural	0.82
10	Organic Bulgarian/Premium Bulgarian	0.03	10	Non-fat lactose-free	0.23
11	Original/Regular/Not stated	62.82	11	Non-fat lactose-reduced	0.02
12	Swiss	1.34	12	Regular	18.03
13	Swiss premium	0.33	13	Sheep milk	0.26
14	Try it frozen too	0.02	14	Whole milk/Whole milk natural	3.15
15	Original Russian	0.02	15	Whole milk lactose-free	0.05
16	Sundae	0.03	16	Light whole milk	0.02
17	Kefir organic	0.03			
18	Real	0.02			

Source: Authors' calculation based on Nielsen data.
Note: Total number of unique UPCs with flavor, style, and type information is 5,747. Some products have no variety information.

The figure below plots the total number of yogurt UPCs and varieties on the U.S. market by month from 2006 to 2016. There is an increasing trend in both variables. The total number of UPCs goes from 2,200 to over 2,700, and the number of varieties increases from 90 to about 145. It is easy to notice a fairly large slowdown in the growth rates of or even decreases in both numbers during the Recession period, suggesting changes in product construction and destruction by manufacturers facing demand shocks.

Figure A3. U.S. Total Numbers of Yogurt UPCs and Varieties from 2006 to 2014



Source: Authors' calculation based on Nielsen data.
Note: Total number of unique UPCs is measured by the left vertical axis, and the number of varieties is measured by the right vertical axis. The gray area covers September 2008 to December 2010.

Appendix 4. Demand Estimation

We first select the 30 most populated counties based on 2006 census statistics. The counties are located in 12 states, including California, Florida, New York, and Taxes. Within the 30 counties, all yogurt products sold in each week from September 2008 to August 2010, the Recession period of 104 weeks, are considered, generating UPC-brand-retailer-week specific observations in the 2008-2010 sample. We exclude the products with the price lower than 1% percentile (i.e., \$0.96/pound) and higher than 99% percentile (i.e., \$6.7/pound), and products with the volume share lower than 10% percentile (i.e., 7×10^{-6}). As a result, about 11.6% of the total observations are dropped. Table A2 shows how diffuse the yogurt market is – even the most popular UPCs on average occupy less than 2% of the market by volume. There is substantial variation in UPC prices and UPC sizes.

Nielsen Household dataset contains demographics of over 60,000 randomly selected households each year. The households are located in 49 U.S. states and considered nationally representative. We extract household demographic information as a proxy for their heterogeneous tastes and build a sample by randomly drawing households without replacement from the Nielsen dataset. For each week, 200 households located in the 30 selected counties are randomly selected from the corresponding year. In total, we have 200×104=20,800 households for the 104 weeks from 2008 to 2010.

We focus on five demographic variables that are widely used in demand estimation (e.g., Nevo 2001). The age of the household head is the average of two ages if both the male and the female member self-report as the head. Otherwise, it is the age of either a male or female head. Income is self-reported and measured by tiers. We take the mean of each nominal income tier as the income value used in our estimation. For example, if the income tier is \$0 to \$10,000, the value is converted to $5,000. There are 16 tiers, and the highest one is $100,000+. This income tier is converted to $150,000. Household size is the number of household members in the year, the education dummy equals one if the head has finished college education or above, and the child dummy equals one if the household has at least one child aged under 18. The market-level demographic variables are generated by taking an average of household variable values in each week by county.

Table A2. Summary Statistics of Variables for Demand Estimation

	Unit	Mean	SD	Min	Max
Prices	$cent/ounce	14.21	5.92	5.96	41.79
Market shares	%	0.03	0.06	7.07×10^{-6}	1.64
Outside shares	%	65.65	18.34	13.31	99.02
UPC size	Ounce	13.26	11.49	1	108
Private label	Dummy	0.16	0.37	0	1
Children	Dummy	0.22	0.05	0.07	0.38
Household size		2.33	0.21	1.60	2.94
Household head education	Dummy	0.56	0.08	0.30	0.80
Household head age		55.86	2.00	51.18	61.97
Household income	1,000 USD	81.44	11.61	53.73	110.82

Source: Authors' calculation based on Nielsen data.
Note: Prices are measured in real U.S. dollars with 2015 as the base year. We do not include variety variables in the regression due to missing variety information of private-label UPCs. Otherwise, we would only be able to estimate the demand for national-brand UPCs. *Child* is an indicator that equals 1 if the household has at least one child under 18. *Household head education* is an indicator that equals 1 if the head has finished college education or above.

To address the endogeneity concern in the demand model, we create the instrumental variable (IV) for retail prices of yogurt products following Allcott et al. (2020). The intuition is that retail chains have different cost advantages in supplying products in different geographic areas, hence their relative prices of different products are different across markets. The calculation of IV involves three steps. The IV reflects the comparative advantages in selling products given other markets, rather than the local market conditions. This ensures that the common supply shocks shared by the selected counties and other counties affect market shares of UPCs only through affecting the retail prices. The IV has a significant impact on prices in the first-stage regression with the F-statistics equal 332.09.[6] Summary statistics of key variables for the estimation are displayed in table A2.

The estimates are summarized in table A3. High R-squared values suggest good fitness of the model. The coefficient of price is significantly negative in all columns. Comparing columns (1) and (2), adding brand and retailer fixed effects changes the coefficient of the price significantly, suggesting the importance of controlling for unobserved brand and retailer features that determine the price and market share of a yogurt product.

Table A3. Logit Model Outcomes

Variables	(1) OLS	(2)	(3)	(4) 2SLS	(5)	(6)
Price ($cent/ounce)	-0.20***	-0.06***	-0.07***	-0.10*	-0.16***	-0.16***
	(0.01)	(0.01)	(0.01)	(0.05)	(0.02)	(0.02)
UPC size (ounce)		0.01***	0.01***		0.01*	0.01*
		(0.002)	(0.002)		(0.003)	(0.003)
Private label (1 if yes)		-7.81***	-48.64**		-6.51***	-47.34**
		(0.12)	(17.70)		(0.25)	(17.62)
Brand and retailer FE	N	Y	Y	N	Y	Y
Year and quarter FE	Y	Y	Y	Y	Y	Y
HH controls	N	N	Y	N	N	Y
R^2	0.93	0.98	0.99	--	--	--
F-statistics	--	--	--	284.04	330.40	332.09
No. Obs.	2,682,871					

Source: Authors' calculation using Nielsen data.
Note: *** p<0.001, ** p<0.01, * p<0.05. Standard errors are clustered at the retail-chain level. HH means household. HH age refers to the age of household head. The demographic variables take the mean value of sampled households in a particular week by county.

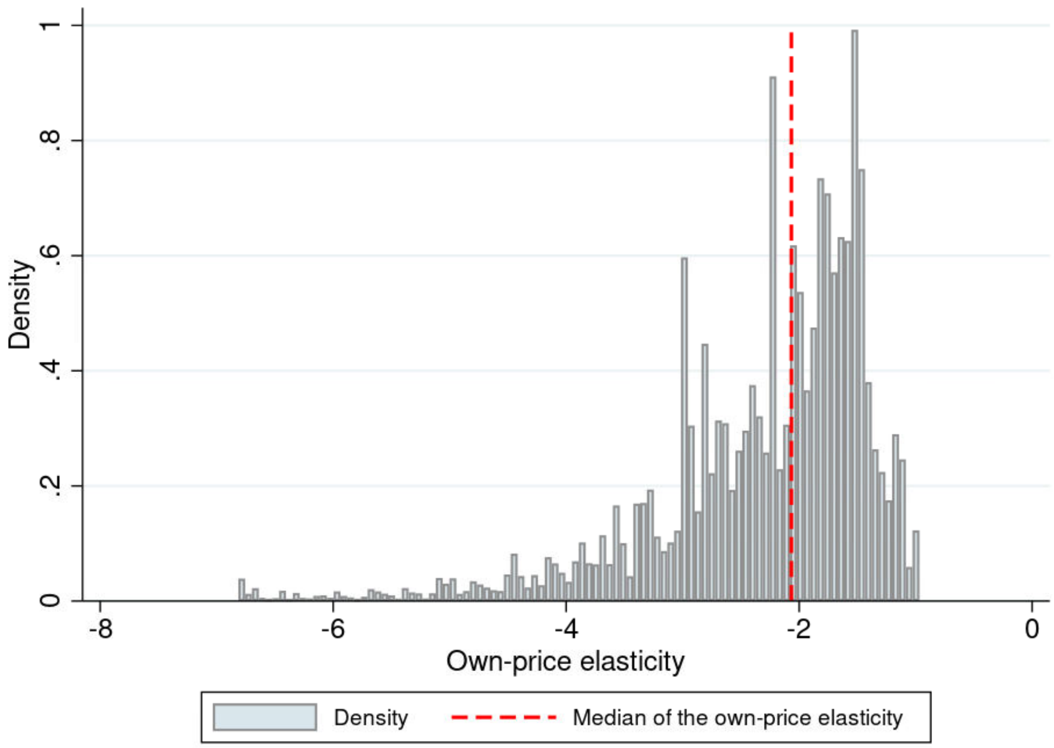
[6] Given that the IV is so strong, using more complicated structural demand models (e.g., random coefficient discrete choice model) is unlikely to generate significantly different price elasticities or substitution patterns.

We take column (6) as the preferred specification. Based on the estimated coefficient of price and volume shares of products, we compute the own-price elasticities of sampled UPCs. Figure A4 shows the histogram of the own-price elasticity. It turns out that the own-price elasticity ranges from -6.81 to -0.97, with a mean of -2.07 and a standard deviation of 0.97. Cross-price elasticities are positive but small. The mean is 0.0003 with a standard deviation of 0.001, suggesting that the products are weak substitutes to each other.

Next, we build the pre-Recession sample of top 100 yogurt UPCs for each county and each of the 52 weeks in 2007. Over 99.95% of these UPCs are carried by the same set of brands and retailers in the 2008-2010 sample. UPCs not in the 2008-2010 sample are excluded from the CS calculation, because we cannot obtain the coefficients of their brand or retailer indicators from the demand estimation and hence are unable to compute their corresponding indirect utility of consuming the UPCs, namely, $x_{jmt}\beta - \alpha p_{jmt} + \xi_j + \tau_t$.

In the simulation, each product is assigned with a random number drawn from (0, 1-$\frac{rank}{200}$) plus $\frac{rank}{200}$ where rank is its rank by market share in the week. For instance, a product is ranked 50 in a week. It gets a random number drawn from (0, 0.5) + 0.5. If we remove 11% products from the baseline product set, we drop UPCs assigned with numbers larger than 1.00-0.11 = 0.89. The way in which random numbers are generated hence ensures that products with smaller shares or ranked lower are more likely to be dropped.

Figure A4. Histogram of the own-price elasticity



Source: Authors' calculation based on Nielsen data.

Online Appendix 1. Additional Robustness Tests

We present outcomes of robustness tests described in Section 5.2. We conduct two robustness tests to address the concern that manufacturers may affect store's product assortment. First, we exclude the three largest yogurt manufacturers' UPCs (Chobani, Dannon, and Yoplait) from the sample. The three major yogurt brands together account for 66% to 76% of the total sales during the period of interest. One concern is that the leading manufacturers may influence retailer assortment via bargaining. Focusing on minor brands in our sample helps eliminate the potential impacts of top manufacturers. Using the monthly data, an average grocery store (mass merchandiser) carries 65.07 (24.02) UPCs and 11.98 (5.30) varieties of minor brands.

Second, we calculate the annual sales HHI of brands for each retail chain and exclude store-month observations with HHIs in the upper quartile. The HHI, ranging from 0 to 1, is widely used to measure the market competitiveness, with the index of 0.25 or greater indicating a highly concentrated market (US Department of Justice, 2018). In our context, HHI higher than 0.33 suggests that the chain's yogurt sales are predominantly contributed by a large manufacturer. The dominant manufacturer may act as the category captain that not only manages its own product prices and assortment, but also those of its rivals (Subramanian et al. 2010; Viswanathan et al. 2021). Excluding stores with high HHI should largely addresses the possibility of "category captaincy". In the monthly sample, an average grocery store (mass merchandizer) offers 180.28 (72.74) UPCs and 27.48 (15.02) brands. The corresponding mean HHI for grocery store (mass merchandiser) is 0.30 (0.47), with a standard deviation of 0.05 (0.13).

Results in the upper panel of table B1 include two major dependent variables in table 3, the number of UPCs and the number of varieties in a store. The outcomes using a sub-sample of minor brands confirm table 3. Columns (1) and (2) show that if the local wealth falls by 1%, on average, a grocery store removes 2.6 UPCs or 4.0% of the mean number of minor-brand UPCs, whereas a mass merchandiser removes 1.5 UPC or 6.0% of the mean number of UPCs in minor brands. The relative magnitudes agree with baseline outcomes. When the employment rate falls by 5%, the number of varieties in the grocery store (mass merchandizers) decreases by 0.6 (0.85) or 5% (16%) of the mean number. The relative magnitude is smaller than the baseline for grocery stores, but larger than the baseline for mass merchandizers.

The lower panel of table B1 presents the results of the second robustness test. The outcomes are largely consistent with the baseline results shown in table 3. Both retail formats remove UPCs and varieties with a decrease of local wealth or income. With a 5% decrease in local wealth, an average grocery store (mass merchandizer) removes 23.4 (34) UPCs or 13% (47%) of the mean number of UPCs in the remaining stores. In addition, if the employment rate decreases by 5%, the grocery store (mass merchandizer) removes 1.75 (0.75) yogurt varieties or 6.4% (5%) of the mean number of varieties in the stores belonging to chains with an HHI less than the third quartile. The magnitudes of shock effects are statistically the same as the baseline, except for that the wealth effect on the number of UPCs for mass merchandizers is larger than the baseline.

Table B1. Store Product Offerings in Response to Demand Shocks

	Monthly		Quarterly		Yearly	
	Grocery	Mass	Grocery	Mass	Grocery	Mass
	(1)	(2)	(3)	(4)	(5)	(6)
Excluding three major brands						
Dep. #UPC						
Income variable	-0.09	0.14	-0.91	2.92*	3.09	1.11
	(0.10)	(0.19)	(1.31)	(1.18)	(2.75)	(2.81)
Log house value	2.59***	1.45*	2.82***	1.22	3.35	3.75*
	(0.47)	(0.66)	(0.75)	(0.71)	(1.81)	(1.41)
R^2	0.72	0.92	0.80	0.92	0.79	0.91
Dep. #varieties						
Income variable	0.12***	0.17***	0.34	0.65	1.34*	-0.67
	(0.03)	(0.04)	(0.46)	(0.43)	(0.50)	(0.76)
Log house value	0.79**	0.42	1.12***	0.39	1.05*	1.00
	(0.24)	(0.25)	(0.31)	(0.34)	(0.41)	(0.64)
R^2	0.71	0.86	0.71	0.86	0.72	0.91
Controls/FE	Y	Y	Y	Y	Y	Y
No. Obs.	331,923	23,722	110,756	8,570	27,868	2,707
Excluding observations with upper quartile HHI						
Dep. #UPC						
Income variable	0.17	0.27	-2.82	14.33***	2.42	12.76*
	(0.21)	(0.23)	(2.42)	(2.94)	(5.01)	(5.62)
Log house value	4.67***	6.80***	6.37***	2.03	8.03**	6.52*
	(0.96)	(1.60)	(1.36)	(1.40)	(2.92)	(2.54)
R^2	0.89	0.92	0.88	0.91	0.88	0.90
Dep. #varieties						
Income variable	0.35***	0.15***	0.003	2.91***	2.28*	2.95***
	(0.06)	(0.03)	(0.64)	(0.41)	(0.89)	(0.79)
Log house value	0.35	1.31***	1.34***	0.52*	0.78	1.02**
	(0.32)	(0.22)	(0.30)	(0.21)	(0.49)	(0.37)
R^2	0.74	0.85	0.74	0.82	0.75	0.83
Controls/FE	Y	Y	Y	Y	Y	Y
No. Obs.	247,943	36,648	82,743	16,833	20,825	4,278

Note: Same as table 3. Due to missing information on private labels, in the upper panel, the total numbers of observations of #varieties for grocery stores and mass merchandisers in monthly data are 325,003 and 14,002, respectively. The numbers in quarterly data are 108,916 and 4,906, respectively. The numbers in yearly data are 27,591 and 1,383, respectively. In the lower panel, the total numbers of observations of #varieties for grocery stores and mass merchandisers in monthly data are 247,923 and 36,579, respectively. The numbers in quarterly data are 82,740 and 16,775, respectively. The numbers in yearly data are 20,825 and 4,245, respectively.

Next, we consider different time windows and alternative measures of assortment as detailed in Section 5.2. Table B2 reports outcomes using the same specification of the baseline. The upper two panels use observations in 2008 and 2009 only, while the lower panel uses alternative variety variables and 2007-2010 observations.

Alternative dependent variables are employed in the lower two panels. Using monthly observations, for example, the mean numbers of flavors, styles, and types are 74.58 (32.79), 4.55 (2.94), and 9.42 (4.36) for grocery stores (mass merchandisers), respectively. Also taking monthly observations as an example, the mean numbers of brands and UPC sizes are 17.21 (7.09) and 13.01 (6.60) for grocery stores (mass merchandisers), respectively. All the patterns demonstrated in the baseline hold in table B2. Worth noticing, the third panel suggests that changes in the number of varieties are mainly driven by changes in types and styles of yogurt products instead of flavors.

Table B2. Store Product Offerings in Response to Demand Shocks

	Monthly		Quarterly		Yearly	
	Grocery	Mass	Grocery	Mass	Grocery	Mass
	(1)	(2)	(3)	(4)	(5)	(6)
Observations: 2008-2009						
Dep. #UPC						
Income variable	0.0004	-0.13	-1.30	4.70	6.64	2.13
	(0.17)	(0.21)	(2.45)	(2.79)	(4.63)	(4.25)
Log house value	4.75***	1.71	5.48***	0.51	4.77*	3.24
	(1.05)	(1.06)	(1.37)	(1.35)	(2.38)	(2.21)
R^2	0.89	0.92	0.89	0.92	0.88	0.93
Dep. #varieties						
Income variable	0.24***	0.04	0.28	0.89**	1.82	1.37*
	(0.05)	(0.02)	(0.71)	(0.30)	(1.09)	(0.57)
Log house value	0.75*	0.40**	1.40***	0.26	1.15*	0.31
	(0.27)	(0.13)	(0.32)	(0.16)	(0.53)	(0.26)
R^2	0.72	0.87	0.72	0.88	0.73	0.89
Dep. Uniqueness index (0-100)						
Income variable	0.08	0.22	-0.56	1.63	0.65	-0.09
	(0.07)	(0.12)	(0.68)	(1.64)	(0.67)	(2.60)
Log house value	0.83*	-0.33	1.18**	-0.57	0.73	-0.77
	(0.37)	(0.76)	(0.33)	(0.84)	(0.46)	(4.12)
R^2	0.38	0.79	0.39	0.75	0.41	0.57
Dep. UPC size						
Income variable	0.01	-0.03*	-0.36**	-0.13	-0.14	0.07
	(0.01)	(0.01)	(0.11)	(0.19)	(0.15)	(0.18)
Log house value	0.01	0.29**	0.13	0.29**	0.11	0.26*
	(0.08)	(0.09)	(0.06)	(0.10)	(0.08)	(0.11)
R^2	0.81	0.68	0.83	0.69	0.85	0.80
No. Obs.	164,350	31,535	54,837	10,738	13,789	3,121

Table B2 (Continued)

Observations: 2007-2010						
Dep. # flavors						
Income variable	0.27	-0.04	0.22	2.73*	2.56	2.61
	(0.15)	(0.07)	(1.28)	(1.17)	(2.08)	(1.56)
Log house value	1.08*	0.96**	1.84*	0.36	1.73	1.45*
	(0.46)	(0.30)	(0.73)	(0.43)	(1.21)	(0.70)
R^2	0.84	0.92	0.85	0.92	0.86	0.93
Dep. # styles						
Income variable	0.06**	0.04***	0.07	0.58***	0.27	0.58***
	(0.02)	(0.01)	(0.09)	(0.09)	(0.16)	(0.15)
Log house value	0.06	0.25***	0.20**	0.16**	0.17	0.15*
	(0.07)	(0.05)	(0.06)	(0.05)	(0.10)	(0.07)
R^2	0.66	0.51	0.66	0.52	0.67	0.64
Dep. # types						
Income variable	0.04**	0.01	0.34	0.59***	0.70**	0.73***
	(0.01)	(0.01)	(0.19)	(0.13)	(0.20)	(0.18)
Log house value	0.49***	0.29***	0.57***	0.16**	0.50**	0.15
	(0.11)	(0.04)	(0.12)	(0.05)	(0.13)	(0.10)
R^2	0.68	0.85	0.68	0.86	0.68	0.85

Table B2 (Continued)

Observations: 2007-2010						
Dep. #brands						
Income variable	-0.02	0.03	-0.51	1.37***	0.57	1.06*
	(0.03)	(0.02)	(0.30)	(0.25)	(0.60)	(0.40)
Log house value	0.79***	0.45***	0.99***	0.21	1.12**	0.48*
	(0.11)	(0.11)	(0.17)	(0.13)	(0.30)	(0.23)
R^2	0.77	0.81	0.77	0.81	0.77	0.86
Dep. #UPC sizes						
Income variable	0.07***	0.03	-0.32	0.83***	-0.03	0.61*
	(0.01)	(0.02)	(0.17)	(0.21)	(0.22)	(0.28)
Log house value	0.05	0.40***	0.34***	0.26*	0.54***	0.41*
	(0.07)	(0.08)	(0.08)	(0.10)	(0.13)	(0.15)
R^2	0.77	0.81	0.78	0.81	0.80	0.87
Controls/FE	Y	Y	Y	Y	Y	Y
No. Obs.	331,939	61,691	110,760	20,899	27,868	5,770

Note: Same as table 3. The number of monthly observations from 2008 to 2009 in the variety equations for grocery stores and mass merchandisers are 198,832 and 37,606, respectively. The number of quarterly observations from 2008 to 2009 in the variety equations for grocery stores and mass merchandisers are 66,340 and 12,800, respectively. The number of yearly observations from 2008 to 2009 in the variety equations for mass merchandisers is 3,693.

In the second set of robustness tests described in Section 5.2, we use two-month/quarter/year rolling average income and wealth variables to conduct the estimation. This specification allows considering relatively persistent variation in income and wealth. Coefficients estimated have the same signs and similar magnitudes as the baseline. Table B3 displays these outcomes.

Table B3. Store Product Offerings in Response to Demand Shocks

	Monthly		Quarterly		Yearly	
	Grocery	Mass	Grocery	Mass	Grocery	Mass
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. #UPC						
Income variable	0.12	0.16	-2.91	10.76***	2.10	18.29***
Two-period avg.	(0.25)	(0.22)	(2.55)	(2.79)	(4.29)	(5.04)
Log house value	4.02***	3.40**	5.75***	1.48	7.98***	2.52
Two-period avg.	(1.08)	(1.01)	(1.49)	(1.26)	(2.07)	(2.01)
R^2	0.89	0.90	0.88	0.90	0.87	0.90
Dep. #varieties						
Income variable	0.36***	0.15***	-0.16	2.14***	1.29	3.93***
Two-period avg.	(0.06)	(0.03)	(0.69)	(0.40)	(1.29)	(0.72)
Log house value	0.42	0.71***	1.41***	0.46*	1.23*	0.34
Two-period avg.	(0.25)	(0.14)	(0.39)	(0.18)	(0.59)	(0.28)
R^2	0.74	0.82	0.73	0.82	0.75	0.84
Dep. Uniqueness index (0-100)						
Income variable	0.11	0.38**	0.14	1.33	1.79	-4.56
Two-period avg.	(0.07)	(0.11)	(0.73)	(1.75)	(0.91)	(2.57)
Log house value	-0.44	-0.30	-0.38	-0.41	-0.91	0.12
Two-period avg.	(0.31)	(0.30)	(0.40)	(0.42)	(0.59)	(1.93)
R^2	0.36	0.73	0.34	0.71	0.28	0.64
Dep. UPC size						
Income variable	0.02	-0.03*	-0.26**	0.05	-0.20	0.36*
Two-period avg.	(0.01)	(0.01)	(0.08)	(0.14)	(0.12)	(0.16)
Log house value	-0.05	0.31***	0.05	0.26**	0.06	0.20*
Two-period avg.	(0.07)	(0.07)	(0.06)	(0.08)	(0.07)	(0.07)
R^2	0.75	0.66	0.77	0.67	0.80	0.73
Controls/FE	Y	Y	Y	Y	Y	Y
No. Obs.	331,939	61,691	110,760	20,899	27,868	5,770

Note: Same as table 3.

Thirdly, we consider an alternative measurement of local competition in variety. In particular, we define local competition in variety as the average number of yogurt UPCs carried by a competitor store in the county. With monthly data, for instance, the mean of this new variable is 77.64 with a standard deviation of 47.57. This alternative control variable generates no significant changes in the coefficients estimated as Table B4 shows.

Table B4. Store Product Offerings in Response to Demand Shocks

	Monthly		Quarterly		Yearly	
	Grocery	Mass	Grocery	Mass	Grocery	Mass
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. #UPC						
Income variable	0.10	0.10	-1.93	12.16***	4.13	12.41**
	(0.23)	(0.20)	(2.22)	(2.49)	(3.86)	(4.17)
Log house value	4.34**	3.88***	5.65**	1.77	6.67*	4.77*
	(1.21)	(1.04)	(1.58)	(1.26)	(2.59)	(2.00)
R^2	0.89	0.90	0.88	0.90	0.87	0.90
Dep. #varieties						
Income variable	0.35***	0.14***	-0.02	2.56***	1.10	2.78***
	(0.06)	(0.02)	(0.67)	(0.39)	(1.05)	(0.61)
Log house value	0.48	0.82***	1.31**	0.46*	1.10	0.72*
	(0.26)	(0.15)	(0.37)	(0.19)	(0.59)	(0.27)
R^2	0.74	0.82	0.73	0.82	0.75	0.84
Dep. Uniqueness index (0-100)						
Income variable	0.09	0.36**	-0.38	1.67	1.92*	-3.52
	(0.06)	(0.11)	(0.70)	(1.63)	(0.82)	(1.92)
Log house value	-0.64*	-0.22	-0.49	-0.64	-1.29*	-0.34
	(0.30)	(0.34)	(0.37)	(0.43)	(0.62)	(2.11)
R^2	0.36	0.72	0.34	0.71	0.28	0.64

Table B4. (Continued)

	Monthly		Quarterly		Yearly	
	Grocery	Mass	Grocery	Mass	Grocery	Mass
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. UPC size						
Income variable	0.02	-0.02	-0.26**	0.16	-0.11	0.52**
	(0.01)	(0.01)	(0.09)	(0.15)	(0.12)	(0.17)
Log house value	-0.06	0.31***	0.03	0.26**	0.02	0.14
	(0.08)	(0.08)	(0.07)	(0.08)	(0.08)	(0.09)
R^2	0.75	0.66	0.77	0.67	0.80	0.73
Controls/FE	Y	Y	Y	Y	Y	Y
No. Obs.	331,939	61,691	110,760	20,899	27,868	5,770

Note: Same as table 3.

Fourthly, we conduct the regressions after adding chain-level income and wealth as the control variables. The new control variables help confirm the causal effect of local demand shocks, given chain-level demand shocks. The chain-level income and wealth variables are the simple average of county-level income and wealth across all stores under one retail chain. Outcomes are shown in table B5 and similar to outcomes in table 3, except that impact on the uniqueness index is generally weakened. Noticeably, the chain-level income and wealth also have significant effects on store-level assortment variables, highlighting the importance of chain-level management in retail markets (DellaVigna and Gentzkow 2019).

We conducted a few other robustness tests not reported here in detail. For instance, because private-label UPCs offered in one retail store are not available for all other stores, using the total number of national-brand and private-label UPCs as a control for UPC availability may not be appropriate. We hence use the total number of national-brand UPCs in the market as an alternative control variable. Outcomes again agree with those in table 3 and are available upon request.

Table B5. Store Product Offerings in Response to Demand Shocks

	Monthly		Quarterly		Yearly	
	Grocery	Mass	Grocery	Mass	Grocery	Mass
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. #UPC						
Income variable	0.20	-0.01	-2.57	10.35***	5.74	12.13**
	(0.17)	(0.20)	(2.26)	(2.68)	(3.81)	(4.16)
Log house value	3.64***	3.60**	5.44***	1.61	5.55*	5.04*
	(0.99)	(1.00)	(1.15)	(1.26)	(2.66)	(1.99)
R^2	0.89	0.90	0.88	0.90	0.87	0.90
Dep. #varieties						
Income variable	0.21***	0.06*	-0.03	2.44***	1.66*	2.86***
	(0.05)	(0.03)	(0.57)	(0.38)	(0.62)	(0.59)
Log house value	0.44	0.77***	0.88**	0.48*	0.52	0.70*
	(0.22)	(0.14)	(0.25)	(0.19)	(0.38)	(0.26)
R^2	0.74	0.82	0.74	0.82	0.75	0.84
Uniqueness index (0-100)						
Income variable		0.17	-1.13	-0.56	0.12	-4.50*
	(0.07)	(0.12)	(0.58)	(1.73)	(0.59)	(2.02)
Log house value	-0.04	-0.23	0.23	-0.27	0.14	0.06
	(0.31)	(0.33)	(0.29)	(0.46)	(0.46)	(2.18)
R^2	0.37	0.73	0.35	0.73	0.30	0.66
Dep. UPC size						
Income variable	0.01	-0.04**	-0.27***	0.04	-0.19	0.43*
	(0.01)	(0.01)	(0.09)	(0.14)	(0.12)	(0.16)
Log house value	-0.03	0.31***	0.04	0.28***	0.07	0.17
	(0.07)	(0.07)	(0.06)	(0.08)	(0.07)	(0.08)
	0.75	0.66	0.77	0.68	0.80	0.76
R^2	0.75	0.66	0.77	0.68	0.80	0.76
Controls/FE	Y	Y	Y	Y	Y	Y
No. Obs.	331,939	61,691	100,760	20,899	27,868	5,770

Note: Same as table 3.

Online Appendix 2. Assortment Mechanism

Which products tend to be dropped by a retailer under negative demand shocks? Stores may first drop products that are preferred by relatively few consumers and contribute less to the total revenue (Hwang et al. 2010). We construct an indicator variable, d_{jimt} that equals 1 if product j was carried by store i in market m and period $t-1$, but is not carried in t. We multiple d_{jimt} by 100, so that it equals 0 or 100 and can be interpreted in percentage. Defining a period t to be a year, the mean of d_{jimt} weighted by observations is 16.3 for grocery stores and 12.3 for mass merchandisers from 2008 to 2010. Variable, $s_{jim,t-1}$, is the store-level volume share of UPC j in $t-1$ and ranges from 0 to 100. The mean of $s_{jim,t-1}$ is 0.34 (1.08) with a standard deviation of 0.46 (2.99) for grocery stores (mass merchandisers).

We estimate the effects of previous volume shares, $s_{jim,t-1}$, and their interactions with changes in local income and wealth on the removal probability of UPCs. The regression is specified as:

(B1) $d_{jimt} = \alpha_0 + \alpha_1 s_{jim,t-1} + \alpha_2 \Delta I_{mt} + \alpha_3 \Delta W_{mt} + \alpha_4 s_{t-1} \Delta I_{jimt} + \alpha_5 s_{t-1} t \Delta W_{jimt}$

$+R_r + M_{imt} + T_t + \epsilon_{jimt},$

where ΔI_{mt} (ΔW_{mt}) is the change in local income (wealth) relative to period $t-1$, and $s_{t-1}\Delta I_{jimt}$ ($s_{t-1}\Delta W_{jimt}$) is the interaction term of $s_{jim,t-1}$ and the income (wealth) change. The income (wealth) change is computed as income (wealth) this year minus that of the previous year and divided by the previous year value. Control variables are defined in equation (1).

Table B6. Assortment Mechanism under Demand Shocks

	Grocery	Mass	Grocery	Mass
	(1)	(2)	(3)	(4)
$s_{jim,t-1}$	-12.59***	-0.53**	-14.49***	-0.54**
	(1.90)	(0.18)	(1.87)	(0.17)
$s_{jim,t-1}$	0.24**	0.02*	0.20**	0.02*
$*\Delta I$	(0.08)	(0.01)	(0.07)	(0.01)
$s_{jim,t-1}$	0.03	0.01	0.04	0.01
$*\Delta W$	(0.10)	(0.01)	(0.10)	(0.01)
ΔI	-0.06	-0.08	-0.04	-0.08
	(0.04)	(0.06)	(0.03)	(0.06)
ΔW	-0.02	-0.01	-0.02	-0.004
	(0.05)	(0.05)	(0.05)	(0.05)
R^2	0.03	0.02	0.04	0.02
UPC shares	Volume shares		Sales shares	
Controls/FE	Y	Y	Y	Y
No. Obs.	7,063,469	525,346	7,063,469	525,346

Source: Authors' estimation based on Nielsen data.
Note: Same as table 3. $s_{jim,t-1}$ is the volume or sales share of a product in a store in year $t-1$. ΔI (ΔW) refers to the change in household median income (house value) in year t compared with $t-1$. Control variables (controls) and fixed effects (FE) are listed in equation (1).

Because we are mostly interested in the sign of $s_{jim,t-1}$, the OLS estimator is applied to equation (B1). Columns (1) and (2) in table 4 show that the probability for a store to discontinue a UPC decreases in the previous-year volume share of the UPC, ΔI_{mt}, and ΔW_{mt}. When a UPC's volume share falls by 1%, its probability of being removed increases by 12.6% in a grocery store and 0.5% in a mass merchandiser. The share-based removal is strengthened by a decreased local demand, indicated by the positive and significant coefficient of the interaction term, $s_{jim,t-1}$.

The effect is stronger for grocery stores than for mass merchandisers, echoing the relatively large room for variety adjustments for grocery stores. Using sales shares of products generates highly consistent outcomes (see columns (3) and (4) of table 4). The estimates speak to the decrease in brand uniqueness in table 3, because niche products by definition have relatively small market shares and are more likely to be removed by the store in a recession, leaving more mainstream products in the store's portfolio and increasing brand proximity.[7]

References

Cox, D. R., & Wermuth, N. (1992). A Comment on the Coefficient of Determination for Binary Responses. *American Statistician*, *46*(1), 1-4. https://doi.org/10.2307/2684400

DellaVigna, S., & Gentzkow, M. (2019). Uniform Pricing in U.S. Retail Chains. *Quarterly Journal of Economics*, *134*(4), 2011-2084. https://doi.org/10.1093/qje/qjz019

Department of Justice. (2018). HERFINDAHL-HIRSCHMAN INDEX. https://www.justice.gov/atr/herfindahl-hirschman-index

Hwang, M., Bronnenberg, B. J., & Thomadsen, R. (2010). An Empirical Analysis of Assortment Similarities across U.S. Supermarkets. *Marketing Science*, *29*(5), 858-879. https://doi.org/10.1287/mksc.1100.0564

Subramanian, U., Raju, J. S., Dhar, S. K., & Wang, Y. (2010). Competitive Consequences of Using a Category Captain. *Management Science*, *56*(10), 1739-1765. https://doi.org/10.1287/mnsc.1100.1211

Sullivan, C. (2020). Split Apart: Differentiation, Diversion, and Coordination in the Market for Superpremium Ice Cream. *AEA Papers and Proceedings* 110, 573-78

Viswanathan, M., Narasimhan, O., & John, G. (2021). Economic Impact of Category Captaincy: An Examination of Assortments and Prices. *Marketing Science*, *40*(2), 261-282. https://doi.org/10.1287/mksc.2020.1251

[7] Compared with table 3, *R*-squared values in table 4 are much smaller, likely due to two reasons. First, *R*-squared is small by construction for a linear regression using a binary dependent variable (Cox and Wermuth 1992). Sometimes with 0.10 as the upper bound for *R*-squared. In that regard, 0.02-0.04 is not too small. Second, portfolio management of retail stores is known to be complex with a large number of products in each category and many related categories which are not captured by our specification. Further investigation is worth conducting, but out of scope for this study. We also checked if national brands or private labels are more likely to be removed, everything else the same. It turns out that private labels are slightly more likely to be maintained. Corresponding outcomes are available upon request.