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How Point-of-Sale Marketing Mix Impacts National-Brand Purchase Shares

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Purchase shares of major national brands in consumer packaged-goods industries vary substantially across stores, both between geographic markets and across stores within markets. We measure the relationship between the variation in national-brand purchase shares and five store-specific marketing mix factors: prices, assortment shares, features, displays, and promotion intensity. We do this by first demonstrating the extent to which purchase shares of the top two national brands across six different categories vary across markets, accounts (defined as chain–market interactions) and stores: market-level variation accounts for approximately 30% of the weekly purchase share variation across stores, whereas account-level and store-level variation explain an additional 13% and 5% of the variation, respectively. We then measure the extent to which assortment, pricing, feature, display, and promotion activities affect the purchase shares of the top national brands. We find that price and assortment share are the two most important point-of-sale factors in determining a brand's purchase share. We also examine how the proximity to a brand's city of origin, the assortment share of a store's private label, the extent of retail competition, and the demographics of the store's neighborhood affect the purchase share's sensitivity to the point-of-sale marketing mix, revealing several subtle effects. Finally, we measure the extent to which the variation in top national-brand purchase shares is explained by these five factors. We find that, on average, approximately 56% of the variation in national-brand purchase shares can be attributed to these five factors. These results demonstrate the potential importance of trade marketing on a brand's purchase shares.

Keywords: retailing; brand market share; assortment; supermarket; distribution; consumer packaged goods
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1. Introduction

There is significant variation in the store-level market shares of the major national brands of consumer packaged-goods (CPG) industries across U.S. supermarkets. For example, Yoplait yogurt has, on average, a 30% store-level market share (or "purchase share"), but these shares vary immensely, with a standard deviation of 13%. This variation in purchase shares exists not only across different metropolitan markets, but also across stores within a given market.

Our paper examines the causes of this variation in purchase shares by measuring the extent to which the purchase share variation of the top two national brands in six popular categories is driven by five point-of-sale (POS) marketing mix elements: assortment share, price, feature, display, and promotion intensity. We use store-level data to measure the impact of these five factors and identify the impact from the changes in purchase shares in response to changes in these factors within a store. We find that a change of one standard deviation for relative price corresponds to a total difference of 7.7% in purchase shares (for example, a 20% purchase share versus a 27.7% purchase share). Similar differences in assortment share, relative display, relative feature, and relative promotion intensity correspond to differences in purchase shares of 2.4%, 1.5%, 2.1% and 1.0%, respectively. We also find that the point-of-sale marketing mix activities we consider account for approximately 56% of the explained variation in purchase shares, on average, across 12 brands in six categories.

Last, but certainly not least, we find that asymmetric POS marketing mix effectiveness (especially in price), which favors brands closer to their city of origin is another underlying mechanism behind observed differences in purchase shares across geographic markets. In other words, order of entry, which is measured by the distance from city of origin, not only works as a main effect, but also works as a moderator on POS marketing mix effectiveness. This asymmetry in POS marketing mix responsiveness also helps early entrants to sustain local market dominance since they have to spend less to achieve the same level of impact on purchase shares.

Our results have several implications. First, the factors we study are under the control of the retailers, not the manufacturers. Of course, manufacturers have worked to gain influence over these variables, and the manufacturer influence on these variables is traditionally under the purview of trade marketing. Our results demonstrate that the marketing instruments that trade marketing seeks to influence have significant impacts on consumer choices. This matches a movement by manufacturers from consumer marketing to trade marketing: In 1968, only 28% of promotional dollars were spent on trade marketing, with the other 72% going to direct consumer advertising (Food Marketing Institute 2001), but by 2010 trade marketing accounted for 60% of marketing spending (Kellen and Kaiser 2010). The importance of these point-of-sale factors may also explain why retailers appear to extract a larger fraction of the surplus created by the retail channel than manufacturers (Kadiyali et al. 2000, Villas-Boas 2007).

Our results are also important for understanding how recent trends in retailing are likely to affect large national brands. For example, although much of the category management literature focuses on the extent to which retailers or consumers benefit from having a category captain (e.g., Gruen and Shah 2000, Carameli 2004, Morgan et al. 2007, Subramanian et al. 2010), an important question is how the presence of category captains affects competing manufacturers. Our results suggest that changes in the marketing instruments over which category captains have influence (e.g., the number of stock-keeping units (SKUs) or prices) can have a significant impact on the sales of even major brands. Similarly, our results suggest that slotting allowances might have a significant impact on consumer choices by changing the composition of products supermarkets offer (e.g., White et al. 2000, Bloom et al. 2000, Sudhir and Rao 2006), and that product proliferation might increase a major brand's market share to the extent to which it shifts the composition of the assortment among the major brands.[1]

Previous studies have shown that market shares of top national brands vary significantly between U.S. metropolitan markets (see Bronnenberg et al. 2007, 2009). An important question is what is driving these differences in market shares. Partially because these same papers show that market-level purchase shares persist over time—decades, or even centuries—many papers have looked at pull factors to explain the market-level differences in market shares. For example, Bronnenberg et al. (2009) show that consumers' quality perceptions about the different brands are correlated with local market shares, whereas Bronnenberg et al. (2011) show that the observed market share variation is consistent with Sutton's (1991) endogenous sunk cost theory, and suggest that advertising may be a significant driver of the market-level differences in purchase shares. Another pull factor that can contribute to purchase share variation is that different stores may cater to different demographics, which have different preferences. These demographic differences are present across cities as well as between different neighborhoods within a given metropolitan area. Bronnenberg et al. (2012) use data from consumers moving between cities to show that consumer preferences explain at least 40% of the market share variation across different metropolitan areas.

Our research is also related to a literature that has examined aspects of trade marketing. Ataman et al. (2010) study mature brands and measure the relative importance of four elements of the marketing mix: advertising, price promotion, product line length, and distribution breadth. They find that product line length and distribution breadth (how many stores stock the brand) are the most important drivers of a brand's success.[2] Ataman et al. (2008) study the importance of several factors in determining the success of new brands. One might hypothesize that different elements of the marketing mix may drive the success of new versus mature products; such logic is confirmed by the different relative importance of the variables common to their studies and our study. Bronnenberg et al. (2012) consider how price, feature, and display affect the relative performance of the top national brand versus the second national brand across cities (ignoring the market shares of other brands) and find that these three variables explain 21% of the variation after controlling for market-level fixed effects. We find that price, feature, display, assortment, and price promotion explain 56% of the total variance in purchase shares across stores. One reason for this difference is that looking at the market-level variation masks the impact of these variables. These factors explain both market-level and store-level variation, and we confirm that examining these data at the market level masks the impact of these five factors by showing that these factors together explain 32% of the market-level variation in purchase shares. Finally, Zhang and Krishna (2007) look at a SKU reduction program at an online store where several SKUs from many brands were eliminated. They show that larger brands benefited from the SKU reduction,

[1] See, e.g., Bayus and Putsis (1999), although their study is not in a consumer packaged-goods industry.

[2] In our paper, we include only stores that stock both of the top two national brands. In general, the top national brands in the common CPG categories we study have very broad distribution breadth.

and that brands losing SKUs could ultimately sell less, especially if they were a smaller brand.[3]

Although we focus on the impact of five point-of-sale factors, there are other store-level marketing variables that could affect purchases shares, including shelf location and the number of facings for the product. Unfortunately, we do not have data on these variables so we cannot assess the impact of these variables. Previous literature states that location on the shelf matters, but debates the impact of facings: Dreze et al. (1995) show that location has a large impact on sales, but changes in the number of facings has less impact as long as a sufficient amount of each product is present to avoid stockouts. Chandon et al. (2009) also find that location on the shelf matters, but that the number of facings can have a significant impact, especially for frequent users of a brand.

We organize the remainder of this paper as follows. Section 2 describes the data and provides a motivating example. Section 3 presents the variance decomposition analysis. Our estimation strategy and results appear in §4. In §5, we calculate the extent to which purchase share variation is explained by our five factors. Section 6 concludes.

2. Data

2.1. Data Description

Our analysis utilizes four main sources of data: store-level scanner data covering six categories of consumer packaged goods from the IRI academic data set (Bronnenberg et al. 2008), retail competition data from Trade Dimensions, store trade area demographics data from IRI, and data on the city of origin manually collected by the author from company websites.

2.1.1. Store-Level Scanner Data. Our primary data are store-level scanner data from the IRI academic data set. The scanner data span 1,589 supermarkets across 48 IRI markets[4] in six CPG categories—cereal, coffee, toilet paper, yogurt, peanut butter, and ketchup. The data are provided at the universal product code (UPC) level, but we aggregate over UPCs to compute purchase shares at the store for the top two national brands in each category. We use weekly data from 2004–2005 to ensure a stable panel and to maximize the validity of our fixed-effects approach (see §4). For reliability, we limit our analysis to stores with more than 80 weeks of data. In addition, we limit our analysis to stores carrying both of the top two national brands in the two-year window to ensure the availability of both brands. After applying these restrictions, we have a final number of 1,092 sample stores in the coffee category, 1,230 in the cereal category, 1,171 in the toilet paper category, 1,200 in the yogurt category, 1,025 in the peanut butter category, and 998 in the ketchup category.

In our analyses, we focus on the top two national brands as measured by total volume across all of the sample stores. Table 1 shows the average purchase shares and the variation in purchase shares of these two brands for each category. Purchase shares are defined as being the total unit-equivalent volume of purchases belonging to the brand, divided by the total unit-equivalent volume of purchases in the category at the particular store. The units are generally measured in ounces—either as weight for coffee or cereal, or as volume for yogurt, peanut butter, or ketchup. Toilet paper is measured in numbers of rolls.

Table 2 presents the summary statistics for the store-level variables for each of these top two brands. Note that we use relative measures for all five factors since our dependent variable, purchase share, is also a relative variable. Assortment share is defined as being the number of SKUs belonging to a brand in a given store, divided by the total number of SKUs in the category at that particular store. Ataman et al. (2008) call assortment share "distribution depth." We believe that this is a reasonable interpretation of assortment share, although other papers have used the term "distribution depth" differently (e.g., Bronnenberg and Mela 2004). One issue that can arise in the IRI data is that the presence of a product is seen in the data

Table 1 **Descriptive Statistics: Unit Purchase Shares of the Two Brands in Each Category**

	#1 brand			#2 brand		
Category	Brand	Mean	Std. dev.	Brand	Mean	Std. dev.
Coffee	Folgers	0.318	0.18	Maxwell House	0.227	0.18
Cereal	Kellogg's	0.311	0.10	General Mills	0.264	0.09
Toilet paper	Charmin	0.215	0.15	Quilted Northern	0.151	0.13
Yogurt	Yoplait	0.299	0.13	Dannon	0.265	0.12
Peanut butter	Jif	0.299	0.14	Skippy	0.255	0.19
Ketchup	Heinz	0.523	0.21	Hunts	0.201	0.17

[3] Our paper is also related to a literature that studies how assortment reductions affect the total sales in a supermarket category. Overall, this research suggests that there is not a large long-run impact on category sales from having different numbers of total SKUs in the category, although consumers may shop at different retailers based on their relative selections. Specifically, Broniarczyk et al. (1998) and Boatwright and Nunes (2001) show that the effect of cutting category SKUs is not too large. Sloot et al. (2006) shows that there may be short-run losses from SKU reductions, but only small long-run effects. On the other hand, Borle et al. (2005) and Briesch et al. (2009) show that having a lower number of SKUs can lead to customers shopping at a particular store less often, so a store's sales could fall if it cuts the number of SKUs.

[4] We do not include data from the test markets of Eau Claire and Pittsfield.

Table 2 Descriptive Statistics: Store-Level Point-of-Sale Variables

		Assortment share		Relative price		Relative display		Relative feature		Relative promotion intensity	
Category	Brand	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Coffee	Folgers	0.17	0.07	0.89	0.32	0.14	0.27	0.14	0.31	0.14	0.20
	Maxwell House	0.15	0.07	0.91	0.31	0.18	0.31	0.17	0.32	0.17	0.22
Cereal	Kellogg's	0.25	0.04	1.05	0.18	0.30	0.23	0.31	0.30	0.28	0.16
	General Mills	0.22	0.03	1.30	0.23	0.25	0.23	0.26	0.28	0.20	0.14
Toilet paper	Charmin	0.26	0.17	1.25	0.33	0.21	0.33	0.19	0.34	0.20	0.23
	Quilted Northern	0.17	0.13	1.19	0.31	0.16	0.30	0.17	0.33	0.18	0.21
Yogurt	Yoplait	0.32	0.08	1.32	0.24	0.08	0.24	0.19	0.31	0.27	0.27
	Dannon	0.29	0.08	1.25	0.22	0.09	0.25	0.27	0.35	0.28	0.35
Peanut butter	Jif	0.24	0.05	1.11	0.21	0.07	0.23	0.10	0.28	0.18	0.27
	Skippy	0.26	0.09	1.17	0.31	0.13	0.31	0.15	0.34	0.24	0.30
Ketchup	Heinz	0.32	0.08	1.32	0.24	0.08	0.24	0.19	0.31	0.27	0.27
	Hunts	0.29	0.08	1.25	0.22	0.09	0.25	0.27	0.35	0.28	0.26

only if at least one customer purchases the item. To ensure that we do not miss the presence of slow-moving items, we smooth the data such that if there is any temporary gap in an store's offering of a product that is four weeks or less, we fill in this gap and assume that the retailer offers the product continuously in that time period. More details of this process can be found at Hwang et al. (2010). Also, if a product is stocked for less than three total weeks, we assume that the product's presence was a coding error and omit it from the analysis. Although this smoothing ensures that slow-moving items are counted for the calculation of assortment share in our analysis, this cleaning of the data does not have much impact on our results.

Relative prices are calculated as prices per unit-equivalent measures. We define relative price of a brand as being the total revenues divided by the total ounces sold for the brand within a store, divided by the total revenues divided by the total ounces for all other products in the category in the same store.[5] Note that relative prices are generally above 1 because the #1 and #2 brands are generally premium brands that command a price premium. The exceptions are in the coffee category, where Folgers and Maxwell House are not premium coffees.

The relative feature variable is measured as the number of a brand's SKUs that are on feature each week[6] divided by the number of SKUs in the category that are on feature in a particular week. Relative display is measured in an analogous manner. If no product is on display or feature at any time in a week at the particular store, then all products are assigned a relative display or feature values of zero. Finally, the relative promotion intensity variable is measured as the number of a brand's SKUs that are under price discount each week divided by the number of SKUs in the category that are under price discount.

The IRI academic data set also provides unique market and chain identifiers for each sample store. We use these identifiers to assign stores to geographic markets and accounts, which are defined as market–chain combinations. We have 204 unique accounts.

2.1.2. Store Trading Area Demographics. We obtain additional data from IRI, which characterize the local clientele of each store in our sample. We include two demographics from the store trading area: the percentage of the population with age 65 and above and the median household income.

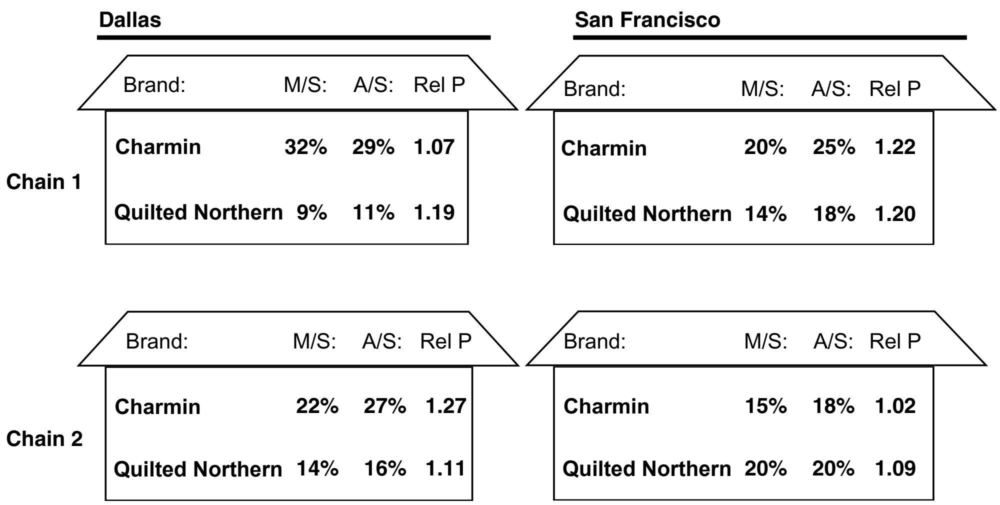
2.1.3. Retail Competition. Retail competition data are obtained from the 2006 Trade Dimensions retail census data. From this data set, we utilize information on store types (i.e., supermarkets, supercenters), store names, and the longitudes and latitudes of the stores. By using the longitudes and latitudes of sample stores separately provided by IRI, we calculate the number of competing supermarkets within three miles of the focal store and the number of competing supercenters within three miles of the focal store.

2.1.4. City of Origin. We collect the geocodes of the centroid of the city of origin for each national brand that we examine by visiting company websites and Wikipedia pages on each brand. Combining these data with geocodes for the centroids of 48 IRI markets allows us to construct the distance from the city of origin for each IRI market. Note that the computed distances vary only by IRI market, not by stores.

[5] As before, toilet paper is measured in number of rolls, not ounces.

[6] In some cases only a subset of the product line is on feature or display. For example, Dannon Light can be on feature, so only Dannon Light SKUs, and not all Dannon SKUs, are on feature.

Figure 1 Purchase Shares, Assortment Shares, and Relative Prices at Two Chains in Two Markets



2.2. Motivating Example

Before moving to our full analysis, we present an example from our data that demonstrates the extent to which purchase shares vary across markets and across chains. Figure 1 compares brand-level average purchase shares of the two top toilet paper national brands in two large multimarket retailers in two cities, Dallas and San Francisco. The IRI data set masks the identities of the chains, so we use the names "chain A" and "chain B." If we compare the purchase shares of Charmin and Quilted Northern in chain A in Dallas and San Francisco, we see that Charmin's purchase shares are higher in Dallas than in San Francisco, whereas the opposite is true for Quilted Northern. A similar pattern emerges in chain B. This pattern is consistent with the findings of Bronnenberg et al. (2007).

Looking across chains in Dallas, we see that Charmin's purchase shares are much higher in chain A than they are in chain B, whereas the opposite is true for Quilted Northern. We see the same pattern between these chains in San Francisco, and in fact Quilted Northern actually outsells Charmin in chain B in San Francisco. Thus, we see that purchase shares vary significantly both between metropolitan markets and between chains, even within a market.

Can POS factors explain the differences in Charmin's purchase shares across metropolitan markets and chains? Looking at the brand assortment share, we see that Charmin's brand assortment shares are higher in Dallas than in San Francisco for both chains, and higher in chain A than chain B in both metropolitan areas. Note, however, that the stocking decisions do not translate one to one into purchase shares. Furthermore, this correlation between assortment shares and purchase shares does not imply causality—whereas consumers may respond to the assortment that retailers offer, retailers also likely set their assortments to reflect the preferences of their clientele.

In Figure 2, we show the purchase shares and assortment shares of stores across the United States. Each circle represents a different store, and the size of the circle is proportional to the purchase share (or assortment share) of Charmin in that store. A dot is white if the purchase (assortment) share is below the average purchase (assortment) share in the data. We see that the patterns from the Dallas/San Francisco example hold more broadly across the country. First, there is a large amount of variation in the purchase shares of Charmin, both across metropolitan areas and within metropolitan areas. Furthermore, the stores with smaller purchase shares for Charmin are interspersed with stores with higher purchase shares of Charmin. Finally, the variation in purchase shares is highly correlated with the variation in assortment shares of Charmin, as in the Dallas/San Francisco example.

Looking at relative prices, we see in Figure 1 that there is a negative correlation between the relative prices of Charmin and Quilted Northern and the ratio of the purchase shares of the two brands, as would be expected if consumers respond to the prices of the products. However, the pattern does not hold in chain B in San Francisco. Furthermore, whereas the pattern of endogeneity for assortment share goes in the same direction as consumer behavior (consumers buy more of a brand as the brand's assortment share increases, and retailers stock more of the brand that consumers want), the pattern of endogeneity for

Figure 2 Purchase Shares and Assortment Shares for Stores Across the United States

relative price is more complex. Although consumers are drawn to products with lower prices, retailers have an incentive to increase the prices of the most popular brands among their clientele. However, firms also have an incentive to offer promotions on items that consumers want as traffic generators, similar to the logic of why prices are low for products during times of peak demand (Chevalier et al. 2003). Thus, there are several effects that affect the correlation between relative prices and purchase shares in different directions, leading to the looser relationship between relative price and purchase shares.

This motivating example shows that purchase shares vary across both markets and chains. Furthermore, the example suggests that POS marketing mix elements could be a potential driver of national-brand purchase shares across stores.

3. Variance Decomposition Analysis

In this section, we measure the extent to which market-, account-, and store-level effects explain the variation in each brand's purchase shares. We do this decomposition in two ways—(1) a nested analysis of variance (ANOVA) and (2) a components-of-variance (COV) estimation to ensure Robustness (McGahan and Porter 1997). First, we estimate a series of linear regression models to conduct nested fixed effects ANOVA. Specifically, we run the following set of regressions:

$$PS_{s,c,m,t} = \gamma_t + \varepsilon_{s,c,m,t}; \tag{1a}$$

$$PS_{s,c,m,t} = \alpha_m + \gamma_t + \varepsilon_{s,c,m,t}; \tag{1b}$$

$$PS_{s,c,m,t} = \beta_{c,m} + \gamma_t + \varepsilon_{s,c,m,t}; \tag{1c}$$

$$PS_{s,c,m,t} = \eta_{s,c,m} + \gamma_t + \varepsilon_{s,c,m,t}. \tag{1d}$$

In these equations, $PS_{s,c,m,t}$ is the purchase share of a focal national brand at store s in chain c and market m at time t. The γ_t terms are time (weekly) fixed effects, α_m represents market fixed effects for each IRI market, $\beta_{c,m}$ represent account-level (defined as chain–market combinations) fixed effects, and $\eta_{s,c,m}$ represents store-level fixed effects. Note that the account-level indicator variables consist of chain-market indicator variables, so they nest the market-level variables. Similarly, the store-level dummy variables nest the account-level dummy variables. Therefore, adding α_m to Equations (1c) or (1d) or adding $\beta_{c,m}$ to Equation (1d) would be redundant and introduce perfect multicollinearity.

The variance decomposition then calculates how much adding each level of fixed effects marginally increases the regression's R^2 as we move from Equations (1a) to (1d). We run separate variance decompositions for each of the 12 brands.

Table 3 reports the average results for the 12 different sets of variance decompositions, together with ranges across 12 brands. Looking at the first column in Table 3, we see that regressing purchase shares on weekly dummies alone leads to an R^2 of 0.042, indicating that time effects explain small variations in purchase shares in weekly data. It is perhaps surprising that the weekly dummies do not explain more of the purchase share variation, since it might be expected that national advertising campaigns lead to large swings in brand choice. For example, one could imagine that Jif runs a strong national advertising campaign in one week while Skippy runs a strong national advertising campaign in another week, and that these advertising campaigns lead to large swings in purchase shares.[7]

Regressions of purchase shares on week and market dummy variables yield an average R^2 of 0.355,

[7] Note that the low R^2 for the time trend does not mean that national advertising campaigns are not effective. For example, competing brands may adjust their strategies to counteract the tactics of their rivals.

Table 3 Incremental Explanatory Power: Brand Purchase Share

	Nested ANOVA								Variance components			
	Weekly data				Quarterly data				Weekly data			
	All		Top brands		All		Top brands		All		Top brands	
Type of effect	Average	Ranges	Average	Ranges	Average	Ranges	Average	Ranges	Average	Ranges	Average	Ranges
Time	4.2	(1.1~9.4)	4.9	(1.5~9.4)	1.7	(0.1~6.4)	1.5	(0.6~2.2)	4.0	(1.0~9.1)	4.8	(1.4~9.1)
Market	31.3	(10.2~69.3)	29.5	(12.2~49.2)	54.8	(34.0~85.9)	53.3	(36.8~73.7)	29.8	(5.4~65.8)	26.8	(10.7~46.1)
Account	9.6	(3.6~17.8)	9.8	(6.7~17.0)	20.1	(5.0~37.2)	19.9	(10.8~29.4)	13.1	(5.1~22.5)	13.5	(9.8~22.5)
Store	4.8	(2.2~10.2)	5.4	(3.7~10.2)	9.2	(3.0~15.2)	10.7	(5.6~15.2)	4.9	(2.4~12.1)	5.9	(3.7~12.1)
Full Model	49.6	(28.4~76.3)	49.7	(30.9~62.3)	85.7	(77.8~94.1)	85.3	(77.8~91.9)	51.8	(26.2~74.7)	51.0	(30.8~62.8)
Ratio												
Account/Market	0.31		0.33		0.37		0.37		0.44		0.50	
Store/Account	0.50		0.55		0.46		0.54		0.37		0.44	

Notes. Values in parentheses are ranges across 12 brands in six categories. For weekly data, standard errors are less than 0.21 or 1.98 for all the types of estimated effects for nested ANOVA and variance components, respectively. Across six categories, there are 4.0 accounts per each market and 5.8 stores per each account, on average.

so we attribute 31.3% (= 0.355 − 0.042) of the variation in national-brand purchase shares to city-level (or "market") effects. A regression of purchase shares on week plus account dummies yields an R^2 of 0.451, so an additional 9.6% (= 0.451 − 0.355) of the purchase share variation can be explained by account-level effects above and beyond what can be explained by market effects. Finally, 4.8% of the variation can be explained by store-level effects after controlling for market- and account-level affects. Thus, whereas market-to-market differences explain 31% of the variation in purchase shares, an additional 14% of the purchase share variation occurs within metropolitan markets and can be systematically explained at the chain or store level. Finally, we find that cross-sectional variables explain 45% (= 49.6% full model—4.2% time only) of the variation in purchase shares in weekly data.

We also examine whether there are significant differences between the variation of the top national brand and the second-largest national brand in each category. The results in Table 3 show that the results for the variance decomposition are very similar when we include only the top national brand for each category. If anything, the results consistently show that the store- and chain-level variation are relatively more important for the top brands than the second brands.

Table 3 also presents the results for a variance decomposition with quarterly data. We find that the relative importance of each effect remains very consistent, as demonstrated in the ratio of 37% in the case of account effect/market effect for the quarterly data (compared to 31% for the weekly data). Similarly, the ratio of store effect over account effect for quarterly data is 46% on average, which is very similar to 50% for the weekly data. However, the explained variance from cross-sectional effects increases significantly from 50% in the weekly data to 86% in quarterly data, which is a result of the additional variance in purchase shares from week to week. Our results confirm that the frequency of the data plays a large role in assessing the relative importance of cross-sectional variation compared to time variation. Also, these results comparing quarterly data with weekly data suggest that most of the within-store variation across weeks due to promotions cancels out and cross-sectional variation becomes more important when one uses lower-frequency data. This is consistent with previous empirical findings in time series studies, which note that stationarity is a dominant characteristic in brand purchase shares in consumer packaged-goods categories (Dekimpe and Hanssens 1995).

The variance decomposition results from a nested ANOVA are very informative, but this approach largely attributes covariance between types of effects to the first effect introduced. Because of the existence of many single-market retailers in the data, it is difficult to separate out the market effects from chain effects. As an example, since the market effect is always introduced first in our nested ANOVA, the market effect can be overstated compared to the account effects. Thus, we also conduct a variance decomposition analysis based on a COV approach. The COV approach is based on the assumption that effects are independently generated under the given nesting structure of data. Specifically, we estimate the following variance component model:

$$PS_{s,c,m,t} = \alpha_m + \beta_{c,m} + \eta_{s,c,m} + \gamma_t + \varepsilon_{s,c,m,t}; \tag{2a}$$

$$\sigma^2(PS_{s,c,m,t}) = \sigma^2(\alpha_m) + \sigma^2(\beta_{c,m}) + \sigma^2(\eta_{s,c,m}) + \sigma^2(\gamma_t) + \sigma^2(\varepsilon_{s,c,m,t}\cdot) \tag{2b}$$

Table 3 also presents the variance decomposition results from a COV approach, which are qualitatively similar to the variance decomposition results from a nested ANOVA approach. As expected, account effects increase from 9.6% to 13.1% under a COV approach, whereas the market effect declines by a smaller amount, from 31.3% to 29.5%. Overall, the account and store effects are about 60% the size of the market effects. We take this as the right measure of local variation.

Finally, because many chains operate only in one market, it is empirically difficult to estimate a true chain-level effect. To better separate out chain effects from market effects, we conduct another ANOVA with a subset of multimarket retailers in our data. Specifically, we analyze data from the three largest multimarket retailers in markets where all three of these chains are present. Using only markets where all of the chains are present ensures orthogonality between chain effects and market effects in variance decomposition based on a nested ANOVA. Since multimarket retailers tend to use different local banners in different markets, we define chain membership as stores having a common owner, rather than having a common banner.[8] Note that this is a conservative test for the relative impact of chain effects since we reduce the across-chain variation by focusing only on top three multimarket retailers. It might be reasonable to expect that there would be greater across-chain variation when comparing multimarket retailers with single-market retailers.

[8] Note that the selected stores are predominantly from West and Southwest regions. The included IRI markets are Los Angeles, Seattle, Dallas, Sacramento, San Diego, Portland, Phoenix, Spokane, and West Texas/New Mexico.

Table 4 **Incremental Explanatory Power for a Subset of Multimarket Retailers**

	Nested ANOVA			
Type of effect	All		Top brands	
Time	13.2	(4.7∼23.0)	14.1	(6.0∼23.0)
Time + Market	28.5	(16.7∼67.3)	26.4	(18.6∼33.8)
Time + Owner	19.2	(5.7∼37.2)	20.4	(12.4∼28.5)
Time + Market + Owner	33.9	(19.0∼67.6)	31.7	(24.1∼37.4)
Time + Market + Owner + Market × Owner	36.6	(20.7∼70.2)	34.9	(26.0∼43.5)
Time + Account	36.9	(20.8∼70.4)	35.2	(26.4∼43.5)
Time + Store	43.6	(23.7∼74.3)	43.6	(30.9∼53.2)
Ratio				
Owner/Market (%)	39		51	
Store/Account (%)	78		72	

Notes. Values in parentheses are ranges across 12 brands in six categories. Standard errors are less than 0.45 for all the type of estimated effects.

The advantage of using the large multimarket retailers is that we can observe how R^2 changes when we add either market and then owner or owner and then market effects. Table 4 shows that the results from this sample are very similar to the previous results. On average, owner effects explain 5% (= 33.9% − 28.5%) to 6% (= 19.2% − 13.2%) of the variation in purchase shares. Similarly, market-level effects explain about 14%–15% of the purchase share variation. Both of these numbers are significantly reduced from Table 3 because we have limited ourselves to a selection of chains that have similar (multimarket, mainstream) attributes, and the markets where these stores are located are in the West or Southwest regions, which Bronnenberg et al. (2009) find should reduce the market-level variation. However, the ratio for the owner to market effect is similar to the ratio of the account to market effects from Table 3. Thus, overall, these results demonstrate the robustness of our variance decomposition results.

4. Measuring the Impact of Point-of-Sale Variables on Purchase Shares

4.1. Homogeneous Response Across Stores

In this section, we quantify the extent to which the POS marketing mix elements affect the purchase shares of a given brand at each store. Note that we run our analysis separately for each of the 12 brands; that is, we run each of the regressions that we describe below separately for each of the 12 brands and report the results brand by brand.

As a baseline, we first regress purchase shares on the POS variables dummies:

$$PS_{st} = \beta_{AS} \cdot AS_{st} + \beta_P \cdot P_{st} + \beta_F \cdot F_{st} + \beta_D \cdot D_{st} + \beta_{PR} \cdot PR_{st} + \gamma_t + \varepsilon_{st}, \tag{3}$$

where PS_{st} represents the purchase share of the focal brand at store s in week t, AS represents the assortment share of the focal brand in store s in week t, P represents the relative prices, F represents the relative feature, D represents the relative display, and PR represents relative promotion intensity. We include (weekly) time fixed effects, γ_t, to account for national advertising or other temporal demand shocks that might occur.

The results of these regressions for each brand are presented in the first column of Table 5. Because many of the customers at a store shop at the same chain in different weeks, and because promotions are often coordinated within an account, we utilize the two-way clustering technique of Cameron et al. (2011) and cluster the standard errors at the account and market-week levels to ensure robust inference. Most of the coefficients on the POS marketing mix variables are estimated to be statistically significant.

One issue with the estimates that have only time fixed effects is that the stores may be setting the POS marketing mix in response to the preferences of its customers. For example, a store whose customers prefer Maxwell House to Folgers is likely to stock more Maxwell House than a typical store,[9] and it is also likely to sell more Maxwell House than a typical store. In such a case, we would estimate a positive coefficient on assortment share even if changes in assortment share had no impact on consumer purchases. The estimates of the other POS variables have a similar issue. We can partially address this form of endogeneity to the extent that the elements of consumer preferences within a store that affect the marketing mix remain stable (at least over the two-year window we use for the estimation) by putting in fixed effects for each of the stores.[10] In this case, the set of store customers is assumed to remain (approximately) fixed, so the estimated effects are then identified from how much the sales of each brand change from changes in the point-of-sale variables.[11] We report the results with the store-level fixed effects in the next columns of Table 5.

Note that these store-level fixed effects can also capture (among other effects) different demand patterns that may be driven by differences in private labels across stores. If different stores have different qualities of store brands, and if these differences are correlated with assortment share or the other POS variables, this could cause differences in purchase shares of the top brands across stores that, without the store-level fixed effects, would look like they were caused by assortment share (or the other variables), but would be captured by the store-level fixed effects. A similar story applies to differences in the decision to stock regional brands across stores or differences in relationships with suppliers. One advantage of using a two-year window is that the clientele demographics and private label quality at each store is likely to be relatively stable within a reasonably narrow time period.

Comparing the coefficients when we include store-level fixed effects compared to when we do not include these fixed effects, we find that putting in the fixed effects does have an effect on the estimated coefficients. The estimated coefficients on all of the POS variables except price shrink (or sometimes stay within the confidence interval) when store fixed effects are added into the regression. The change in the price coefficients do not show a consistent pattern—the coefficients are sometimes larger or smaller, or even statistically the same as when the store fixed effects are not included. This is likely to be the result of the fact that there are multiple endogenous effects with respect to relative prices, some of which pull in opposing directions, as explained in §2.2, which makes it impossible to sign the anticipated endogeneity bias for the price coefficients.

Whereas store-level fixed effects can accommodate different brand choices due to consumer heterogeneity across stores, it is also possible that brand preferences vary at the market-time level. For example, many advertising campaigns for national brands occur at a regional level. Furthermore, the demand for a particular brand may be affected by the promotional activity of regional brands, which intrinsically only affects purchases in some markets. Because we do not observe advertising data, we run each of the 12 regressions again with market-week interaction dummies in addition to store-level fixed effects to account for variation in promotional activities across time and markets. Mathematically, we run

$$PS_{st} = \beta_{AS} \cdot AS_{st} + \beta_P \cdot P_{st} + \beta_F \cdot F_{st} + \beta_D \cdot D_{st} + \beta_{PR} \cdot PR_{st} + \eta_s + \gamma_{mt} + \varepsilon_{st}. \tag{4}$$

The results of this model are presented in the third set of columns. Overall, the results are generally statistically equivalent to those in the second set

[9] This could occur for a variety of reasons, but is consistent with "Space-to-Movement" (Dreze et al. 1995), where slow-moving items are removed from the shelves. Similarly, Reibstein and Farris (1995) show that the causality between market shares and distribution breadths goes both ways.

[10] Because we run separate regressions for each of the brands, the store fixed effects are effectively brand-store fixed effects.

[11] There could still be some endogeneity, for example, if assortments adjusted to changes in purchase shares in a store and purchase shares exhibit strong state dependence.

Table 5 Estimation Results for Store-Level National-Brand Share Regressions

		Estimator	Time fixed effects		Store fixed effects + time fixed effects		Store fixed effects + market-time fixed effects		Store + market-time fixed effects heterogeneous response	
Category	Brand	Independent variable	Coefficient	(Standard error)	Coefficient	(Standard error)	Coefficient	(Standard error)	Coefficient	(Standard error)
Coffee	Folgers	*Relative price*	−0.304	(0.129)***	−0.371	(0.013)***	−0.367	(0.013)***	−0.379	(0.009)***
		Assortment share	1.281	(0.060)***	0.610	(0.043)***	0.601	(0.044)***	0.626	(0.041)***
		Relative display	0.090	(0.007)***	0.063	(0.004)***	0.059	(0.003)***	0.057	(0.003)***
		Relative feature	0.101	(0.006)***	0.092	(0.006)***	0.094	(0.006)***	0.096	(0.004)***
		Relative promotion intensity	0.082	(0.010)***	0.047	(0.007)***	0.051	(0.007)***	0.051	(0.006)***
		Sample size	110,627		110,627		110,627		110,627	
		R^2	0.696		0.860		0.885		0.891	
	Maxwell House	*Relative price*	−0.234	(0.013)***	−0.274	(0.017)***	−0.269	(0.017)***	−0.294	(0.009)***
		Assortment share	1.153	(0.060)***	0.400	(0.036)***	0.420	(0.035)***	0.446	(0.028)***
		Relative display	0.096	(0.007)***	0.072	(0.006)***	0.063	(0.004)***	0.061	(0.005)***
		Relative feature	0.120	(0.006)***	0.104	(0.006)***	0.107	(0.006)***	0.096	(0.005)***
		Relative promotion intensity	0.052	(0.010)***	0.062	(0.008)***	0.064	(0.008)***	0.070	(0.007)***
		Sample size	110,627		110,627		110,627		110,627	
		R^2	0.691		0.817		0.853		0.871	
Cereal	Kellogg's	*Relative price*	−0.384	(0.012)***	−0.404	(0.008)***	−0.403	(0.007)***	−0.406	(0.006)***
		Assortment share	0.787	(0.046)***	0.399	(0.026)***	0.399	(0.025)***	0.410	(0.026)***
		Relative display	0.380	(0.003)***	0.034	(0.002)***	0.031	(0.002)***	0.031	(0.002)***
		Relative feature	0.345	(0.003)***	0.029	(0.003)***	0.029	(0.002)***	0.028	(0.002)***
		Relative promotion intensity	0.007	(0.008)	0.013	(0.006)**	0.014	(0.006)***	0.020	(0.005)***
		Sample size	124,865		124,865		124,865		124,865	
		R^2	0.719		0.808		0.845		0.848	
	General Mills	*Relative price*	−0.284	(0.006)***	−0.290	(0.006)***	−0.291	(0.006)***	−0.291	(0.005)***
		Assortment share	0.328	(0.054)***	0.210	(0.028)***	0.225	(0.028)***	0.254	(0.027)***
		Relative display	0.046	(0.003)***	0.036	(0.003)***	0.033	(0.002)***	0.033	(0.002)***
		Relative feature	0.027	(0.004)***	0.028	(0.003)***	0.028	(0.002)***	0.030	(0.002)***
		Relative promotion intensity	0.063	(0.011)***	0.044	(0.008)***	0.039	(0.006)***	0.039	(0.006)***
		Sample size	124,865		124,865		124,865		124,865	
		R^2	0.705		0.795		0.836		0.838	
Toilet paper	Charmin	*Relative price*	−0.186	(0.008)***	−0.217	(0.007)***	−0.212	(0.006)***	−0.221	(0.006)***
		Assortment share	0.552	(0.035)***	0.132	(0.021)***	0.117	(0.020)***	0.119	(0.020)***
		Relative display	0.086	(0.006)***	0.076	(0.005)***	0.070	(0.004)***	0.068	(0.004)***
		Relative feature	0.092	(0.006)***	0.087	(0.006)***	0.092	(0.005)***	0.094	(0.005)***
		Relative promotion intensity	0.077	(0.008)***	0.068	(0.006)***	0.066	(0.006)***	0.065	(0.005)***
		Sample size	118,993		118,993		118,993		118,993	
		R^2	0.691		0.807		0.840		0.846	
	Quilted Northern	*Relative price*	−0.156	(0.0088)***	−0.191	(0.0104)***	−0.185	(0.009)***	−0.181	(0.008)***
		Assortment share	0.653	(0.0480)***	0.153	(0.0223)***	0.166	(0.024)***	0.167	(0.020)***
		Relative display	0.133	(0.0090)***	0.122	(0.0079)***	0.114	(0.006)***	0.107	(0.005)***
		Relative feature	0.071	(0.0082)***	0.072	(0.0076)***	0.076	(0.007)***	0.085	(0.005)***
		Relative promotion intensity	0.067	(0.0082)***	0.055	(0.0064)***	0.055	(0.005)***	0.053	(0.005)***
		Sample size	118,993		118,993		118,993		118,993	
		R^2	0.680		0.765		0.811		0.819	

Table 5 (Continued)

		Estimator	Time fixed effects		Store fixed effects + time fixed effects		Store fixed effects + market-time fixed effects		Store + market-time fixed effects heterogeneous response	
Category	Brand	Independent variable	Coefficient	(Standard error)	Coefficient	(Standard error)	Coefficient	(Standard error)	Coefficient	(Standard error)
Yogurt	Yoplait	*Relative price*	−0.245	(0.008)***	−0.279	(0.007)***	−0.274	(0.007)***	−0.269	(0.006)***
		Assortment share	1.032	(0.031)***	0.485	(0.034)***	0.471	(0.027)***	0.496	(0.024)***
		Relative display	0.042	(0.004)***	0.035	(0.003)***	0.032	(0.002)***	0.032	(0.002)***
		Relative feature	0.035	(0.005)***	0.031	(0.004)***	0.031	(0.004)***	0.033	(0.003)***
		Relative promotion intensity	0.046	(0.006)***	0.036	(0.003)***	0.037	(0.003)***	0.032	(0.003)***
		Sample size	121,849		121,849		121,849		121,849	
		R^2	0.780		0.879		0.902		0.906	
	Dannon	*Relative price*	−0.277	(0.012)***	−0.246	(0.011)***	−0.245	(0.112)***	−0.249	(0.007)***
		Assortment share	0.765	(0.037)***	0.521	(0.027)***	0.504	(0.022)***	0.555	(0.022)***
		Relative display	0.030	(0.005)***	0.033	(0.003)***	0.028	(0.002)***	0.026	(0.002)***
		Relative feature	0.195	(0.004)***	0.025	(0.003)***	0.025	(0.002)***	0.026	(0.002)***
		Relative promotion intensity	0.019	(0.005)***	0.039	(0.004)***	0.038	(0.004)***	0.033	(0.003)***
		Sample size	121,849		121,849		121,849		121,849	
		R^2	0.751		0.881		0.903		0.912	
Peanut butter	Jif	*Relative price*	−0.297	(0.019)***	−0.309	(0.011)***	−0.309	(0.010)***	−0.323	(0.007)***
		Assortment share	1.514	(0.083)***	0.497	(0.031)***	0.387	(0.032)***	0.405	(0.027)***
		Relative display	0.069	(0.006)***	0.058	(0.004)***	0.054	(0.003)***	0.050	(0.003)***
		Relative feature	0.069	(0.006)***	0.059	(0.004)***	0.061	(0.004)***	0.059	(0.003)***
		Relative promotion intensity	0.038	(0.007)***	0.049	(0.004)***	0.047	(0.003)***	0.045	(0.003)***
		Sample size	104,718		104,718		104,718		104,718	
		R^2	0.679		0.855		0.878		0.884	
	Skippy	*Relative price*	−0.212	(0.022)***	−0.189	(0.018)***	−0.201	(0.018)***	−0.221	(0.014)***
		Assortment share	1.120	(0.052)***	0.297	(0.026)***	0.287	(0.028)***	0.326	(0.027)***
		Relative display	0.046	(0.007)***	0.051	(0.004)***	0.047	(0.003)***	0.044	(0.003)***
		Relative feature	0.072	(0.008)***	0.067	(0.007)***	0.066	(0.007)***	0.077	(0.005)***
		Relative promotion intensity	0.050	(0.010)***	0.072	(0.005)***	0.068	(0.004)***	0.056	(0.004)***
		Sample size	104,718		104,718		104,718		104,718	
		R^2	0.755		0.887		0.907		0.916	
Ketchup	Heinz	*Relative price*	−0.358	(0.016)***	−0.322	(0.006)***	−0.318	(0.005)***	−0.318	−0.005***
		Assortment share	0.988	(0.077)***	0.286	(0.021)***	0.276	(0.020)***	0.278	−0.017***
		Relative display	0.072	(0.009)***	0.073	(0.003)***	0.068	(0.003)***	0.069	−0.003***
		Relative feature	0.055	(0.008)***	0.058	(0.005)***	0.062	(0.004)***	0.063	−0.004***
		Relative promotion intensity	0.001	(0.009)	0.012	(0.003)***	0.011	(0.003)***	0.011	−0.002***
		Sample size	101,169		101,169		101,169		101,169	
		R^2	0.624		0.869		0.890		0.893	
	Hunts	*Relative price*	−0.280	(0.012)***	−0.308	(0.012)***	−0.309	(0.012)***	−0.312	−0.011***
		Assortment share	0.851	(0.046)***	0.255	(0.024)***	0.257	(0.024)***	0.236	−0.023***
		Relative display	0.154	(0.008)***	0.132	(0.005)***	0.121	(0.004)***	0.118	−0.004***
		Relative feature	0.089	(0.006)***	0.083	(0.005)***	0.087	(0.005)***	0.087	−0.005***
		Relative promotion intensity	0.057	(0.006)***	0.047	(0.005)***	0.045	(0.004)***	0.043	−0.003***
		Sample size	101,169		101,169		101,169		101,169	
		R^2	0.675		0.809		0.843		0.847	

***$p < 0.01$.

of columns when we only included store (but not market-time) fixed effects. This suggests that the any differences in purchase shares due to differences in local pull campaigns are either small or orthogonal to the POS marketing mix elements.

4.2. Heterogeneous Response Across Stores

The above results are based on the assumption that the impact of the five POS elements are constant across all stores. However, it is possible that the marketing mix sensitivities vary across stores. To address this concern, we interact the marketing mix variables with one market-level variable and five store-level variables that have been suggested in the literature to affect marketing mix responsiveness: (1) the distance from the city of origin for the brand (market-level factor), (2) the assortment share of the store's private label, (3) the number of competing supermarkets within three miles of the store, (4) the number of competing supercenters within three miles of the store, (5) the median income within a two-mile radius of the store, and (6) the fraction of people who are seniors (over 65) within a two-mile radius of the store.

The distance from the city of origin is included as a proxy for the date in which the brand entered a market, which we do not have. Bowman and Gatignon (1996) show that the order of entry affects consumers' response to price, promotion, quality, and advertising, whereas Bronnenberg et al. (2012) show that the date of entry affects a brand's market share. Taken together, asymmetric POS marketing mix effectiveness, which favors brands closer to their city of origin (i.e., early entrants), could be another underlying mechanism behind observed differences in purchase shares across geographic markets. The assortment share of the private label brand is a measure of how strong of a presence the private label has in a particular store, and is also correlated with the strength of the private label. The number of competing supermarkets and the number of supercenters within three miles of the store are measures of competition. Competition by similar stores might be expected to increase the level of price sensitivity. Competition in general can also affect how consumers respond to feature advertising, since if there is a nearby supermarket, a shopper might have limited attention and therefore focus on only a subset of the feature advertisements. Supercenters can also affect the marketing mix responsiveness, although the effect of a supercenter is not always clear. For example, Zhu et al. (2011) show that having a supercenter nearby often reduces the price sensitivity for some items. Zhu et al. (2011) also show that consumers shop at supermarkets for products that they cannot get at a supercenter, which can affect how consumers respond to assortments. Measures of income and the fraction of customers who are senior citizens have been used as common controls for retail promotions (e.g., Ailawadi et al. 2006), as well as factors in which types of brands consumers purchase (e.g., Dhar and Hoch 1997, Hwang et al. 2010). We also include the price, assortment share, display, feature, and price-promotion intensity directly into the regression as well.

We begin by analyzing the coefficients on the main effects. We subtract the mean of each of the six moderating variables discussed above before interacting them with the POS marketing mix, so that the coefficients of the POS marketing mix terms without the interaction terms represent the response for a store with the mean attributes and are comparable to the estimated coefficients in the other columns (described in §4.1) of Table 5. Overall, the coefficients on the terms without the interaction, which are presented in the last columns of Table 5, are very similar to the coefficients with the store-level fixed effects and the coefficients with the store- and market-time fixed effects. Thus, the homogeneous models are good at capturing the mean effects.

We next judge the relative importance of each of the POS marketing mix elements. Because the POS factors except price are all expressed in relative terms between 0 and 1, we can compare the coefficients across variables directly to compare the relative magnitudes of the effects. Similarly, because we normalize the mean of the interacting store-level demographic variables to be zero, the coefficients on the noninteracted relative price, assortment share, relative display, relative feature, and relative promotion intensity variables also represent the mean effects. The point-of-sale marketing mix element that has the largest impact on purchase shares is assortment share. On average, across all 12 brands, we find that a 1% change in the assortment share of a major brand (e.g., movement from 22% to 23%) leads to a 0.34% increase in the purchase share of the brand (e.g., movement from 22% to 22.34%). The impacts of relative feature, display, and promotion are all smaller: 0.06%, 0.05%, and 0.05%, respectively. One can look at the coefficient of price, too. A 1% increase in the relative price of the brand on average leads to a decrease in the purchase share of 0.29%.

An alternative way to measure the impact of these POS elements on purchase shares is to calculate how much a change of one standard deviation for each of our five factors affects the purchase shares of each brand. This measure combines the direct impact through the estimated coefficients with the actual observed amount of variation in each of the five POS elements. The results are presented in Table 6. We observe that a decrease of one standard deviation in relative price increases the purchase share of the brand by 7.6% (e.g., a movement from 20% purchase

Table 6 Impact of One-Standard-Deviation Change in the Point-of-Sale Marketing Mix Variables on Purchase Shares

Category	Brand	Relative price	Assortment share	Relative display	Relative feature	Relative promotion intensity
Coffee	Folgers	−12.0% (0.2953)	4.5% (0.2937)	1.6% (0.0816)	3.0% (0.1362)	1.0% (0.1222)
	Maxwell House	−9.2% (0.2836)	3.2% (0.2002)	1.9% (0.1415)	3.1% (0.1731)	1.5% (0.1508)
Cereal	Kellogg's	−7.3% (0.1095)	1.6% (0.1039)	0.7% (0.0412)	0.9% (0.0650)	0.3% (0.0727)
	General Mill's	−6.6% (0.1155)	0.8% (0.0854)	0.8% (0.0410)	0.9% (0.0700)	0.6% (0.0819)
Toilet paper	Charmin	−7.2% (0.1833)	0.8% (0.1310)	2.3% (0.1236)	3.2% (0.1665)	1.5% (0.1122)
	Quilted Northern	−5.6% (0.2325)	0.9% (0.1058)	3.2% (0.1422)	2.8% (0.1726)	1.1% (0.1064)
Yogurt	Yoplait	−6.4% (0.1359)	4.0% (0.1915)	0.8% (0.0520)	1.0% (0.0834)	0.9% (0.0826)
	Dannon	−5.5% (0.1638)	4.3% (0.1731)	0.7% (0.0414)	0.9% (0.0646)	0.9% (0.0814)
Peanut butter	Jif	−6.6% (0.1523)	2.1% (0.1449)	1.1% (0.0645)	1.7% (0.0962)	1.2% (0.0827)
	Skippy	−6.8% (0.4411)	3.1% (0.2531)	1.4% (0.0834)	2.6% (0.1766)	1.7% (0.1104)
Ketchup	Heinz	−9.9% (0.1664)	2.4% (0.1514)	2.5% (0.0931)	2.2% (0.1548)	0.4% (0.0811)
	Hunts	−7.4% (0.2723)	2.0% (0.1963)	3.1% (0.1058)	2.7% (0.1424)	1.3% (0.0976)
Average		−7.6%	2.5%	1.7%	2.1%	1.0%

Note. Values in parentheses are standard errors.

share to 27.6% purchase share). The next-largest factors are the assortment share and relative feature, with impacts of 2.5% and 2.1% from a one-standard-deviation change, respectively. If we take the approximation that the reasonable range of the underlying variables is ±2 standard deviations, then we can multiply these numbers by four to obtain an estimate of how much the POS marketing mix elements can truly affect assortment share. The effects of relative display and relative feature are smaller. The reason why the effect of assortment share shrinks to being closer to that of relative feature even though its coefficient is much higher is that the variation in assortment share is much lower than the variation in the other four factors. Some of this comes from the greater intertemporal variation in prices and other promotional variables, which are easier to change frequently than assortment share. However, even the cross-sectional variation in prices is larger than the cross-sectional variation in assortment share.

We now consider how the one market-level and five store-level descriptive variables affects the POS marketing mix sensitivities. Table 7 summarizes signs and statistical significance of the results for these interaction effects. We find that many of the results are not statistically significant, and that few interaction effects hold the same sign consistently across all 12 brands (although the main effects are all statistically significant and consistent across all 12 brands). Nevertheless, some patterns can be found.

Markets that are closer to the city of origin for a brand (i.e., with smaller distances from the brand of origin) exhibit greater price responsiveness for the brand. On the surface, this may seem surprising, given that brands are likely to be more dominant in markets close to their city of origin (Bronnenberg et al. 2009, and confirmed below). However, the greater popularity of the top national brand is likely to attract price-sensitive consumers, who in other markets may be attracted to the store brand or other regional brands, to the national brand, leading to our findings. This effect also demonstrates that a price cut will be more effective for a national brand near the city of origin. The price responsiveness results are in general consistent with the order-of-entry finding of Bowman and Gatignon (1996). There also is evidence that greater proximity to the brand's city of origin increases the impact of assortment size, and there appears to be a weak trend that feature advertising promoting a brand is somewhat stronger in cities closer to the city of origin. This suggests asymmetric POS marketing mix effectiveness, which favors brands closer to their city of origin (i.e., early entrants), as another underlying mechanism behind observed differences in purchase shares across geographic markets. In contrast, the responsiveness to display and promotion intensity is smaller in stores in markets closer to the city of the brand's origin.

A retailer's private label strength affects the consumer's responsiveness to the POS marketing mix, with the most significant effects coming from the responsiveness to prices and promotions. We observe that demand for national brands at stores with a greater private label presence tend to be less price sensitive, but more deal (price-promotion) sensitive. This is consistent with consumers who are very price sensitive choosing the private label brand, leaving only the less price-sensitive consumers in the market for national brands, consistent with Bronnenberg and Wathieru (1996). The national brands then have a hard time attracting these price-sensitive consumers at any of the regular prices they may charge. However, during price promotions, the prices for these national brands get low enough that they can steal

Table 7 Impact of Point-of-Sale Marketing Mix Sensitivity Moderators

	# Positive # Positive & Significant	# Negative # Negative & Significant
Relative price		
Dist_City_Origin	8 8	4 1
Private_Label_AS	9 7	3 0
Num_Supermarket_Competitors	5 3	7 3
Num_Supercenter_Competitors	6 3	6 4
Med_HH_Income	4 1	8 6
Age_GT_65	7 3	5 2
Assortment share		
Dist_City_Origin	3 1	9 4
Private_Label_AS	3 1	9 5
Num_Supermarket_Competitors	7 2	5 2
Num_Supercenter_Competitors	6 0	6 1
Med_HH_Income	7 4	5 2
Age_GT_65	5 0	7 1
Relative display		
Dist_City_Origin	9 5	3 1
Private_Label_AS	4 1	8 1
Num_Supermarket_Competitors	6 0	6 0
Num_Supercenter_Competitors	1 0	11 3
Med_HH_Income	4 1	8 6
Age_GT_65	6 1	6 0
Relative feature		
Dist_City_Origin	4 3	8 4
Private_Label_AS	4 0	8 7
Num_Supermarket_Competitors	0 0	12 4
Num_Supercenter_Competitors	10 4	2 0
Med_HH_Income	1 0	11 5
Age_GT_65	9 4	3 0

Table 7 (Continued)

	# Positive # Positive & Significant	# Negative # Negative & Significant
Relative price discount		
Dist_City_Origin	10 3	2 0
Private_Label_AS	11 6	1 1
Num_Supermarket_Competitors	8 3	4 1
Num_Supercenter_Competitors	7 1	5 3
Med_HH_Income	7 5	5 0
Age_GT_65	9 1	3 0

back some of the market share from the private labels. The presence of a strong private label also decreases the effectiveness of feature advertising. Perhaps this reflects that price-sensitive consumers at stores with strong national brands choose to get their price savings from the private label rather than by reading the feature advertising.

Greater competition by other supermarkets reduces the effectiveness of feature advertising, whereas greater competition by supercenters increases the effectiveness of feature advertising. Greater supermarket competition could reduce the effect of feature advertising because in general there would be more features for consumers to read, leading to each store's feature getting less attention from consumers. On the other hand, supercenters likely attract bargain-focused consumers, so feature advertising may be an effective way to grab these consumers back from the supercenter.

Stores with more affluent customers exhibit lower feature and display responsiveness. This may reflect that more affluent customers are looking less for deals because of their higher opportunity costs of time. More surprisingly, stores with more affluent customers do not appear to exhibit less price sensitivity, and, if anything, show greater price sensitivity. Although this result may seem counterintuitive, a plausible explanation is that because we only include the top two national brands, perhaps at less affluent supermarkets the price-sensitive consumers tend to purchase either private label brands or other non-top brands to save money. However, at more affluent supermarkets, the price-sensitive consumers can afford to buy the top national brands, leading to more price-sensitive demand for those brands. Consistent with this explanation, one of the exceptions where higher income leads to greater price sensitivity is

Hunts. Heinz is so dominant that stores with more affluent customers have lower purchase shares for Hunts.

Overall, there are no clear patterns about how age affects sensitivity to the market mix, except that there is some evidence that seniors are more sensitive to feature advertising, perhaps reflecting that seniors have more time to look through feature advertising.

We include store-level fixed effects to control for the possibility that the POS marketing mix is set partially based on the unobserved preferences of the store's customers. However, these fixed effects will also reflect other elements of a store's underlying demand for each brand. We test whether the six store-level demographics—distance from the brand's city of origin, extent of private label presence, number of competing supermarkets and supercenters in a market, median income, and fraction of senior citizens—impact the mean demand for the top two national brands. Table 8 summarizes these results. Most of the coefficients show no systematic patterns, but we highlight the effects of two variables. First, purchase shares are higher for a brand in a store that is closer to the brand's city of origin (or the smaller the distance to this city). This is consistent with the previous literature that has shown that the order of entry into a market is a factor in determining the market shares of the brands (Bronnenberg et al. 2009). Second, the national brands usually have increased purchase shares in stores where their customers have higher income, as long as the brands are considered premium products. Although it is true that 5 out of 12 of the brands demonstrate a negative relationship between income and purchase share, 3 of these (and 2 of the 3 that are statistically significant) are Folgers, Maxwell House, and Hunts. Folgers and Maxwell House are the leading coffee brands, but they are not generally considered to be premium coffees. Hunts is the number 2 Ketchup, but Heinz is so dominant that Hunts also might be considered by most consumers not to be a premium product. We find that the assortment share of a store's private label does not always hurt the top national brands, consistent with Dhar and Hoch (1997). Interestingly, it appears that the presence of a private label hurts number 2 brands more than number 1 brands.[12]

Throughout all of this analysis, we have focused on results from a linear regression. We focus on this model because it is easy to interpret the results. For example, above we note that we can read the coefficient on assortment share to read that if a top national brand gains access to an additional 1% of the store's shelf, on average its purchase shares will increase by 0.34% of the market. However, a critique of the linear model is that theoretically predicted purchase shares can lay outside of the interval from 0 to 1. In the appendix, we demonstrate the robustness of the results by presenting regression results using a logit transformed dependent variable. Specifically, instead of using the purchase share as the dependent variable, the dependent variable becomes $\ln(PS_{st}/(1-PS_{st}))$. The results generally follow a pattern similar to those described above. Note that when we described the pattern of interaction terms above, we looked for results that were robust to either functional form.

Table 8 **Impact of Fixed Effect Moderators**

	# Positive Significant	# Negative Significant
Dist_City_Origin	4	8
	3	7
Private_Label_AS	6	6
	3	5
Num_Supermarket	5	7
	3	3
Num_Supercenter	7	5
	6	5
Med_HH_Income	7	5
	7	3
Age_GT_65	6	6
	5	3

5. Fraction of Purchase Share Variation Explained by Point-of-Sale Variables

In this section, we examine how much of the variation in a brand's purchase shares is explained by the POS variables. In measuring the explained variation, one could first compare the average R^2 from the regressions of purchase share on the market-week and store fixed effects in Table 9 (first column) with the R^2 from the regression with the five marketing mix factors plus market-week and store fixed effects (second column). The difference in R^2 is $86.6\% - 61.5\% = 25.1\%$.

However, this measure underestimates the extent to which the point-of-sale factors explain the variation in purchase shares because the store-level fixed effects themselves are partially set by the average values of these same POS marketing mix elements.[13] Thus, we follow Bronnenberg et al. (2012)

[12] Similarly, there is weak evidence that a presence of a competing supercenter may help the number 1 brand and hurt the number 2 brand. We do not have a theory for why this might occur.

[13] There is another smaller reason why this calculation underestimates the impact of the POS marketing mix: we compare the R^2 of the model with store and market-time effects to a model with only main effects, not interaction effects. This means that we overlimit the extent to which the POS variables are able to impact purchase shares.

Table 9 Explained Variation in Purchase Shares

Category	Brand	Store fixed effects + market-time fixed effects (%)	Store fixed effects + market-time fixed effects + POS variables (%)	Incremental explained variance from POS variables (%)
Coffee	Folgers	60.7	88.5	27.8
	Maxwell House	59.0	85.3	26.3
Cereal	Kellogg's	45.9	84.5	38.6
	General Mills	46.6	83.6	37.0
Toilet paper	Charmin	49.9	84.0	34.1
	Quilted Northern	46.5	81.1	34.6
Yogurt	Yoplait	71.2	90.2	19.0
	Dannon	75.8	90.3	14.5
Peanut butter	Jif	69.5	87.8	18.3
	Skippy	81.2	90.7	9.6
Ketchup	Heinz	71.0	89.0	18.0
	Hunts	60.6	84.3	23.7
Average		61.5	86.6	25.1

and calculate the impact of the POS elements as $\sigma^2(X\hat{\beta})/\sigma^2(\mathit{Purchase\ Shares})$, where the X variables are the five POS variables. Table 10 presents the results. We find that, on average across the 12 brands, 56% of the purchase share variation is explained by these five elements of the POS marketing mix.

This finding that the five POS market mix elements explain 56% of the purchase share variation can be compared with the finding of Bronnenberg et al. (2012), who use monthly data and find that price, feature, and display explain 21% of the variation after controlling for market-level fixed effects. To see why we measure a larger effect, we calculate how much the POS elements explain purely cross-sectional variation in purchase shares as well as market-level purchase shares. To calculate the cross-sectional variation in purchase shares, we calculate the purchase shares of each brand across the two-year time period we use for our data and calculate the average POS marketing mix for that time period as well. We then conduct the same analysis as in the first column of Table 10. The results are reported in the second column of Table 10. We find that aggregating across time reduces the fraction of the purchase share variation that is explained by these POS marketing mix elements to 45.3%. In the third column of Table 10, we examine how market-level aggregation impacts the amount of purchase share variation that is explained by the POS factors by calculating the market-level average purchase shares for each brand in the market along with the average POS market mix within that market. We find that market-level aggregation has a significant effect, reducing the amount of explained variation down to 32%, which is still meaningfully higher than the 21% of Bronnenberg et al. (2009), but substantially lower than the 56% total effect that we find.

Table 10 Explained Variation in Purchase Shares $\mathrm{Var}(X\beta)/\mathrm{Var}(PS)$

Category	Brand	Overall variation (%)	Store-level variation (%)	Market-level variation (%)
Coffee	Folgers	61.5	44.9	26.5
	Maxwell House	58.9	44.8	51.4
Cereal	Kellogg's	78.9	95.8	41.7
	General Mills	68.9	64.7	63.6
Toilet paper	Charmin	62.8	44.5	21.1
	Quilted Northern	63.5	56.4	48.3
Yogurt	Yoplait	51.2	40.7	29.2
	Dannon	53.8	49.6	40.6
Peanut butter	Jif	42.0	24.9	15.5
	Skippy	30.6	21.7	12.8
Ketchup	Heinz	44.0	24.1	15.0
	Hunts	49.8	31.1	18.8
Average		55.5	45.3	32.0

In summary, these results highlight the extent to which purchase shares vary at a store level, and the extent to which this variation can be explained by the POS marketing mix. Furthermore, the results demonstrate that measuring the impact of the POS marketing mix at the market (city) level significantly underestimates the impact of the POS marketing mix.

6. Discussion and Conclusion

This study examines how five key point-of-sale marketing mix variables impact the purchase shares of top national brands in six popular CPG categories. To do this, we first show that the purchase shares of the major national brands varies widely not only across different markets, but also across supermarkets within these markets. These findings reinforce the idea that national brands are not truly national—not only is there large variation in national-brand purchase shares across metropolitan markets, but the importance of national-brand purchase shares differs substantially even across chains within a particular market.

After analyzing the variation in purchase shares, we then estimate an empirical model of how purchase shares are affected by five point-of-sale marketing mix factors to understand how this local nature of brands is affected by retailer-controlled marketing mix factors. We show that relative prices and assortment shares have the largest impact on a brand's purchase shares. Furthermore, the variation of these factors across stores is large enough that the choices of retailers can have an extreme effect on the success of a national brand within its stores. This is likely a contributing factor of why retailers have been found to have so much power in the retailer–manufacturer channel.

We also examine how six store-level factors moderate the impact of the POS marketing mix. Because we look at the top national brands, these impacts are not always in the intuitive directions. For example, greater private label presence decreases the impact that prices have on the top national brands' purchase shares, whereas greater clientele affluence increases the price sensitivity. This is because of the selection of consumers who are considering buying the top national brands versus other cheaper brands. We also uncover that there is an asymmetric POS marketing mix effectiveness (especially with respect to price) that favors brands closer to their city of origin, which is another underlying mechanism behind observed differences in purchase shares across geographic markets.

As a last step, we decompose the explained variance to show that, on average, 56% of the variance in a brand's purchase shares can be explained by our five POS factors. These findings are larger than those that have been found previously in the literature and demonstrate further that the point-of-sale marketing mix elements are important inputs in determining the final purchase shares. These results also suggest why the practice of category captainship is so appealing. Very little empirical research has been done on the effectiveness of category captainship, especially because these relationships tend to be very secretive. However, our results suggest that being able to influence assortment, prices, and even displays will have a huge impact on the sales of even the top national-brand products. Similarly, our research suggests that a category captain's decisions are likely not only to affect the purchase shares of less-popular brands, but also to significantly change the purchase shares of top national-brand competitors. Although a retailer's oversight of a category captain might check the extent to which a category captain limits the number of competing SKUs they place on the shelf or the extent to which prices on competing brands are raised, our results show that even moderate changes in the point-of-sales marketing mix can affect purchase shares in meaningful ways.

Importantly, our results confirm and expand the critique of Bruno and Vilcassim (2008) showing aggregation biases due to varying brand availability. Indeed, Weinberg (2011) presents evidence that market-level merger simulations do not make good price predictions, using the acquisition of Tambrands by Proctor and Gamble as a case study. We show that if one aggregates the analysis to the market level, then the estimated effects of these POS marketing mix elements would be reduced by over 40%. Such a miscalculation would lead to a severe underinvestment in trade marketing. Similarly, we show that aggregating the data across time also leads to a bias as well.

Finally, Bronnenberg et al. (2007) demonstrate that national-brand market shares are extremely consistent across markets over long periods of time (decades). Our results also suggest that if the long-run persistence of order-of-entry effects are the result of Sutton-style endogenous sunk costs (Bronnenberg et al. 2011), at least some of these endogenous sunk costs should take the form of the elements of the point-of-sale marketing mix we consider. For example, we might look for historical stability in the trade marketing relationships as a factor explaining the persistence of purchase shares. Alternatively, to the extent that firms are putting greater emphasis on trade marketing, and that new forms of influencing these point-of-sale variables are invented, such as the advent of the category captain, we might expect that there will be disruption in the historical stability of these market shares.

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Appendix. Estimation Results for Store-Level National-Brand Share Regressions: Logit Transformed Purchase Share as a Dependent Variable

Category	Coffee				Cereal				Toilet paper			
Brand	Folgers		Maxwell House		Kellogg's		General Mills		Charmin		Quilted Northern	
Independent variable	Coefficient	(Standard error)	Coefficient	(Standard error)	Coefficient	(Standard error)	Coefficient	(Standard) error)	Coefficient	(Standard error)	Coefficient	(Standard error)
Relative price	−2.158	(0.037)	−2.122	(0.034)	−1.974	(0.026)	−1.541	(0.022)	−1.512	(0.025)	−1.636	(0.022)
Relative price × Dist_City_Origin	0.239	(0.049)	0.403	(0.069)	0.151	(0.045)	0.062	(0.063)	0.127	(0.041)	−0.001	(0.063)
Relative price × Private_Label_AS	0.873	(0.289)	0.510	(0.312)	−0.707	(0.443)	0.027	(0.387)	−0.353	(0.283)	−0.664	(0.387)
Relative price × Num_Supermarket	0.002	(0.001)	0.000	(0.002)	0.000	(0.002)	−0.004	(0.002)	−0.006	(0.002)	0.001	(0.002)
Relative price × Num_Supercenter	−0.047	(0.027)	0.049	(0.031)	−0.098	(0.029)	−0.061	(0.020)	−0.023	(0.025)	0.056	(0.020)
Relative price × Med_HH_Income	−0.001	(0.002)	−0.002	(0.001)	0.001	(0.001)	−0.001	(0.001)	−0.002	(0.001)	−0.002	(0.001)
Relative price × Age_GT_65	−0.003	(0.005)	−0.007	(0.006)	0.012	(0.004)	0.005	(0.003)	0.001	(0.002)	−0.004	(0.003)
Assortment share	3.577	(0.233)	4.073	(0.177)	1.960	(0.122)	1.666	(0.138)	1.660	(0.122)	2.357	(0.138)
Assortment share × Dist_City_Origin	−0.181	(0.358)	2.550	(0.448)	0.232	(0.192)	0.555	(0.367)	0.874	(0.307)	−0.651	(0.367)
Assortment share × Private_Label_AS	−2.483	(1.459)	−1.196	(1.617)	2.249	(1.958)	0.997	(2.246)	3.254	(1.529)	4.268	(2.246)
Assortment share × Num_Supermarket	0.090	(0.025)	−0.004	(0.018)	−0.023	(0.008)	−0.004	(0.005)	0.029	(0.009)	0.006	(0.005)
Assortment share × Num_Supercenter	0.085	(0.181)	0.544	(0.203)	0.044	(0.127)	0.242	(0.133)	−0.174	(0.133)	−0.409	(0.133)
Assortment share × Med_HH_Income	0.037	(0.010)	0.007	(0.006)	−0.004	(0.005)	−0.006	(0.005)	0.006	(0.005)	−0.005	(0.005)
Assortment share × Age_GT_65	0.045	(0.026)	−0.008	(0.023)	0.012	(0.019)	−0.041	(0.024)	0.005	(0.014)	−0.038	(0.024)
Relative display	0.242	(0.013)	0.271	(0.019)	0.154	(0.008)	0.167	(0.008)	0.352	(0.019)	0.580	(0.008)
Relative display × Dist_City_Origin	0.011	(0.017)	0.207	(0.050)	−0.021	(0.011)	−0.047	(0.021)	0.113	(0.037)	0.090	(0.021)
Relative display × Private_Label_AS	0.292	(0.120)	−0.014	(0.147)	0.187	(0.130)	0.037	(0.159)	−0.633	(0.365)	−0.635	(0.159)
Relative display × Num_Supermarket	0.002	(0.001)	0.001	(0.001)	−0.001	(0.001)	−0.001	(0.001)	0.003	(0.001)	0.005	(0.001)
Relative display × Num_Supercenter	−0.020	(0.012)	0.006	(0.016)	−0.011	(0.008)	−0.013	(0.009)	−0.002	(0.018)	0.008	(0.009)
Relative display × Med_HH_Income	0.000	(0.001)	0.000	(0.001)	−0.001	(0.000)	−0.001	(0.000)	0.000	(0.001)	0.000	(0.000)
Relative display × Age_GT_65	0.003	(0.002)	0.000	(0.002)	−0.001	(0.001)	−0.002	(0.001)	0.001	(0.002)	−0.002	(0.001)
Relative feature	0.382	(0.018)	0.437	(0.024)	0.131	(0.010)	0.155	(0.011)	0.440	(0.022)	0.535	(0.011)
Relative feature × Dist_City_Origin	0.118	(0.022)	0.267	(0.062)	−0.032	(0.016)	−0.042	(0.035)	−0.109	(0.050)	−0.241	(0.035)
Relative feature × Private_Label_AS	0.281	(0.163)	0.219	(0.184)	−0.336	(0.245)	−0.388	(0.238)	−0.596	(0.437)	−0.397	(0.238)
Relative feature × Num_Supermarket	−0.002	(0.002)	−0.001	(0.002)	−0.001	(0.001)	−0.001	(0.001)	0.000	(0.003)	−0.003	(0.001)
Relative feature × Num_Supercenter	0.038	(0.016)	0.053	(0.022)	−0.006	(0.008)	0.005	(0.009)	0.002	(0.018)	0.000	(0.009)
Relative feature × Med_HH_Income	−0.001	(0.001)	−0.001	(0.001)	−0.001	(0.000)	−0.001	(0.000)	−0.001	(0.001)	−0.002	(0.000)
Relative feature × Age_GT_65	0.000	(0.002)	−0.001	(0.002)	−0.001	(0.001)	−0.001	(0.001)	0.005	(0.002)	0.005	(0.001)
Relative promotion intensity	0.192	(0.026)	0.379	(0.034)	0.101	(0.022)	0.188	(0.026)	0.324	(0.023)	0.441	(0.026)
Relative promotion intensity × Dist_City_Origin	0.001	(0.040)	0.795	(0.104)	0.067	(0.045)	0.066	(0.071)	0.127	(0.056)	0.184	(0.071)
Relative promotion intensity × Private_Label_AS	0.565	(0.221)	1.086	(0.280)	1.851	(0.388)	2.151	(0.516)	2.675	(0.410)	−0.878	(0.516)
Relative promotion intensity × Num_Supermarket	0.007	(0.003)	0.001	(0.002)	0.004	(0.001)	−0.002	(0.001)	0.000	(0.002)	0.004	(0.001)
Relative promotion intensity × Num_Supercenter	−0.053	(0.020)	0.041	(0.024)	−0.062	(0.019)	−0.102	(0.024)	0.020	(0.022)	0.041	(0.024)
Relative promotion intensity × Med_HH_Income	0.004	(0.001)	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)	−0.002	(0.001)
Relative promotion intensity × Age_GT_65	0.004	(0.003)	−0.002	(0.004)	0.004	(0.003)	0.005	(0.003)	−0.005	(0.003)	−0.007	(0.003)
Sample size	110,627		110,627		124,865		124,865		118,993		118,993	
R^2	0.910		0.915		0.861		0.864		0.877		0.864	

Appendix. (Continued)

Category	Yogurt				Peanut butter				Ketchup			
Brand	Yoplait		Dannon		Jif		Skippy		Heinz		Hunts	
Independent variable	Coefficient	(Standard error)	Coefficient	(Standard error)	Coefficient	(Standard error)	Coefficient	(Standard) error)	Coefficient	(Standard error)	Coefficient	(Standard error)
Relative price	−1.407	(0.028)	−1.394	(0.029)	−1.977	(0.032)	−1.580	(0.053)	−1.602	(0.025)	−2.690	(0.038)
Relative price × Dist_City_Origin	0.010	(0.026)	0.129	(0.040)	0.344	(0.041)	0.004	(0.045)	0.062	(0.030)	−0.231	(0.054)
Relative price × Private_Label_AS	1.108	(0.264)	0.478	(0.187)	1.392	(0.342)	1.357	(0.457)	−0.242	(0.286)	−0.365	(0.328)
Relative price × Num_Supermarket	−0.005	(0.001)	−0.004	(0.002)	0.003	(0.001)	−0.008	(0.003)	−0.001	(0.001)	0.002	(0.002)
Relative price × Num_Supercenter	0.027	(0.020)	0.024	(0.021)	0.029	(0.020)	0.180	(0.031)	−0.047	(0.026)	0.063	(0.033)
Relative price × Med_HH_Income	−0.002	(0.001)	−0.002	(0.001)	−0.003	(0.001)	0.000	(0.002)	0.004	(0.001)	0.003	(0.002)
Relative price × Age_GT_65	0.004	(0.003)	0.000	(0.004)	−0.008	(0.004)	0.001	(0.007)	0.006	(0.004)	0.013	(0.005)
Assortment share	2.632	(0.121)	3.502	(0.157)	2.173	(0.134)	3.294	(0.256)	1.449	(0.091)	2.738	(0.227)
Assortment share × Dist_City_Origin	−0.451	(0.156)	−0.072	(0.225)	−0.381	(0.203)	0.760	(0.231)	0.702	(0.160)	−0.034	(0.336)
Assortment share × Private_Label_AS	−2.116	(0.999)	0.092	(0.776)	−4.804	(1.639)	−5.189	(1.789)	1.763	(0.885)	0.828	(1.295)
Assortment share × Num_Supermarket	−0.006	(0.010)	−0.010	(0.016)	0.004	(0.014)	−0.039	(0.014)	0.003	(0.008)	0.042	(0.010)
Assortment share × Num_Supercenter	−0.102	(0.175)	0.108	(0.243)	0.019	(0.106)	0.275	(0.146)	0.019	(0.096)	−0.097	(0.215)
Assortment share × Med_HH_Income	−0.014	(0.005)	−0.020	(0.006)	0.009	(0.005)	−0.011	(0.007)	0.011	(0.003)	0.002	(0.008)
Assortment share × Age_GT_65	−0.016	(0.015)	0.004	(0.017)	0.007	(0.015)	−0.039	(0.031)	0.008	(0.019)	−0.005	(0.027)
Relative display	0.142	(0.010)	0.128	(0.008)	0.205	(0.012)	0.225	(0.014)	0.345	(0.013)	0.558	(0.022)
Relative display × Dist_City_Origin	−0.012	(0.011)	0.037	(0.013)	−0.003	(0.014)	0.063	(0.014)	0.039	(0.018)	−0.008	(0.027)
Relative display × Private_Label_AS	0.034	(0.152)	−0.188	(0.134)	−0.016	(0.259)	0.195	(0.212)	−0.057	(0.174)	−0.414	(0.349)
Relative display × Num_Supermarket	0.000	(0.001)	0.000	(0.001)	−0.002	(0.002)	−0.001	(0.001)	0.001	(0.002)	0.009	(0.002)
Relative display × Num_Supercenter	−0.028	(0.011)	−0.004	(0.015)	−0.028	(0.011)	0.011	(0.015)	−0.005	(0.012)	−0.020	(0.019)
Relative display × Med_HH_Income	−0.001	(0.000)	−0.001	(0.000)	−0.001	(0.001)	−0.001	(0.001)	−0.002	(0.001)	−0.001	(0.001)
Relative display × Age_GT_65	0.000	(0.001)	−0.002	(0.001)	0.003	(0.002)	0.002	(0.002)	−0.002	(0.002)	−0.002	(0.004)
Relative feature	0.159	(0.012)	0.117	(0.008)	0.237	(0.014)	0.330	(0.024)	0.331	(0.022)	0.418	(0.023)
Relative feature × Dist_City_Origin	−0.030	(0.013)	−0.033	(0.011)	−0.082	(0.017)	0.161	(0.021)	−0.098	(0.034)	0.093	(0.028)
Relative feature × Private_Label_AS	−0.831	(0.147)	−0.438	(0.102)	−0.579	(0.282)	−0.053	(0.374)	−0.469	(0.299)	0.915	(0.298)
Relative feature × Num_Supermarket	−0.002	(0.001)	−0.003	(0.001)	−0.002	(0.001)	−0.004	(0.002)	−0.002	(0.003)	0.003	(0.002)
Relative feature × Num_Supercenter	0.032	(0.010)	0.021	(0.007)	0.028	(0.013)	0.055	(0.019)	0.018	(0.016)	0.024	(0.020)
Relative feature × Med_HH_Income	−0.001	(0.000)	−0.001	(0.000)	−0.001	(0.000)	−0.001	(0.001)	−0.001	(0.001)	0.001	(0.001)
Relative feature × Age_GT_65	0.001	(0.001)	0.002	(0.001)	0.003	(0.001)	0.003	(0.002)	−0.001	(0.002)	0.006	(0.002)
Relative promotion Intensity	0.135	(0.013)	0.149	(0.015)	0.170	(0.013)	0.262	(0.022)	0.053	(0.012)	0.175	(0.017)
Relative promotion intensity × Dist_City_Origin	0.028	(0.020)	0.092	(0.028)	0.047	(0.018)	0.021	(0.018)	0.051	(0.018)	−0.091	(0.026)
Relative promotion intensity × Private_Label_AS	0.142	(0.149)	−0.055	(0.188)	0.262	(0.271)	1.064	(0.360)	0.102	(0.199)	0.162	(0.280)
Relative promotion intensity × Num_Supermarket	0.000	(0.001)	0.001	(0.001)	0.001	(0.001)	−0.002	(0.001)	0.003	(0.001)	0.004	(0.003)
Relative promotion intensity × Num_Supercenter	0.005	(0.012)	0.012	(0.013)	−0.012	(0.012)	0.074	(0.018)	−0.003	(0.012)	0.014	(0.019)
Relative promotion intensity × Med_HH_Income	−0.001	(0.001)	−0.001	(0.001)	0.000	(0.000)	−0.001	(0.001)	0.002	(0.001)	0.003	(0.001)
Relative promotion intensity × Age_GT_65	0.000	(0.002)	−0.001	(0.002)	0.000	(0.002)	0.000	(0.003)	0.001	(0.002)	0.005	(0.003)
Sample size	121,849		121,849		104,718		104,718		101,169		101,169	
R^2	0.914		0.919		0.885		0.941		0.894		0.871	

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