WHEN PUSH COMES TO SHELF: HOW POINT-OF-SALE MARKETING MIX IMPACTS NATIONAL-BRAND PURCHASE SHARES [1]

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Abstract

Purchase shares of major national-brands in consumer packaged-goods industries vary substantially across stores, both between geographic markets and across stores within markets. This paper measures the extent to which the variation in national-brand purchase shares depends on four store-specific marketing mix factors: prices, assortment shares, features and displays. These variables are traditionally targets of influence of trade marketing by manufacturers through various mechanisms. We do not directly measure the impact of trade (or "push") marketing because we do not observe the actual arrangements between manufacturers and retailers. Rather, we measure the impact that the actual prices, assortment shares, features and displays in a supermarket have on the store-level market shares of the top-two national brands across 6 product categories. We do this by first demonstrating the extent to which purchase shares of the top two national brands across 6 different categories vary across markets, accounts (defined as chain-market interactions) and stores: market-level variation accounts for almost 55% of the variation in purchase shares across stores, while account-level and store-level variation explain an additional 20% and 9% of the variation, respectively. We then measure the extent to which assortment, pricing, feature and display activities affect the purchase shares of the top national brands. We find that prices and assortment shares are the two most-important push factors in determining a brand's purchase share: changes from the 10th percentile to the 90th percentile (which we call the "reasonable range") would, on average, cause a brand to lose 11.7% of the market for price, and the brand to gain 6.6% of the market for assortment share. We then measure the extent to which the variation in top national-brand purchase shares is explained by these four factors. Using two different calculations that bound the impact of the push factors and a novel point-estimate model, we find that, on average, approximately 42% of the variation in national-brand purchase shares can be attributed to these four factors. Despite the fact that these four factors have such a large impact on purchase shares, we note that it would be difficult for a number 2 brand to "push" its way to being the top brand in the category. 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*

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 across stores from 5% to 75%, with a standard deviation of 11%. 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 four point-of-sale marketing mix factors: assortment share, price, feature and display.

While our goal is only to measure how these four factors affect store-level market shares, we note that these four factors are traditionally under the purview of trade marketing. Trade-marketing decisions are often called "push" effects because they push the products through the retail channel and into the arms of the consumer. In contrast, marketing that is directed to consumers, such as advertising or couponing, is sometimes referred to as "pull" effects because the consumers pull the purchases through the retail channel based on their preferences (Olver and Farris 1989, Kotler and Keller 2007).[1] Thus, we think of our results as being informative of the potential effect that push marketing has on purchase shares for the top two national brands. For this reason, we refer to the four point-of-sale variables we study – price, assortment, feature and display – as "push" factors in this paper. However, we acknowledge that some people define push marketing differently, instead defining push marketing as the actual payments or control exerted by the manufacturer on the retailer; we do not study the impact of such payments, arrangements or influence because of data limitations.

[1] Feature advertising might be considered a pull variable, but in this paper we lump it with the other push variables because it is usually under the realm of trade marketing. Ultimately, we find that feature advertising plays the smallest role among these four factors.

We use store-level data to identify the impact that the four point-of-sale marketing mix variables we consider – assortment share, price, feature and display – from the changes in purchase shares in response to changes in these factors within a store. We find that differences between the 10th and 90th percentiles for relative prices, which we consider to be the "reasonable range" for prices, correspond to a total difference of 11.7% of the market (for example, a 20% purchase share vs. a 31.7% purchase share). Similar differences in assortment share, display and feature activity correspond to differences in purchase shares of 6.6%, 2.0% and 1.7% of the market, respectively. Using two different approaches that bound the impact of our four factors, we find that the point-of-sale marketing mix activities we consider account for approximately 42% of the explained variation in purchase shares, on average, across 12 brands in 6 categories. Despite the large impact that these four factors have on purchase shares, we show that it would be very difficult for a #2 brand to "push" its way to become a #1 brand in its category.

Our results have several implications. First, 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,[2] but by 2010 trade marketing accounted for 60% of marketing spending.[3]

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

[2] "Slotting Allowances in the Supermarket Industry," by the Food Marketing Institute, November 2001. Available at http://www.fmi.org/media/bg/slottingfees2002.pdf (accessed April 18, 2012).
[3] "Six Trade Promotion Tips: Why Less Can Be More," by David Kellen and Kurt Kaiser, April 16, 2010. Written for Nielsen Wire, and available at http://blog.nielsen.com/nielsenwire/consumer/six-trade-promotion-tips-why-less-can-be-more/ (accessed April 18, 2012).

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 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 be a good strategy for building market share even if the product proliferation does not keep out small brands but rather shifts the composition of the assortment among the major brands.[4]

Previous studies have shown that market shares of top national brands vary significantly between U.S. metropolitan markets (see Bronnenberg, Dhar and Dubé 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, Dhar and Dubé (2009) shows that consumers' quality perceptions about the different brands are correlated with local market shares, while Bronnenberg Dhar and Dubé (2011) shows that the observed market share variation is consistent with Sutton's (1991) endogenous sunk cost theory, and suggests 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 both across cities, as well as between different neighborhoods within a given metropolitan area. Bronnenberg, Dubé and Gentzkow (2010) 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.

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

Our research is also related to a literature that has examined aspects of trade marketing. Ataman, van Heerde and Mela (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.[5] Ataman, Mela and van Heerde (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 both of our studies. Bronnenberg, Dubé and Gentzkow (2010) consider how price, feature and display affect the relative performance of the top national brand vs. the second national brand across cities (ignoring the market shares of other brands), and find that these 3 variables explain 21% of the variation after controlling for market-level fixed effects. This calculation of the importance of these 3 variables likely represents a lower-bound on the market-level effect, as we discuss in Section 5. We calculate a similar lower bound, but using a measure of explained variation that we believe is more accurate, estimate that, on average, 32% of the market-level variation in purchase shares can be attributed to assortment share, price, display and feature activity. 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, and that brands losing SKUs could ultimately sell less, especially if they are a smaller brand.[6]

[5] In our paper we only include 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.

[6] 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.

While we focus on the impact of four 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, Hoch and Purk (1994) 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 stock-outs. 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 the 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 Section 4. In Section 5, we calculate the extent to which purchase-share variation is explained by our four factors. Section 6 provides a cursory examination of how hard it would be for a number 2 brand to push its way to becoming a number 1 brand. Section 7 concludes.

2. Data

2.1 Data Description

Our data consists of the IRI academic dataset (Bronnenberg, Kruger, and Mela 2008). The scanner data span 1,589 supermarkets across 48 IRI markets[7] 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 data from 2004–5 in order to ensure a stable panel, and to maximize the validity of our fixed-effects approach (see Section 4). For reliability, we limit

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

our analysis to stores with more than 80 weeks of data. We aggregate weekly data to quarter level. 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, 1,231 in the cereal category, 1,171 in the toilet paper category, 1,201 in the yogurt category, 1,026 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, as well as 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 1 about here ———

Table 2 presents the summary statistics for the store-level variables for each of these top two brands. 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, Mela and Van Heerde (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). Our quarterly assortment share variables are created by averaging the measured assortment share across weeks in the data in order to account for any changes in assortments during a particular quarter. One issue that can arise in the IRI data is that the presence of a product is seen in the data only if at least one customer purchases the item. In order 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 4 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 3 total weeks, we assume that the product's presence was a coding error and omit it from the analysis. While 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.

——— Table 2 about here ———

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.[8] 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, and Hunts, where the category is so dominated by Heinz that prices for Hunts are below the category average.

The relative feature variable is measured as the average number of a brand's SKUs that are on feature each week[9] divided by the average 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 quarter at the particular store, then all products are assigned a relative display or feature values of zero.

Note that we use relative measures for all four factors since our dependent variable, purchase share, is also a relative variable. For robustness, we ran other versions of the model that used alternative definitions of our measures, which yielded qualitatively similar results. One model

[8] As before, toilet paper is measured in number of rolls, and not ounces.
[9] 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.

we ran measured prices as being the total revenues per volume of the focal brand divided by the revenues per volume of the category and measured display and feature in absolute rather than relative terms. The disadvantage of the price variable being measured in this way is that the relative prices can change even if no shelf prices change due to changes in consumer choices. Also, because we consider only the inside purchase shares (i.e., we do not account for an outside good), feature and display should be measured in relative terms.

Another model we ran measured relative prices as the average price across SKUs for the brand divided by the average price across all SKUs in the category, and feature was measured as the number of weeks any SKU for the brand was on feature, divided by sum of the number of weeks the top, second, store or "other" brands were on feature. Display was calculated in a similar measure. However, this measure of relative price over-weights the prices of SKUs that have almost no purchases, and these measures of features and display do not account for the scope of the feature or display activity by each brand. Despite the different strengths and weaknesses of the different measures, our main results proved to be fairly robust to the way we construct these variables.[10]

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

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 purchase shares of the two top toilet paper national brands in two large multi-market retailers in two cities, Dallas and San Francisco. The IRI dataset masks the identities of the chains,

[10] Results are available upon request.

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, while 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).

——— Figure 1 about here ———

Looking across chains in Dallas, we see that Charmin's purchase shares are much higher in Chain A than they are in Chain B, while 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. In this example, it appears that the variation of purchase shares across chains within a city is approximately the same size as the variation across cities within a chain. This aspect of the example is slightly atypical, as the variation in purchase shares across cities is somewhat larger than the variation in purchase shares across chains, as detailed in Section 3.

Can push 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. Further, this correlation between assortment shares and purchase shares does not imply causality – while consumers may respond to the assortment that retailers offer, retailers also likely set their assortments to reflect the preferences of their clientele. Looking at relative prices, we see that there is a negative correlation between the relative prices of Charmin vs. 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. Further, while

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 relative price is more complex. While 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 (Chevaier 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. Further, the example suggests that push factors could be a potential driver of national-brand purchase shares across stores. Indeed, we show in Section 4 that, among the push-variables we consider, assortment shares and relative prices have the two largest effects on purchase shares.

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 by estimating a series of linear regression models to conduct fixed effect analysis of variance (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 this equation, $PS_{s,c,m,t}$ 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 (quarter) 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, each store has a chain and market affiliation built into it, so 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 equation (1a)-(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. Looking at the first column in Table 3, we see that regressing purchase shares on time dummies alone leads to an R^2 of 0.017, indicating that time effects explain almost none of the variation in purchase shares. One implication of this is that the variation of purchase shares is not the result of different timing on national advertising campaigns. For example, one could imagine that JIF runs a strong national advertising campaign in one quarter while Skippy runs a strong national advertising campaign in another quarter, and that these advertising campaigns lead to large swings in purchase shares. In such a case, we would expect to find a larger R^2 for the quarter dummies. The low R^2 for the quarter-dummy regression, combined with the fact that we show below that we can explain a large amount of the purchase-share variance as being attributed to stores in a cross-sectional manner, reinforces our finding that the variation in these purchase shares are not being driven by large-scale national advertising campaigns.

Regressions of purchase shares on time and market dummy variables yield an average R^2 of 0.565, so we attribute 54.8% (=0.565 – 0.017) of the variation in national-brand purchase shares to city-level (or "market") effects. A regression of purchase shares on time plus account dummies yields an R^2 of 0.766, so an additional 20.1% (=0.766 – 0.565) of the purchase-share variation can be explained by account-level effects above and beyond what can be explained by market effects. Finally, 9.2% of the variation can be explained by store-level effects after controlling for market and account-level affects. Thus, while city-to-city differences explain a lot of the variation in purchase shares, 29% of the purchase-share variation occurs within a metropolitan-market and can be systematically explained at the chain or store level. The fact that cross-sectional variables explain 84% (= 85.7% full model – 1.7% time only) of the variation in purchase shares demonstrates that the market share variation is mostly occurring across stores.

In column 2 of Table 3, we 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 of the variance decomposition are virtually unchanged when we include only the largest national brand for each category.

——— Table 3 about here———

In order to assess the plausibility of whether the variation of national-brand purchase shares across stores could be driven by the four point-of-sale factors, we conduct similar variance decompositions for each of our four push variables. Column 3 of Table 3 reports the results for assortment share, averaged across the 12 brands. We find that market-level effects explain 48% of the assortment-share variation across stores, account-level effects explain an additional 33% of the variance, and store effects explain another 10%. The fact that assortment shares have strong account-level components is consistent with the findings in Hwang et al. (2010) that most supermarket assortment decisions are made at the market-chain level. In general, the explained

variation in assortment shares reveals a similar pattern as the explained variation in purchase shares, suggesting that it is plausible that assortment shares are a significant driver of purchase shares. However, more of the variation in the assortment shares occurs at the account level rather than the market level compared to what we observe for purchase shares. The variation in relative prices, display and feature occur even more at the account or store levels, although we see that just under half of the variation in display and feature can be accounted for with cross-sectional store effects.

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

In this section, we quantify the extent to which the point-of-sale push factors 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 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 push variables and quarter dummies:

$$PS_{st} = \beta_{AS} \cdot AS_{st} + \beta_P \cdot P_{st} + \beta_F \cdot F_{st} + \beta_D \cdot D_{st} + \gamma_t + \varepsilon_{st} \qquad (2)$$

where PS_{st} represents the purchase share of the focal brand at store s in quarter t, AS represents the assortment share of the focal brand in store s in quarter t, P represents the relative prices, F represents the relative feature, and D represents the relative display.

The results of these regressions for each brand are presented in the first column of Table 4. Because many of the customers at a store shop at the same chain in different quarters, 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-quarter levels to ensure robust inference. Most of the coefficients on the point-of-sale marketing mix variables are estimated to be statistically significant. The coefficients on assortment shares, in particular, are generally extremely large – often above 1. While it is theoretically possible that gaining an additional

1% of brand assortment share locally increases purchase shares by over 1%, there is also a potential endogeneity problem if, for example, retailers supply more SKUs of brands consumers prefer.[11] Feature and display can also exhibit the same types of endogeneity problems. As we noted in Section 2.2, price endogeneity can also be an issue, but the direction of the endogeneity for price cannot be signed from theory alone.

——— Table 4 about here ———

We control for the simultaneity problem, where the push variables can be set as a response to store-level demographics or other preference variation of consumers across stores, by running another set of regressions that include store-level fixed effects. This is represented as:

$$PS_{st} = \beta_{AS} \cdot AS_{st} + \beta_P \cdot P_{st} + \beta_F \cdot F_{st} + \beta_D \cdot D_{st} + \eta_s + \gamma_t + \varepsilon_{st} \qquad (3)$$

where η_s represents store-level fixed effects. The results of these regressions appear in column 2 of Table 4. The β coefficients in equation (3) are identified from the within-store changes in the push variables in our two-year window.

The presence of these store-level fixed effects controls for the different preferences of consumers across different stores to the extent that the fixed effects capture the differences in preferences between the clientele that frequents one store versus the clientele that frequents another store.[12] The store-level fixed effects can also capture 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 push 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

[11] This could occur for a variety of reasons, but is consistent with "Space-to-Movement" (Dreze, Hoch and Purk 1994), 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.

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

captured by the store-level fixed effects. A similar story applies to differences in stocking of regional brands across stores, or differences in relationships with suppliers. Note that 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.[13]

Comparing the coefficients in column 2 with those in column 1, we find that stores do, in fact, set their assortments, features and displays to match the preferences of their customers. The estimated coefficients on each of these variables shrink (or occasionally 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 in column 1. This is likely to be the result of the fact that the endogeneity of relative prices leads to opposing effects, as explained in Section 2.2, that make it impossible to sign the anticipated endogeneity bias for the price coefficients.

While store-level fixed effects can accommodate different brand choices due to consumer heterogeneity across stores, it is also possible that brand preferences could vary at the market-time level. While we show in Section 3 that differences in national advertising across quarters does not explain much of the variation in purchase shares in the data, many promotions are run at the local level. For example, some markets may be exposed to advertising campaigns in certain quarters that are not active in other regions because many promotional campaigns for national brands occur at a regional level. Further, the demand for a particular brand may be affected by the promotional activity of regional brands, which intrinsically only affect purchases in some markets. Because we do not observe advertising data, we run each of the 12 regressions again with market-time interaction

[13] Note that differences in private label programs or regional-brand stocking decisions can be thought of as push effects in the sense that these may be affected by trade marketing, so by putting in store-level fixed effects we may be underestimating the importance of push variables.

dummies in addition to store-level fixed effects to account for variation in promotional activities across time and markets. Mathematically, we run

$$PS_{st} = \beta_{AS} \cdot AS_{st} + \beta_P \cdot P_{st} + \beta_F \cdot F_{st} + \beta_D \cdot D_{st} + \eta_s + \eta_{mt} + \varepsilon_{st} . \quad (4)$$

The results of this model are presented in column 3. Overall, with one exception, the results are statistically equivalent to those in column 2, although the point estimates are mostly smaller, suggesting that the differences in purchase shares due to local pull campaigns are present but small.

While it is possible that some endogeneity effects occur even after we include store-level and market-time-level fixed effects, the scope for such endogeneity would seem to be limited. It is possible that some point-of-sale activity could be misattributed. For example, if greater assortment share was generally correlated with obtaining a better position on the store shelf, then our estimates of assortment share would inherently include the confound with shelf location. That might affect some policy decisions, but should not affect our main conclusion about what fraction of purchase-share variation can be attributed to point-of-sale marketing mix variables, since both variables are point-of-sale variables. Similarly, factors that affect overall demand for a category would not affect our results, since we are only measuring inside purchase share, and not total category size. Thus, any remaining endogeneity would have to come from a pull-side variable that only temporarily affects the brand that is chosen at one store in a particular city in a particular quarter, but has no effect at a different store in that same metropolitan market and quarter. Since most non-feature CPG advertising is run at a market level, that rules out most advertising as a source of such endogeneity. Rather, one would need to find something like a holiday celebrated only by a certain demographic group that is highly localized, and which also prefers one brand over another. While surely some such effects occur, the lack of an obvious candidate suggests that these effects are likely to be small and do not affect our overall results. This is especially likely given that controlling for a more obvious first-order effect of localization of promotional campaigns, by adding market-quarter fixed effects, does not statistically affect our results.

——— Table 5 about here ———

Table 5 shows the impact of each of the four variables: The first 12 rows present the brand-by-brand impact that a change from going from the 10th percentile to the 90th percentile for each of the push variables would have on purchase shares. For example, if a retailer whose assortment share for Folgers was at the 10th percentile for all stores across the country changed their assortment such that they would now stock Folgers at a level consistent with the 90th percentile, then we would expect that Folger's purchase share would increase by an increment of 9.6% (e.g., a movement from 30% to 39.6%). On average across all brands, we see that going from the 10th percentile of assortment share to the 90th percentile of assortment share is associated with the brand gaining an additional 6.6% of the market. The results indicate that prices have the largest effect on consumer purchases (11.7%), followed by each brand's assortment share. Display and feature each have much smaller effects on purchase share.

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

In this section, we measure how much of the variation in a brand's purchase shares is explained by the point-of-sale variables. To see how we calculate this, consider that we can parse the purchase shares of the focal brand[14] as

$$PS_{st} = X_{st}\widehat{\beta} + \xi_{st} . \tag{5}$$

X includes the four point-of-sale variables, and $\widehat{\beta}$ represented the estimated causal coefficients, as given in the third column of Table 4. ξ_{st} does *not* represent a regression error, but instead represents all other factors – observed and unobserved – that affect purchase shares.

If we take the variance of equation (5), we obtain

[14] As in Section 4, each analysis is run separately for each brand.

$$\sigma_{PS}^2 = \sigma_{X\hat{\beta}}^2 + \sigma_{\xi}^2 + 2\sigma_{X\hat{\beta},\xi}\,. \tag{6}$$

In a classic regression setting, $2\sigma_{X\hat{\beta},\xi} = 0$, and the extent to which purchase share is explained by the point-of-sale variables would be measured as $R^2 = \frac{\sigma_{X\hat{\beta}}^2}{\sigma_{PS}^2} = 1 - \frac{\sigma_{\xi}^2}{\sigma_{PS}^2}$. However, generally $2\sigma_{X\hat{\beta},\xi} > 0$ in our case because we constrain on X to be the causal effect of X on the purchase shares, and the stores choose X in a way that is correlated with factors in ξ. In light of this, we can bound the effect of our variables on purchase shares. $\frac{\sigma_{X\hat{\beta}}^2}{\sigma_{PS}^2}$ represents a lower bound of the impact that the four "push" variables have on purchase shares. We note that this underestimates the extent to which $X\hat{\beta}$ explains PS because we know that PS is fully explained by $X\hat{\beta}$ and ξ, but $\frac{\sigma_{X\hat{\beta}}^2}{\sigma_{PS}^2} + \frac{\sigma_{\xi}^2}{\sigma_{PS}^2} < 1$. Similarly, $1 - \frac{\sigma_{\xi}^2}{\sigma_{PS}^2}$ represents an upper bound on the explained variance.[15] We propose that the best point estimate of the extent to which our four factors explain the variation in purchase shares is

$$\frac{\sigma_{X\hat{\beta}}^2}{\sigma_{X\hat{\beta}}^2 + \sigma_{\xi}^2}\,. \tag{7}$$

Note that the fraction of variation explained by both variables, $X\hat{\beta}$ and ξ, is then $\frac{\sigma_{X\hat{\beta}}^2}{\sigma_{X\hat{\beta}}^2 + \sigma_{\xi}^2} + \frac{\sigma_{\xi}^2}{\sigma_{X\hat{\beta}}^2 + \sigma_{\xi}^2} = 1$. These point estimates, lower and upper bounds are presented in the first 3 columns of Table 6. We can see that the four point-of-sale marketing mix factors explain, on average, 1/3 to 1/2 of the variation in purchase shares, with an average point estimate of 42%.

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[15] For Folgers, $\sigma_{X\hat{\beta},\xi}$<0 (but very small). Then $\frac{\sigma_{X\hat{\beta}}^2}{\sigma_{PS}^2}$ is an upper bound and $1 - \frac{\sigma_{\xi}^2}{\sigma_{PS}^2}$ is a lower bound of the explained variance. The correlation for Folgers becomes positive when we aggregate to the market level.

——— Table 6 about here ———

Note that the impact of the point-of-sale marketing mix is strongest in the most-differentiated categories (cereal and yogurt).[16] This is consistent with the idea that in categories where there is differentiation, we expect pull marketing to be less effective, so we expect that more of the variation in purchase shares would be explained by push marketing variables. We also would expect there to be less variation in the purchase shares of these less-differentiated products, consistent with the summary statistics presented in Table 1.

The remaining columns report the extent to which the store-to-store or market-to-market level variation in purchase shares can be attributed to these four "push" factors. We report these results partially because there is a prior literature about the extent and persistence of market-share variation that occurs between different metropolitan markets, and we want to calculate the extent to which our results carry over to this market-level analysis.

To calculate the lower bounds, upper bounds and point estimates on this explained variance at the store or market levels, we first average the purchase share as well as the X variables at the store or market levels, respectively. We then use the same β coefficients as reported in the third column of Table 4 and calculate each value as explained above. We see that the approximately 36% of the store-level variation and 32% of the market-level variation is explained by these point-of-sale marketing mix variables. Note that explained variation at the market level is much lower than the overall 42% explained variance, or the 36% store-level explained variance. This reduction in explained variation when we aggregate at the market level is consistent with the fact aggregating across stores and across time reduces the variation in the point-of-sale variables. However, since

[16] While it is probably clear that cereal and yogurt are the most differentiated categories, one way to formalize this is to note that, on average, stores stock over 200 SKUs of cereal and yogurt, while they stock, on average, less than 132 SKUs of any of the other categories.

advertising is done at a market (or higher) level, the apparent importance of our push factors is reduced, while the omitted (and assumed pull) factors are not affected as much by the aggregation.

6. How Hard is it for #2 to Become #1 Through Trade Marketing

The results in the previous sections demonstrate that four point-of-sale factors explain a large fraction of the variation in purchase shares. Further, in Table 1 we see that the differences in purchase shares between the top brand and the #2 brand in each category is often small – usually less than 8%. Given these findings, it may seem plausible for the second-largest brand in each category to work with retailers to change the assortments or prices and become the top brand in the category. Of course, this logic is incomplete because the top brand in the category would likely make a counter-offer to the retailers, requiring a full game theoretic analysis. We see some of this competition play out between manufacturers when the manufacturers compete to become category captains.

In this section, we have the more modest goal of showing that it would be difficult for the second brand in each category to become the top brand using the push-side factors, even in the absence of such a competitive response. To do this, we calculate the amount – expressed as percentage change – that the second brand would have to increase their assortment share or decrease their relative price to become the top brand.

Specifically, we calculate how much of an increase in average assortment share would be required for the second-largest brand to become the top brand in the category. The percentage increase in assortment share that is needed is calculated as

$$\text{\% increase in assortment share} = \frac{\left(\dfrac{\text{difference in market share}}{\text{assortment share coefficient for \#2 brand}}\right)}{\text{current average assortment share}}. \qquad (8)$$

The results are reported in Table 7. The first column reports the difference in purchase shares between the top two brands in each of the 6 categories. The purchase share difference in Ketchup is very large, 34%. The differences in purchase shares for the other categories are all 8% or less. The estimates of how much the second-largest brand would have to increase their assortment share in order to grab the top spot appear in column 2. In general, we see that the second-largest brands would have to increase their assortment shares substantially to claim the top spot – usually by 38% or more. This suggests that it would be difficult for the second-largest brands to increase their presence in stores enough to become the top brand.

——— Table 7 about here ———

In column 3, we report an analogous calculation as the one in equation (8) except that the strategic variable is relative price instead of assortment share. The decreases in relative prices needed to grab the top spot range from 10% to 41%, except for ketchup where Hunts would require a drastic price-cut to displace Heinz. For perspective on how large these price cuts are, consider that McKinsey estimates that, on average across consumer packaged goods categories, 37¢ out of every dollar in the price a consumer pays goes to the manufacturer. This 37¢ is not entirely profit, though: while the 37¢ does not include the costs of raw materials, it does include revenue that is needed to pay for costs associated with manufacturing, research and development, and marketing. Thus, if the manufacturer bore the full burden of even a 10% price reduction, its revenue would fall by approximately 25%; Its profit per unit would fall even more. Thus, a price cut of 10% is very costly, especially given that the firm would only gain a 3% market share in the case of peanut butter. Even if the retailer bore some of the changes in prices, such a large drop in price is generally very costly. The larger price cuts are also clearly very expensive and burdensome.

The calculations in Table 7 assume that the changes in the assortments or prices of the number 2 brand do not come at the expense of the top brand. While this may be reasonable for

price cuts, one might think that new SKUs from the #2 brand would displace SKUs from the top brand. This is not necessarily the case – the new SKUs could displace store or other brands instead. However, in Table 8 we consider how large the cuts would have to be if the #2 SKUs displaced the #1 SKUs item-by-item. In such a case, the amount of new SKUs that would have to be added is about half of what was observed in Table 7.[17] Nevertheless, growing the average shelf presence by 13% or more is not a trivial thing to do. Thus, "pushing" a #2 brand into a #1 brand is generally difficult, even before accounting for any competitive responses.

7. Discussion and Conclusion

This study examines how four key point-of-sale marketing mix variables impact the purchase shares of top national brands in six popular consumer packaged goods (CPG) categories. In particular, we first show that not only are there large levels of variation present in the purchase shares of major national brands across different markets, but significant variation is also present in the purchase shares of these brands across supermarkets within 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 four point-of-sale marketing mix factors. We show that relative prices and assortment shares have the largest impact on a brand's purchase shares. Finally, we decompose the explained variance to show that, on average, 42% of the variance in a brand's purchase shares can be explained by our four "push" factors.

[17] It is not exactly ½, because the coefficients on the #1 and #2 brands are somewhat different.

These findings demonstrate that although advertising and other pull factors might explain some of the purchase-share variation for top national brands across markets, variables that are influenced by trade marketing are also important inputs in determining the final purchase shares. While these point-of-sales marketing mix variables are not conventionally thought of as being as rigid in time as consumer brand valuations, the "push"-variables that we consider show large amounts of persistence. 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.

The fact that assortment shares and prices vary significantly at the account- and store-levels, as well as the sizable impact these variables have on consumer purchase decisions, also means that demand estimates based on data aggregated at the market level are likely to be biased, especially if the estimates make no correction for the variation in the assortment, prices, feature or display choices across chains. Our results confirm and expand the critique of Bruno and Vilcassim (2008) showing aggregation biases due to varying brand availability. Moreover, the fact that assortment shares and relative prices have strong account components suggest that merger or market simulations conducted at market levels of aggregation can be biased and potentially lead to misleading policy recommendations. 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.

Finally, our results speak to a deeper understanding of how slotting allowances or category captains impact not just a retailer's profits but also the profits of competing manufacturers. For example, our research suggests that a category captain's decisions are likely to not only 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.

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

Dallas

	Brand:	M/S:	A/S:	Rel P
Chain 1		**32%**	**29%**	**1.07**
		**9%**	**11%**	**1.19**
Chain 2		**22%**	**27%**	**1.27**
		**14%**	**16%**	**1.11**

San Francisco

	Brand:	M/S:	A/S:	Rel P
Chain 1		**20%**	**25%**	**1.22**
		**14%**	**18%**	**1.20**
Chain 2		**15%**	**18%**	**1.02**
		**20%**	**20%**	**1.09**

Table 1. Descriptive statistics: Unit market shares of the top two brands in each category

	#1 Brand			#2 Brand		
Category	Brand	Market Share	Std. Dev.	Brand	Market Share	Std. Dev
Coffee	Folgers	32%	14%	Maxwell House	24%	13%
Cereal	Kellogg's	31%	6%	General Mills	26%	6%
Ketchup	Heinz	54%	17%	Hunts	20%	13%
Peanut Butter	JIF	29%	12%	Skippy	26%	18%
Toilet Paper	Charmin	22%	9%	Quilted Northern	15%	8%
Yogurt	Yoplait	30%	11%	Dannon	26%	10%

Table 2. Descriptive statistics of the outlet-level supply variables

		Assortment Share		Relative Price		Relative Display		Relative Feature	
Category	Brand	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Coffee	Folgers	17%	7%	0.83	0.22	0.18	0.21	0.20	0.17
	Maxwell House	15%	7%	0.81	0.18	0.22	0.24	0.26	0.21
Cereal	Kellogg's	25%	4%	1.02	0.10	0.31	0.14	0.37	0.16
	General Mills	22%	3%	1.27	0.13	0.24	0.13	0.27	0.14
Ketchup	Heinz	46%	9%	1.30	0.18	0.38	0.31	0.42	0.26
	Hunts	22%	8%	0.93	0.15	0.17	0.22	0.27	0.25
Peanut Butter	JIF	24%	5%	1.10	0.15	0.13	0.23	0.23	0.21
	Skippy	26%	9%	1.12	0.25	0.26	0.33	0.31	0.25
Toilet Paper	Charmin	27%	6%	1.15	0.20	0.27	0.18	0.22	0.14
	Quilted Northern	17%	5%	1.09	0.18	0.17	0.14	0.19	0.13
Yogurt	Yoplait	32%	8%	1.28	0.16	0.15	0.26	0.31	0.19
	Dannon	29%	8%	1.23	0.16	0.15	0.25	0.23	0.15

Table 3. Incremental Explanatory Power

	Purchase Shares		Push Factors			
	All	Top Brands	Assortment Share	Relative Price	Relative Display	Relative Feature
Time	1.7	1.5	1.4	3.2	2.2	3.1
Market	54.8	53.3	48.4	26.0	11.6	21.3
Account	20.1	19.9	32.6	27.3	15.2	22.4
Store	9.2	10.7	9.6	10.4	13.0	2.3
Full Model	85.7	85.3	91.9	66.9	42.0	49.2

Table 4. Estimation results for store-level national brand share regressions

		Estimator	Time Fixed Effect			Store + Time Fixed Effect			Store + Market-time Fixed Effect		
Category	Brand	Independent	Coefficient	(Standard error)		Coefficient	(Standard error)		Coefficient	(Standard error)	
Coffee	Folgers	Assortment Share	1.256	(0.067)	***	0.586	(0.048)	***	0.602	(0.056)	***
		Relative Price	-0.313	(0.019)	***	-0.415	(0.018)	***	-0.418	(0.018)	***
		Relative Display	0.080	(0.010)	***	0.032	(0.004)	***	0.030	(0.004)	***
		Relative Feature	0.136	(0.024)	***	0.038	(0.006)	***	0.039	(0.008)	***
		Sample size	8664			8664			8664		
		R^2	0.658			0.963			0.970		
	Maxwell House	Assortment Share	1.324	(0.082)	***	0.519	(0.053)	***	0.531	(0.057)	***
		Relative Price	-0.280	(0.042)	***	-0.324	(0.053)	***	-0.319	(0.052)	***
		Relative Display	0.109	(0.014)	***	0.032	(0.006)	***	0.030	(0.005)	***
		Relative Feature	0.022	(0.019)		0.020	(0.009)	**	0.030	(0.011)	***
		Sample size	8664			8664			8664		
		R^2	0.680			0.951			0.960		
Cereal	Kellogg	Assortment Share	0.820	(0.050)	***	0.310	(0.038)	***	0.309	(0.036)	***
		Relative Price	-0.327	(0.024)	***	-0.375	(0.013)	***	-0.384	(0.012)	***
		Relative Display	0.052	(0.008)	***	0.052	(0.004)	***	0.047	(0.003)	***
		Relative Feature	0.026	(0.009)	***	0.023	(0.003)	***	0.024	(0.004)	***
		Sample size	9774			9774			9774		
		R^2	0.703			0.938			0.949		
	General Mills	Assortment Share	0.279	(0.053)	***	0.302	(0.035)	***	0.312	(0.034)	***
		Relative Price	-0.281	(0.010)	***	-0.247	(0.011)	***	-0.256	(0.011)	***
		Relative Display	0.089	(0.010)	***	0.050	(0.004)	***	0.047	(0.004)	***
		Relative Feature	0.035	(0.013)	***	0.017	(0.004)	***	0.018	(0.004)	***
		Sample size	9774			9774			9774		
		R^2	0.696			0.934			0.945		
Toilet paper	Charmin	Assortment Share	0.698	(0.046)	***	0.274	(0.029)	***	0.244	(0.027)	***
		Relative Price	-0.133	(0.016)	***	-0.194	(0.008)	***	-0.199	(0.009)	***
		Relative Display	0.120	(0.014)	***	0.066	(0.005)	***	0.059	(0.004)	***
		Relative Feature	0.021	(0.016)		0.050	(0.006)	***	0.050	(0.006)	***
		Sample size	9302			9302			9302		
		R^2	0.569			0.934			0.947		
	Quilted Northern	Assortment Share	0.766	(0.051)	***	0.222	(0.033)	***	0.222	(0.033)	***
		Relative Price	-0.114	(0.011)	***	-0.149	(0.009)	***	-0.148	(0.008)	***
		Relative Display	0.140	(0.012)	***	0.102	(0.006)	***	0.095	(0.006)	***
		Relative Feature	0.059	(0.016)	***	0.066	(0.007)	***	0.067	(0.007)	***
		Sample size	9302			9302			9302		
		R^2	0.683			0.925			0.940		
Store dummies			No			Yes			Yes		
Market-Quarter dummies			No			No			Yes		

Table 4. Estimation results for store-level national brand share regressions (Continued)

		Estimator	Time Fixed Effect		Store + Time Fixed Effect		Store + Market-time Fixed Effect	
Category	Brand	Independent	Coefficient	(Standard error)	Coefficient	(Standard error)	Coefficient	(Standard error)
Yogurt	Yoplait	Assortment Share	1.047	(0.033) ***	0.475	(0.041) ***	0.464	(0.033) ***
		Relative Price	-0.217	(0.012) ***	-0.252	(0.012) ***	-0.236	(0.012) ***
		Relative Display	0.026	(0.004) ***	0.013	(0.002) ***	0.010	(0.002) ***
		Relative Feature	0.057	(0.010) ***	0.039	(0.007) ***	0.037	(0.007) ***
		Sample size	9535		9535		9535	
		R^2	0.827		0.964		0.973	
	Dannon	Assortment Share	0.772	(0.041) ***	0.558	(0.031) ***	0.538	(0.026) ***
		Relative Price	-0.281	(0.020) ***	-0.209	(0.013) ***	-0.206	(0.014) ***
		Relative Display	0.014	(0.005) ***	0.013	(0.002) ***	0.010	(0.001) ***
		Relative Feature	0.030	(0.016) *	0.044	(0.006) ***	0.038	(0.006) ***
		Sample size	9535		9535		9535	
		R^2	0.798		0.972		0.978	
Peanut butter	JIF	Assortment Share	1.562	(0.084) ***	0.575	(0.038) ***	0.437	(0.047) ***
		Relative Price	-0.283	(0.030) ***	-0.320	(0.015) ***	-0.324	(0.014) ***
		Relative Display	0.042	(0.010) ***	0.032	(0.003) ***	0.030	(0.003) ***
		Relative Feature	0.061	(0.011) ***	0.019	(0.005) ***	0.022	(0.005) ***
		Sample size	8176		8176		8176	
		R^2	0.712		0.964		0.970	
	Skippy	Assortment Share	1.159	(0.063) ***	0.326	(0.047) ***	0.326	(0.049) ***
		Relative Price	-0.236	(0.031) ***	-0.246	(0.025) ***	-0.278	(0.025) ***
		Relative Display	0.052	(0.009) ***	0.026	(0.003) ***	0.024	(0.003) ***
		Relative Feature	0.034	(0.017) **	0.034	(0.005) ***	0.032	(0.006) ***
		Sample size	8176		8176		8176	
		R^2	0.804		0.971		0.978	
Ketchup	Heinz	Assortment Share	1.044	(0.085) ***	0.297	(0.034) ***	0.298	(0.035) ***
		Relative Price	-0.361	(0.033) ***	-0.312	(0.010) ***	-0.310	(0.001) ***
		Relative Display	0.073	(0.012) ***	0.045	(0.003) ***	0.042	(0.003) ***
		Relative Feature	0.052	(0.016) ***	0.033	(0.004) ***	0.030	(0.005) ***
		Sample size	7919		7919		7919	
		R^2	0.574		0.956		0.964	
	Hunts	Assortment Share	0.879	(0.053) ***	0.316	(0.044) ***	0.333	(0.043) ***
		Relative Price	-0.236	(0.021) ***	-0.325	(0.017) ***	-0.320	(0.018) ***
		Relative Display	0.118	(0.013) ***	0.071	(0.007) ***	0.066	(0.007) ***
		Relative Feature	0.084	(0.010) ***	0.046	(0.008) ***	0.047	(0.009) ***
		Sample size	7919		7919		7919	
		R^2	0.670		0.915		0.933	
Store dummies			No		No		Yes	
Market-Quarter dummies			No		Yes		Yes	

* Significant at 0.10 level; ** Significant at 0.05 level; *** Significant at 0.01 level

Table 5. Impact of Push Variables - Effect of going from 10th %ile to 90th %ile

Category	Brand	Assortment Share	Relative Price	Relative Display	Relative Feature
Coffee	Folgers	9.6%	-24.0%	1.4%	1.6%
	Maxwell House	9.5%	-14.0%	1.6%	1.7%
Cereal	Kellogg's	3.2%	-8.7%	1.7%	1.0%
	General Mill's	2.5%	-8.1%	1.5%	0.7%
Toilet paper	Charmin	4.0%	-9.7%	2.7%	1.8%
	Quilted Northern	2.7%	-6.3%	3.3%	2.1%
Yogurt	Yoplait	9.8%	-9.4%	0.5%	2.0%
	Dannon	10.7%	-8.2%	0.5%	1.6%
Peanut butter	JIF	5.5%	-11.2%	1.4%	1.2%
	Skippy	8.2%	-15.8%	2.1%	2.1%
Ketchup	Heinz	6.2%	-13.7%	3.8%	1.9%
	Hunts	7.3%	-11.7%	3.3%	3.0%
Average		6.6%	-11.7%	2.0%	1.7%

Table 6. Explained Variation in Purchase Shares

		Overall Variation			Store-Level Variation			Market-Level Variation		
		$\frac{\sigma^2_{X\hat{\beta}}}{\sigma^2_{PS}}$	$1-\frac{\sigma^2_{\xi}}{\sigma^2_{PS}}$	$\frac{\sigma^2_{X\hat{\beta}}}{\sigma^2_{X\hat{\beta}}+\sigma^2_{\xi}}$	$\frac{\sigma^2_{X\hat{\beta}}}{\sigma^2_{PS}}$	$1-\frac{\sigma^2_{\xi}}{\sigma^2_{PS}}$	$\frac{\sigma^2_{X\hat{\beta}}}{\sigma^2_{X\hat{\beta}}+\sigma^2_{\xi}}$	$\frac{\sigma^2_{X\hat{\beta}}}{\sigma^2_{PS}}$	$1-\frac{\sigma^2_{\xi}}{\sigma^2_{PS}}$	$\frac{\sigma^2_{X\hat{\beta}}}{\sigma^2_{X\hat{\beta}}+\sigma^2_{\xi}}$
Category	Brand	Lower Bound	Upper Bound	Estimate	Lower Bound	Upper Bound	Estimate	Lower Bound	Upper Bound	Estimate
Coffee	Folgers	44%	42%	43%	38%	36%	37%	34%	59%	45%
	Maxwell House	23%	42%	29%	18%	40%	23%	12%	44%	17%
Cereal	Kellogg's	48%	60%	55%	41%	56%	48%	20%	49%	28%
	General Mills	49%	66%	60%	44%	65%	56%	35%	64%	49%
Toilet Paper	Charmin	33%	41%	36%	24%	34%	27%	12%	20%	14%
	Quilted Northern	32%	54%	41%	26%	52%	36%	17%	32%	20%
Yogurt	Yoplait	29%	62%	43%	25%	60%	39%	22%	64%	38%
	Dannon	42%	73%	61%	41%	75%	62%	36%	77%	61%
Peanut Butter	JIF	25%	44%	31%	19%	40%	24%	11%	30%	14%
	Skippy	29%	62%	43%	27%	63%	42%	34%	71%	54%
Ketchup	Heinz	18%	41%	23%	11%	37%	15%	11%	37%	15%
	Hunts	29%	50%	36%	21%	48%	29%	16%	53%	25%
Average*		33%	53%	42%	28%	51%	36%	22%	50%	32%

* The average for the bounds is for the upper and lower bounds, accounting for the negative correlation for Folgers.

Table 7. Changes Needed For #2 Brand to Become #1

Category	Difference in Market Share	Increase in Assortment Share	Decrease in Relative Price
Coffee	8%	104%	33%
Cereal	5%	70%	15%
Ketchup	34%	467%	114%
Peanut Butter	3%	38%	10%
Toilet Paper	7%	178%	41%
Yogurt	4%	24%	15%

Table 8. Assortment Increase Needed For #2 Brand to Become #1 if New SKUs Displace Top Brand

Category	Difference in Market Share	Increase in Assortment Share
Coffee	8%	49%
Cereal	5%	35%
Ketchup	34%	247%
Peanut Butter	3%	16%
Toilet Paper	7%	85%
Yogurt	4%	13%