THE EFFECT OF RETAILER STOCKING DECISIONS ON NATIONAL BRAND PERFORMANCE ACROSS U.S. SUPERMARKETS[1]

Minha Hwang
McGill University
minha.hwang@mcgill.ca

Raphael Thomadsen
UCLA Anderson School of Management
raphael.thomadsen@anderson.ucla.edu

24 May 2011

[1] We thank SymphonyIRI Group, Inc. for providing the data. All estimates and analyses in this paper based on SymphonyIRI Group, Inc. data are by the authors and not by SymphonyIRI Group, Inc. We wish to thank Bart J. Bronnenberg for comments and suggestions.

THE EFFECT OF RETAILER STOCKING DECISIONS ON NATIONAL BRAND PERFORMANCE ACROSS U.S. SUPERMARKETS

Abstract

This paper examines the extent to which major national-brand market shares are dependent upon the stocking decisions of retailers. We first demonstrate the extent to which national-brand market shares vary across chains: chain-level effects account for 23% of the variation in market shares across stores, even after controlling for market-level variation. These chain-level differences correlate closely with the variation in the assortments different chains offer. We demonstrate that this association between market shares and assortment shares is causal, and that a chain's assortment decisions explain, on average, 38% of the variance in market shares that can be attributed to chain-level components. These results shed light on the importance of supply-side stocking decisions on market shares, and have implications on demand estimation strategies.

Keywords: *Retailing, brand market share, assortment, supermarket, distribution, consumer packaged goods*

1. Introduction

This paper examines the impact of retailer decisions on the market shares of top national brands in U.S. supermarkets. Specifically, we study the top-two national brands in popular categories (coffee, cereal, ketchup, peanut butter, toilet paper, and yogurt), and examine how retailers' decisions regarding how many stock-keeping units (SKUs) to offer of a particular brand affect market shares for that brand.[1]

We begin our analysis by first demonstrating the importance of chain-level effects on national-brand market shares. Using a store-level dataset, we investigate across stores the proportion of variance in national-brand market shares that we can attribute to market-level effects and to chain-level effects within these markets. We find that market effects explain 62% of the variation of the market shares for the top-two national brands across stores, on average, and account-level effects explain an additional 23% of market-share variation in yearly data. These results confirm those found by Bronnenberg, Dubé and Dhar. (2009)—51% and 20%, respectively—in their analysis demonstrating that national-brand market shares exhibit large variations across markets in the United States. Our results are also consistent with Ataman, Mela, and Van Heerde (2007)'s finding that market shares of products in France vary from chain to chain.

Having confirmed these results, we then seek to explain the source of the chain-level variation. Motivated by Hwang et al. (2010), who show that assortments differ substantially across supermarket chains (even within a given market), we posit that the differences in the distributional depth each chain allocates to a brand might cause the variation in national-brand market shares across chains within a given market. We therefore measure the extent to which the stocking decisions of retailers drive these chain-level effects. As a first step, we test the plausibility of such a

[1] Because we examine the top national brands for popular categories, very few stores do not carry these brands. However, we limit our analysis to only stores that carry both of top two national brands.

link by conducting a variance decomposition of national-brand assortment shares, which we define as the percentage of a given category's SKUs belonging to a particular brand in a given store. We find that account effects explain, on average, 35% of the variation in the assortment shares of the top-two national brands within a category, even after controlling for market-level effects, which explain 51% of the variation.

We then measure the impact of assortment decisions on consumer choices by regressing a brand's market share on its assortment share in a particular store. However, although the size of chain-level effects on national-brand market shares and assortment shares are similar, demand-side factors might directly impact both market shares and assortment shares. We account for this potential simultaneity by including store-level fixed effects. Thus, our measured impact of assortment share is the impact of a change in assortment at a particular store over a short time horizon.[2] We also confirm these results by utilizing a regression discontinuity approach. Ultimately, we find that national-brand assortment shares explain 38% of the variation of national-brand market shares. Taken together, these results indicate that retailer effects—and retailer assortment decisions, specifically—are among the major drivers of national-brand market shares across stores.

These results are important for understanding how customers decide which brands to purchase, as well as for understanding what types of strategic actions manufacturers should take. 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 number of SKUs for even major-brand competitors can have a significant impact on the sales of these

[2] Since store-level fixed effects capture heterogeneity in preferences that vary from store to store, and trends in preferences generally take a longer time than we use in our data to have significant impact, our measured responses should then be mostly supply-side effects.

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). Further, our results suggest 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 balance in terms of the composition of the assortment among the major brands.[3]

Our paper is also related to a literature examining how product placement on store shelves affects brand choice. Dreze and Hoch (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 locations of products matters, but that the number of facings can have a significant impact, especially for frequent users of a brand. Although we do not have data on the number of facings or the location of products on the shelves, we find that having more SKUs belonging to a brand increases the total sales for the brand, suggesting that the scale of the brand's presence affects consumers' ultimate choices.

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. Section 4 discusses the extent to which product assortment is causing the variation in market shares. Section 5 concludes.

2. Data

2.1 Data Description

We base our analysis on the IRI academic dataset (Bronnenberg, Kruger, and Mela 2008). The scanner data span 1,589 supermarkets across 48 IRI markets in six CPG categories—cereal,

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

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 market shares for the top-two national brands in each store. We also compute brand assortment shares for each store, which are measured as the percentage of a given category's UPCs belonging to a particular brand in a given store. We use data from 2004–5, focusing on a relatively short time frame to minimize potential changes in consumer tastes. 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. For the calculation of assortment shares, we smooth the weekly sales status by following a procedure in Hwang et al. (2010) to ensure the detection of slow-moving products. The original data contain 1,589 supermarkets. After excluding stores that do not meet above criteria, 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.

Table 1 shows unit market shares of the three largest brands across all stores in our sample for each category. In all cases, the store brand is among the three largest brands. In our analyses, we focus on the top-two national brands as measured by total volume across all the sample stores. Table 2 shows the sample mean, standard deviation, and the minimum and maximum market shares for the top-two brands in each category.

——— Table 1 about here ———

——— Table 2 about here ———

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 48 IRI markets and 204 accounts.

2.2 Motivating Example

In Sections 3 and 4, we present evidence that account-level (chain–market combination) fixed effects can explain a significant amount of the variation in the top-two national-brand market shares across stores; the chains' assortment stocking decisions, in turn, explain these account-level effects. In this subsection, we present an illustrative example that is suggestive of this outcome.

Table 3 compares brand-level market shares of the top-two toilet paper national brands in two large multi-market retailers. Note the IRI dataset masks the identities of the chains, so we use the names "Retailer A" and "Retailer B." The table reveals that, across seven large metropolitan markets, a significant amount of market-share variation is present both within a chain across cities and within a city but across chains. Charmin has a greater market share in Retailer B stores than in Retailer A stores in all markets, whereas Quilted Northern's market share in Retailer A stores is higher than its market share in Retailer B stores. This example illustrates the existence and size of account-level components in national-brand market shares. Note that despite the fact that the market shares differ in the two chains, Charmin generally has a larger share than Quilted Northern in both Retailer A and Retailer B's stores in most markets (with exceptions in San Francisco and Sacramento for Retailer A), which underscores that some brands are stronger than other brands, even when the strength of each brand differs across markets.

——— Table 3 about here ———

Why are Charmin market shares higher in Retailer B stores than in Retailer A stores, even in the same regional market? Table 4 demonstrates that brand assortment shares could plausibly explain the variation in the observed market shares across retailers. For example, in Los Angeles, Charmin enjoys a larger brand assortment share at Retailer B than at Retailer A, consistent with the much larger market share Charmin commands at Retailer B. On the other hand, Quilted Northern's brand assortment share is larger at Retailer A than at Retailer B, consistent with Quilted Northern's stronger

relative performance at Retailer A. Note, however, that the stocking decisions do not translate one to one into market shares. Returning to the example of the Los Angeles market, we observe that, on average, Retailer A stocks more Quilted Northern SKUs than Charmin SKUs. However, more consumers in Los Angeles Retailer A outlets buy Charmin than Quilted Northern. Also, we see that the differences in assortment shares across retailers within a market are greater than the differences in market shares.

——— Table 4 about here ———

Taken together, this motivating example suggests the role of brand assortment shares as a potential driver of national-brand market shares across stores. We test this conjecture in the subsequent analyses.

3. Variance Decomposition Analysis

3.1 Market Share Analysis

We begin our analysis by investigating the extent to which chain-level effects can explain variation in market shares across supermarkets once one controls for market-level effects. We restrict our analysis to the top-two national brands for six popular categories, and measure the extent to which the market-share variance has account components by estimating a series of linear regression models to conduct fixed effect analysis of variance (ANOVA). The analysis relies on the following model of store-level national-brand market share:

$$Y_{s,c,m,t} = \alpha_m + \beta_{c,m} + \gamma_t + \varepsilon_{s,c,m,t} \quad . \tag{1}$$

In this equation, $Y_{s,a,m,t}$ is the market share of a focal national brand at store s in chain c and market m at time t. α_t represents geographic-market fixed effects, and $\beta_{c,m}$ represent account-level (defined as chain–market combinations) fixed effects, which capture the incremental variation chain affiliation

explains after we control for market effects. Note that due to perfect multicollinearity, we include in a particular regression, either α_m or $\beta_{c,m}$, but not both. The γ_t terms are time fixed-effects.

By comparing the fit of regressions that include only time and market fixed effects with the fit of regressions that include time and chain-market fixed effects, we measure the amount of variation in national-brand market shares that market- and account-level fixed effects can explain. Thus, account-level effects are defined as the incremental explained variance that is obtained when we add account effects after controlling for market effects and time effects.[4]

Table 5 reports the average results for the variance decomposition across the 12 brands when we aggregate the data at the annual level. The first column in Table 5 reveals that, on average, market effects explain 62% of the variation of national-brand market shares across stores in yearly data, and account effects explain an additional 23% of the market-share variation. Further, because market and account effects jointly explain 85% of the variation of national-brand annual shares across stores, the average variation of national-brand market shares across stores within a chain in a particular market must be smaller than the variation across chains within that market.

——— Table 5 about here———

The remaining columns in Table 5 show the robustness of these results. In column 2, we examine whether significant differences are present in the magnitude of the market-level versus account-level effects between the top national brand and the second-largest national brand: the results of the variance decomposition are virtually unchanged when we include only the largest national brand in the category. The annual aggregation of market shares masks the impact of short-term promotions such as temporary price cuts, features, and displays. Because of these short-term promotions, weekly market shares vary a lot more than annual market shares. In columns 3 and 4, we report the results of a variance decomposition conducted with weekly aggregation. The amount of variation that either

[4] Specifically, we introduce time effects first, market effects second, and the account (market-chain indicators) effects last.

market- or account-level fixed effects explains shrinks, as would be expected due to the week-to-week variation in market shares due to price or other promotions. However, the ratio of size of the account-level effects to the size of the market-level effects remains similar: 0.38 with the annual data versus 0.31 with the weekly data. Thus we confirm the findings of Bronnenberg et al. (2009), which show that the size of chain-level effects is 39% of the size of market-level effects.

3.2 Assortment Share Analysis

To assess whether the variation of national-brand market shares across chains are supply driven, we first assess the plausibility of this mechanism by measuring the extent to which account-level components can explain the variation in assortment shares for each brand across stores. We base the analysis on a model similar to equation (1), except that we use assortment shares instead of market shares as the dependent variables.

——— Table 6 about here ———

Table 6 reports the average assortment-share variance decomposition results. When we aggregate the data at the annual level, we find that market-level effects explain 51% of the assortment-share variation across stores, and account-level effects explain an additional 35% of the variance. The ratio of the size of the account-level effects to the size of the market-level effects is larger for assortment shares than for market shares: 0.68 versus 0.38, respectively. Thus, market shares have less than a one-to-one response to a retailer's assortment shares. This finding is consistent with the results of Hwang et al. (2010), which show that almost all retailers stock core products, and that the marginal stocking decisions are for products that appeal to smaller numbers of consumers.

Column 2 of Table 6 demonstrates that no meaningful difference exists between the variance decomposition results for the top brand or the second-largest national brand in the category. In columns 3 and 4, we observe that unlike the results for the market-share variance decomposition, the

loss of explanatory power for the various components is minimal when we analyze the data at a weekly instead of annual level; this finding reflects the fact that weekly promotions are not generally accompanied with a change in the assortment that a supermarket offers.

Table 6 also reveals that market- and account-level effects together explain, on average, 86% of the variation in national-brand assortment shares across stores. Thus the variation of national-brand assortment shares across stores within a chain is small compared with the variation across chains within a market or the variation across markets. The fact that assortment shares have strong market- and account-level components, but not store-level components, is consistent with the findings in Hwang et al. (2010), which shows that most supermarket assortment decisions are made at the market-chain level.

Finally, we note that the magnitude of the variation of national-brand assortment shares explained by market- and account-level fixed effects is similar to the magnitude of the variation of market shares explained by the same effects. This similarity suggests that the differences in brand assortment shares of a focal national brand might be an origin for the presence of account effects for national-brand market shares. We examine this conjecture in more detail in section 4.

4. Measuring the Impact of Retailer Assortment Choices on Market Shares

In this section, we seek to quantify the extent to which retailer stocking decisions drive the variance in market shares within a particular market. This analysis contains two steps. The first step establishes a causal relationship between assortment shares and market shares. One could instead conjecture that the correlation between assortment shares and market shares observed in the previous sections are merely based on the preferences of customers at each of the different chains; that is, customers of specific chains uniquely prefer certain brands, and the retailers therefore adjust their assortment in response to these preferences. After demonstrating a causal relationship between

assortment shares and market shares, we estimate the percentage of the account-level fixed effects that can be attributed to assortment shares. We conduct each of these analyses in turn.

4.1 The Impact of Assortment Share on Market Share

We measure the impact a retailer's assortment decision has on a brand's market share. Before controlling for simultaneity concerns, we first present basic regression results in which we regress the impact of assortment share on market share, conditioning on market and time fixed effects. The market-level fixed effects account for differences in market share that are known to occur at the local level (Bronnenberg et al. 2007). The week-level fixed effects capture variation that can occur if a store advertises a particular product, promotes it with a feature or display, or puts it on a temporary price promotion. In summary, we run the following regression:

$$MS_{bst} = \alpha_m + \beta \cdot AS_{bst} + \gamma_t + \varepsilon_{bst}, \tag{2}$$

where MS_{bst} is the observed (store-level) market share of the focal national brand *b* at store *s* in week *t*, α_m and γ_t are market and time fixed effects, respectively, and AS_{bst} is the brand *b* assortment share at the store on a particular week. Because many of the customers at a store shop at the same chain in different weeks, and because promotions are often coordinated across stores within a week, we cluster the standard errors at the chain and week levels to ensure robust inference.[5]

In column 1 of Table 7, we report the estimated coefficient on assortment share for each of the 12 products. The coefficients are less than 1, as expected, but large, suggesting a chain's decision of how many SKUs of each brand to stock has a significant impact on consumers' ultimate brand choices.

——— Table 7 about here ———

[5] We calculate the standard errors over two dimensions as proposed by Cameron, Gelbach and Miller (2011).

One problem with interpreting the estimates in column 1 as measuring supply-side effects is that a simultaneity bias can be present if unobserved demand effects determine both market shares and assortment shares. For example, if, at the time they make assortment decisions, supermarkets know which products their consumers want then the preferences of the store's clientele will in part determine assortment shares. To isolate the direct impact of assortment share, we run another set of regressions whereby we include store-level fixed effects. In particular, we run the following regression:

$$MS_{bst} = \alpha_s + \beta \cdot AS_{bst} + \gamma_t + \varepsilon_{bst}, \tag{3}$$

where α_s are store-level fixed effects. Note that we take market-level fixed effects out of equation (3) because market dummies are collinear in design with store dummies.

The coefficient on assortment choice in the regression in equation (3) is identified from the changes in the brand's assortment share within our two-year window: the presence of these store-level fixed effects removes issues of demand-side simultaneity 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. We report the coefficient of assortment share for the regression including store fixed effects in column 2 of Table 7. The estimated β coefficients have similar magnitudes as the results in column 1, but the estimated coefficients are generally somewhat smaller. This finding indicates that some of the correlation between assortment shares and market shares comes from supermarkets customizing their assortments to match the demand of their local clientele, except possibly in the cereal category. However, the similarity in the size of the coefficients in columns 1 and 2 indicates that most of the measured conditional correlation between the two variables is causal. In total, increased assortment shares lead to increased market shares, where a

change in assortment shares of Δ leads to changes in market shares of approximately $\Delta/2$, across categories.

Theoretically, one could still worry that the differences in assortment shares reflect differences in how preferences evolve over time at each store; we seek to avoid this issue by conducting the analysis over a short time period of two years, which should see only modest changes in preferences for the mature and established categories we examine. As an additional robustness check, we also estimate the impact of assortment share on market share using a regression discontinuity approach, which is potentially more robust against demand-side trends or fads that could cause both assortment share and market share to co-vary. Researchers have applied regression discontinuity analysis to a broad range of applications (e.g., Angrist and Lavy 1999, Black 1999, Busse et al. 2010), and Hahn et al. (2001) and Hartmann et al. (2010) discuss the statistical properties of such an approach. For our regression discontinuity analysis, we estimate β by analyzing only store-week observations that belong to four-week windows on either side of a change in a retailer's assortment share of the focal brand. To ensure that our estimates are identified from meaningful changes in assortment, we limit our analysis to assortment changes involving more than 2% of the SKUs. As column 3 of Table 7 shows, the β coefficients from the regression discontinuity approach are similar to our estimates from the regressions that include store-level fixed effects (column 2), with the exception of the coefficient for Maxwell House. Because we correct for the potential simultaneity of assortment share and market share in two different ways that yield similar results, we are confident we have correctly measured the causal relationship between assortment share and market share. For the remaining analysis, we use the estimated coefficients from column 2, since the average standard errors for our estimates are smaller than the standard errors in column 3.

4.2 Fraction of Retailer Effect Explained by Assortment Share

Given that a national brand's assortment share at a particular store impacts the brand's market share, we now measure how much of the account-level variation in the brand's market share can be ascribed to stocking decisions. We first conduct a decomposition analysis, and then regress each brand's market share on a different set of variables and compare the R^2 of the regression as we add variables. Table 8 presents the output of the decomposition analysis.

——— Table 8 about here ———

The first column of Table 8 shows the R^2 from a regression that includes only market- and week-level fixed effects. In column 2, we report the R^2 from a regression in which we add account-level fixed effects. Because the account variables are chain-market-specific indicator variables, we drop the redundant market dummy variable. Column 3 presents the R^2 from a constrained regression of market shares on the brand's assortment share, as well as market and week fixed effects, where we constrain the coefficient on assortment share to be the coefficients on assortment shares as estimated in column 2 of Table 7. We constrain the coefficients because, as section 4.1 shows, if we merely run an unconstrained regression of market shares on assortment shares without controlling for store-level fixed effects, we capture both the causal effect of assortment share on market share as well as a simultaneity effect of local variations of demand driving customized assortments at different supermarkets. Thus the R^2 measured in column 3 of Table 8 reflects the fit of the regression including only the causal correlation of assortment share on market share. Column 4 shows the results of a constrained regression with week-level fixed effects, account-level fixed effects, and the brand's assortment share, where we again constrain the coefficient on assortment share to be equal to the coefficient from column 2 of Table 7.

Column 5 reports how much of the account-level effect on market shares can be explained by a brand's assortment share. Specifically, we evaluate the percentage of the retailer fixed effect that can be attributed to assortment shares as

$$\frac{(\text{column 2} - \text{column 1}) - (\text{column 4} - \text{column 3})}{(\text{column 2} - \text{column 1})}. \tag{4}$$

The difference between the R^2 in column 2 versus column 1 represents the incremental variance in market shares that is explained when we add account-level fixed effects to a regression including only market-level effects, whereas the difference in R^2 in column 4 versus column 3 gives us the incremental-explained market-share variation from adding account-level fixed effects once we have already accounted for a brand's assortment share at a particular supermarket. If the assortment shares explain most of the same market-share variance that the account-level effects explain then adding account-level effects to a regression where assortment shares have been included should explain almost no additional variance, in which case (column 4 – column 3) will be small and the measure in equation (4) will be close to 1. On the other hand, if the difference between columns 4 and 3 is large then the assortment shares must explain only a little of the variation account-level fixed effects explain. On average, we find we can attribute 38% of the market-share variation due to account-level effects to the brand assortment shares at the different chains.

Combining our results with those of Bronnenberg, Dubé, and Gentzkow (2010) can provide further insight. Bronnenberg et al. show that when consumers move from one market to another, their behavior moves 60% toward matching the behavior of the new market instantaneously. Since a person's preference is unlikely to change immediately, Bronnenberg et al. attribute this 60% shift to supply-driven changes in purchasing behavior. Our results suggest that assortment decisions drive roughly 2/3 ($= \frac{38\%}{60\%}$) of this supply-side effect, whereas other supply-side effects, which might include pricing decisions (different brands are relatively cheaper in different markets), feature

decisions (local favorites might be displayed more often), and short-term advertising effects, drive the other third.[6]

5. Discussion and Conclusion

This study examines how a retailer's assortment decisions impact the market shares of top national brands in its stores. In particular, we first show that not only is large local variation present in the market shares of major national brands across different markets, consistent with Bronnenberg et al. 2007, but significant variation is also present in the market shares of these brands across supermarkets within markets, even after we control for market-level effects. For example, we show that across seven large markets, Charmin's market share is, on average, more than 40% larger in Retailer B stores than in Retailer A stores located in the same market. At the same time, we observe that Charmin's assortment share at Retailer B is 34% larger than its assortment share at Retailer A. Formal analysis of the data confirms that these patterns are not outliers. Specifically, we first show that, after controlling for market-level variation, the chain to which the supermarket belongs can explain almost 23% of the variation in national-brand market shares across all stores. Further, we show that the variation in brand assortment shares causes about 38% of this account-level component.

These findings demonstrate that although advertising and other demand-side factors might explain some of the market-share variation for top national brands across markets (Bronnenberg et al. 2011), supply-side effects, and assortment choices in particular, are also important inputs in

[6] We are agnostic as to whether short-term advertising effects should be thought of as a demand- or supply-side effect. We adopt the language of Bronnenberg et al. in attributing the 60% shift in purchasing behavior to "supply-side effects," but the 60% figure will capture any short-term effects from advertising differences in one market versus another. Note that Leone (1995) demonstrates that most of the effect of advertising is felt in the first 69 months, whereas Lodish et al. (1995) show that half of the impact of an ad within the first year. Dekimpe and Hanssens (1995) find that the short-term effects of advertising are especially high in print advertising and relatively smaller in TV advertising.

determining the final market shares. Ultimately, we find that on average across categories, an increase of 1% in a brand's assortment share in a supermarket (e.g., a change from a 20% assortment share to a 21% assortment share) leads to a change of approximately 0.5% in that brand's market share (e.g., a change from 30% to 30.5%). The magnitude of this effect might be surprising given that the stocking decisions we observe are not whether to stock a given brand but rather how many of the marginal SKUs of these brands to stock. For example, the decision is not whether to stock Charmin, but rather how many different package sizes to stock, with the retailer choosing from among the less-popular package sizes.

The fact that significant account-level components are present in brand assortment shares 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 across chains. In addition to aggregation biases due to varying brand availability that have been noted by Bruno and Vilcassim (2008), our results indicate that an additional aggregation bias due to varying national brand assortment shares across accounts can exist.

Our results also 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 market shares of less-popular brands but also to significantly change the market shares of top national 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, our results show that even changes in the marginal national-brand SKUs affect market shares in meaningful ways.

Finally, we find significant variations in the distribution depths of top national brands across chains even within the same market. In the current study, we focus on documenting the magnitude

of variation and its impacts on market shares. An interesting avenue for further research would be to assess whether the difference in brand assortment shares are due to manufacturer policies or differences in the strength of store brands across chains. We leave the deeper analysis of this question to future research.

References

Angrist, J.D., Lavy, V., (1999). "Using Maimonides' Rule to Estimate the Effect of Class Size on Scholastic Achievement," *Quarterly Journal of Economics*, 114, 533–575.

Ataman, M. Berk, Carl F. Mela and Harald J. Van Heerde (2007), "Consumer Packaged Goods in France: National Brands, Regional Chains, and Local Branding, *Journal of Marketing Research*, 44(1), 14-20.

Bayus, Barry L. and William P. Putsis, Jr. (1999), "Product Proliferation: An Empirical Analysis of Product Line Determinants and Market Outcomes," *Marketing Science*, 18 (2), 137-153.

Black, S., (1999). "Do Better Schools Matter? Parental Valuation of Elementary Education," *Quarterly Journal of Economics*, 114, 577–599.

Bloom, Paul N, Gregory T. Gundlach and Joseph P. Cannon (2000), "Slotting Allowances and Fees: Schools of Thought and the Views of Practicing Managers," *Journal of Marketing*, 64(2), 92-108.

Bronnenberg, Bart J., Sanjay K. Dhar, and Jean-Pierre Dubé (2007), "Consumer Packaged Goods in the United States: National brands, Local branding," *Journal of Marketing Research*, **44**(1), 4-13.

Bronnenberg, Bart J., Sanjay K. Dhar, and Jean-Pierre Dubé (2009), "Brand History, Geography, and the Persistence of Brand Shares," *Journal of Political Economy*, **117**(1), 87-115.

Bronnenberg, Bart J., Sanjay K. Dhar, and Jean-Pierre Dubé (2011), "Endogenous Sunk Costs and the Geographic Differences in the Market Structures of CPG Categories," *Quantitative Marketing and Economics*, 9(1), 1-23.

Bronnenberg, Bart K., Jean-Pierre Dubé and Matthew Gentzkow (2010), "The Evolution of Brand Preferences: Evidence from Consumer Migration," *American Economic Review*, forthcoming.

Bronnenberg, Bart J., Michael W. Kruger, and Carl F. Mela (2008), "The IRI Marketing Data Set," *Marketing Science*, 4 (July-August), 745-748.

Bruno, Hernan and Naufel J. Vilcassim (2008), "Structural Demand Estimation with Varying Product Availability," *Marketing Science*, **27**(6), 1126-1131.

Busse, Meghan, Duncan Simester and Florian Zettelmeyer (2010), "The Best Price You'll Ever Get: The 2005 Employee Discount Pricing Promotions in the U.S. Automobile Industry," *Marketing Science*,. 29(2): 268–290.

Cameron, A. Colin, Jonah B. Gelbach and Douglas L. Miller (2011), "Robust Inference with Multiway Clustering," *Journal of Business and Economic Statistics*, 29(2), 228-237.

Carameli, Leo. S., Jr. (2004), "The Anti-Competitive Effects and Antitrust Implications of Category Management and Category Captains of Consumer Products," *Chicago-Kent Law Review*, 79(3), 1313-1356.

Chandon, Pierre, J. Wesley Hutchinson, Eric T. Bradlow and Scott H. Young (2009), "Does In-Store Marketing Work? Effects on the Number and Position of Shelf Facings on Brand Attention and Evaluation at the Point of Purchase," *Journal of Marketing*, 73 (6), 1-17.

Dekimpe, Marnik G. and Dominique M. Hanssens (1995), "The Persistence of Marketing Effects on Sales," *Marketing Science*, 14(1), 1-21.

Dreze, Xavier, Stephen J. Hoch and Mary E. Purk, "Shelf Management and Space Elasticity," *Journal of Retailing*, 70(4), 301-326.

Gruen, Thomas W. and Reshma H. Shah (2001), "Determinants and Outcomes of Plan Objectivity and Implementation in Category Management Relationships," *Journal of Retailing*, 76(4), 483-510.

Hahn, Jinyong, Petra Todd, and Wilbert Van Der Klaauw (2001). "Identification and Estimation of Treatment Effects with a Regression Discontinuity Design," *Econometrica*, 69(1), 201–209.

Hartmann, Wesley, Harikesh Nair and Sridhar Narayanan (2010), "Non-Parametric Identification of Causal Marketing Mix Effects Using a Regression Discontinuity Design," *Marketing Science*, forthcoming.

Hwang, Minha, Bart J. Bronnenberg, and Raphael Thomadsen (2010), "An Empirical Analysis of Assortment Similarities across U.S. Supermarkets," *Marketing Science*, 29(5), 858-879.

Leone, Robert P. (1995), "Generalizing What is Known About Temporal Aggregation and Advertising Carryover," *Marketing Science*, 14(3), G141-50.

Lodish, Leanard, Magid M. Abraham, Jeanne Livelsberger, Beth Lubetkin, Bruce Richardson, and Mary Ellen Stevens (1995), "A Summary of Fifty-five In-Market Experiemental Estimates of the Long-Term Effect of TV Advertising," *Marketing Science*, 14(3), G133-40.

Morgan, Neil A., Anna Kaleka and Richard A. Gooner (2007), "Focal Supplier Opportunism in Supermarket Retailer Category Management," *Journal of Operations Management*, 25, 512-527.

Pauwels, Koen and Shuba Srinivasan (2004), "Who Benefits from Store Brand Entry" *Marketing Science*, 23(3), 364-390.

Subramanian, Upender, Jagmohan S. Raju, Sanjay K. Dhar and Yusong Wang (2010), "Competitive Consequences of Using a Category Captain," *Management Science*, 56(10), 1739-1765.

Sudhir, K. and Vithala R. Rao (2006), "Do Slotting Allowances Enhance Efficiency or Hinder Competition," *Journal of Marketing Research*, 43(2), 137-155.

White, J. Chris, Lisa C. Troy and R. Nicholas Gerlich (2000), "The Role of Slotting Fees and Introductory Allowances in Retail Buyers' New-Product Acceptance Decisions," *Journal of the Academy of Marketing Science*, 28(2), 291-298.

Table 1. Descriptive statistics: Unit market shares of top three brands in each category in 2004-2005

Category	Top 1 brand		Top 2 brand		Top 3 brand	
	Brand	Market Share (%)	Brand	Market Share (%)	Brand	Market Share (%)
Coffee	Folgers	31	Maxwell House	25	Store Brand	12
Cereal	Kelloggs	31	General Mills	27	Store Brand	14
Toilet paper	Charmin	21	Store Brand	20	Quilted Northern	16
Yogurt	Yoplait	29	Dannon	28	Store Brand	20
Peanut butter	JIF	30	Skippy	26	Store Brand	26
Ketchup	Heinz	57	Store Brand	21	Hunts	17

Table 2. Descriptive statistics of top two national brand makret shares in 2004-2005

Category	Mean	Standard deviation	Minimum	Maximum
Coffee	0.2835	0.1359	0.0016	0.8163
Cereal	0.2890	0.0601	0.0902	0.5779
Toilet paper	0.1824	0.0837	0.0238	0.6122
Yogurt	0.2819	0.1048	0.0190	0.7157
Peanut butter	0.2782	0.1481	0.0113	0.7262
Ketchup	0.3710	0.2238	0.0151	0.8846

Table 3. Brand shares for toilet paper in two multi-market retailers

	Charmin's share					
	Retailer A			Retailer B		
Region	Mean	Std	N_{obs}	Mean	Std	N_{obs}
Los Angeles	0.174	0.039	31	0.256	0.017	14
Seattle/Tacoma	0.155	0.045	13	0.218	0.028	6
Dallas	0.206	0.033	9	0.300	0.019	9
San Francisco	0.138	0.033	6	0.187	0.022	10
Sacramento	0.177	0.025	2	0.190	0.011	5
San Diego	0.176	0.022	9	0.237	0.035	6
Portland	0.121	0.020	9	0.216	0.017	7
	Quilted Northern's share					
	Retailer A			Retailer B		
Region	Mean	Std	N_{obs}	Mean	Std	N_{obs}
Los Angeles	0.154	0.057	31	0.132	0.029	14
Seattle	0.110	0.011	13	0.055	0.011	6
Dallas	0.121	0.020	9	0.078	0.013	9
San Francisco	0.168	0.063	6	0.163	0.018	10
Sacramento	0.192	0.007	2	0.157	0.016	5
San Diego	0.148	0.047	9	0.127	0.027	6
Portland	0.107	0.011	9	0.074	0.010	7

* Based on 2005 yearly data

Table 4. Brand assortment shares for toilet paper in two multi-market retailers

	Charmin's assortment share					
	Retailer A			Retailer B		
Region	Mean	Std	N_{obs}	Mean	Std	N_{obs}
Los Angeles	0.193	0.023	31	0.276	0.013	14
Seattle/Tacoma	0.253	0.020	13	0.321	0.016	6
Dallas	0.263	0.007	9	0.305	0.008	9
San Francisco	0.159	0.045	6	0.258	0.014	10
Sacramento	0.182	0.008	2	0.265	0.023	5
San Diego	0.201	0.020	9	0.271	0.020	6
Portland	0.254	0.010	9	0.317	0.014	7
	Quilted Northern's assortment share					
	Retailer A			Retailer B		
Region	Mean	Std	N_{obs}	Mean	Std	N_{obs}
Los Angeles	0.212	0.044	31	0.153	0.031	14
Seattle	0.164	0.025	13	0.139	0.016	6
Dallas	0.155	0.005	9	0.116	0.017	9
San Francisco	0.194	0.049	6	0.178	0.013	10
Sacramento	0.242	0.013	2	0.168	0.011	5
San Diego	0.195	0.044	9	0.162	0.032	6
Portland	0.184	0.010	9	0.145	0.012	7

* Based on 2005 yearly data

Table 5. Incremental to Explanatory Power: Brand Market Share

	Yearly Aggregation		Weekly Aggregation	
	All	Top Brands	All	Top Brands
Time	0.7	0.5	4.2	5.0
Market	61.8	60.3	31.3	29.5
Account	23.4	23.2	9.6	9.8
Full Model	85.9	84.0	45.1	44.3

Table 6. Incremental to Explanatory Power: Brand Assortment Share

	Yearly Aggregation		Weekly Aggregation	
	All	Top Brands	All	Top Brands
Time	0.7	1.0	1.7	2.0
Market	50.8	50.4	46.8	45.9
Account	34.6	34.3	31.3	31.2
Full Model	86.1	85.7	79.7	79.1

Table 7. Estimation results for store-level national brand share regressions

		Estimator	OLS	Fixed effects	Regression discontinuity
Category	Brand	Independent variable	Coefficient (Standard error)	Coefficient (Standard error)	Coefficient (Standard error)
Coffee	Folgers	Focal brand assortment share	0.643 (0.0533) ***	0.577 (0.1005) ***	0.518 (0.0960) ***
		Sample size	110627	110627	8823
		R^2	0.412	0.496	0.593
	Maxwell House	Focal brand assortment share	0.671 (0.0586) ***	0.498 (0.1106) ***	0.728 (0.0809) ***
		Sample size	110627	110627	9946
		R^2	0.405	0.461	0.419
Cereal	Kellogg's	Focal brand assortment share	0.733 (0.0530) ***	0.711 (0.0972) ***	0.937 (0.2057) ***
		Sample size	124968	124968	2569
		R^2	0.235	0.315	0.507
	General Mills	Focal brand assortment share	0.482 (0.0588) ***	0.570 (0.0674) ***	0.603 (0.1368) ***
		Sample size	124968	124968	1880
		R^2	0.195	0.309	0.466
Toilet paper	Charmin	Focal brand assortment share	0.589 (0.0584) ***	0.412 (0.0455) ***	0.450 (0.0547) ***
		Sample size	118993	118993	58926
		R^2	0.259	0.359	0.357
	Quilted Northern	Focal brand assortment share	0.955 (0.0633) ***	0.442 (0.0962) ***	0.461 (0.0777) ***
		Sample size	118993	118993	37726
		R^2	0.236	0.290	0.336
	Market dummies		Yes	No	No
	Store dummies		No	Yes	Yes
	Week dummies		Yes	Yes	Yes

Table 7. Estimation results for store-level national brand share regressions (Continued)

		Estimator	OLS	Fixed effects	Regression discontinuity
Category	Brand	Independent variable	Coefficient (Standard error)	Coefficient (Standard error)	Coefficient (Standard error)
Yogurt	Yoplait	Focal brand assortment share	0.616 (0.0381) ***	0.438 (0.0535) ***	0.537 (0.0629) ***
		Sample size	121952	121952	14139
		R^2	0.555	0.628	0.686
	Dannon	Focal brand assortment share	0.847 (0.0342) ***	0.660 (0.0340) ***	0.664 (0.0340) ***
		Sample size	121952	121952	16293
		R^2	0.614	0.703	0.743
Peanut butter	JIF	Focal brand assortment share	0.865 (0.0725) ***	0.602 (0.0642) ***	0.606 (0.0961) ***
		Sample size	104821	104821	17017
		R^2	0.492	0.600	0.650
	Skippy	Focal brand assortment share	0.614 (0.0617) ***	0.446 (0.0477) ***	0.451 (0.0457) ***
		Sample size	104821	104821	26759
		R^2	0.722	0.765	0.799
Ketchup	Heinz	Focal brand assortment share	0.811 (0.1088) ***	0.250 (0.0413) ***	0.293 (0.0515) ***
		Sample size	101169	101169	35556
		R^2	0.400	0.523	0.496
	Hunts	Focal brand assortment share	0.576 (0.0583) ***	0.398 (0.0531) ***	0.443 (0.0606) ***
		Sample size	101169	101169	35556
		R^2	0.380	0.476	0.460
		Market dummies	Yes	No	No
		Store dummies	No	Yes	Yes
		Week dummies	Yes	Yes	Yes

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

Table 8. Decomposition of explained variance

Category	Brand	Market + Week Fixed Effects	Account + Week Fixed Effects	Market + Week Fixed Effects + Assortment Share	Account + Week Fixed Effects + Assortment Share	% of Account Effect Explained by Assortment Share
Coffee	Folgers	0.37	0.44	0.41	0.46	33%
	Maxwell House	0.37	0.43	0.40	0.44	41%
Cereal	Kellogg's	0.18	0.27	0.23	0.28	47%
	General Mills	0.18	0.26	0.19	0.26	21%
Toilet paper	Charmin	0.22	0.31	0.26	0.32	36%
	Quilted Northern	0.14	0.26	0.24	0.27	73%
Yogurt	Yoplait	0.51	0.58	0.56	0.59	53%
	Dannon	0.45	0.63	0.61	0.66	75%
Peanut butter	JIF	0.45	0.56	0.49	0.56	36%
	Skippy	0.70	0.74	0.72	0.74	41%
Ketchup	Heinz	0.34	0.51	0.40	0.52	32%
	Hunts	0.34	0.43	0.38	0.44	34%
Average						43%

Note: Weekly data are used for the decomposition of variance.