EXAMINING STORE LOYALTY AS A CATEGORY-SPECIFIC TRAIT

Abstract

The literature on store loyalty views a consumer as possessing store loyalty toward a particular store for her or his overall grocery shopping needs. In this study, we examine store loyalty as a category-specific trait, i.e., a consumer could be loyal to Store A in category 1, but loyal to Store B in category 2. We call this *store-category loyalty* (SCL). We enumerate 10 key drivers – variables relating to product assortments and prices of categories across stores, as well as category characteristics – of SCL and their expected effects. In addition, we also discuss the effects of 2 consumer characteristics (demographics) on SCL. We use a Hierarchical Bayes Multinomial Logit (HB-MNL) model to test our hypotheses using an in-home scanning panel dataset of 1321 households in 284 grocery categories across 16 stores over a 53-week period. The results show that a variety of key drivers and consumer characteristics affect SCL in line with our predictions. We illustrate the managerial implications of our findings, for example, by deriving revenue consequences to stores from changing some of the marketing levers, i.e., variables related to product assortments and prices, which are in their control.

Keywords: Store Loyalty, Store-Category Loyalty, Multinomial Logit, Hierarchical Bayes.

1. INTRODUCTION

The grocery industry in the US is highly fragmented, with even the top retailers (such as Wal-Mart, Kroger, Safeway etc.) accounting for only 5-10% of industry sales (TNS Global Market Research 2009). This being the case, an obvious question that arises is whether US shoppers switch a lot among retailers when shopping for groceries. There is a long and rich tradition of empirical research in marketing that has studied this question. This literature has sought answers to research questions such as these:

1. What factors drive consumers' grocery store choices over time? (Monroe and Guiltinan 1975, Kumar and Leone 1988, Bucklin and Lattin 1992, Bell and Lattin 1998, Bell, Ho and Tang 1998, Broniarczyk, Hoyer and McAlister 1998, Bodapati and Srinivasan 2006, Briesch, Chintagunta and Fox 2009)
2. Are most consumers store loyal or do they switch among grocery stores? What stochastic patterns characterize such switching behavior among stores? (Tate 1961, Cunningham 1961, Aaker and Jones 1971, Blattberg, Peacock and Sen 1976, Keng and Ehrenberg 1984, Uncles and Ehrenberg 1990)
3. What factors – store- and consumer-level – drive consumers' store loyalties? (Tate 1961, Cunningham 1961, Schapker 1966, Arnold, Oum and Tigert 1983, Corstjens and Lal 2000, Rhee and Bell 2002)

The above-mentioned literature largely views a consumer as possessing store loyalty toward a particular store for her or his *overall* grocery shopping needs. For example, while some consumers in a given market may be classified as loyal to Safeway, other consumers within the same market may be classified as loyal to Albertson's, and some other consumers may be classified as loyal to neither (and called switchers), depending on the percentage of their shopping trips that are accounted for by a particular store in the market (Prasad 1972, Fox and Hoch 2005, Gauri, Sudhir and Talukdar 2008). We contend in this study that such a view of overall store loyalty may be limiting from both research and practitioner perspectives. We provide an example next to explain this point.

Jane Smith does her grocery shopping at three different stores – Safeway, Wal-Mart Supercenter and Albertson's – visiting each store about equally over time so that none can claim to be her favorite store. Such a consumer is labeled under the traditional view of store loyalty as a store switcher. However, unlike a store switcher who is usually assumed to switch among stores either to redeem the lowest available price in each product category (also called a "cherry picker," see Fox and Hoch 2005, Gauri, Sudhir and Talukdar 2008), or because of travel exigencies that take the consumer closer to one store or another on a given week, Jane always purchases some categories (e.g., soft drinks) in Safeway, some categories (e.g., produce) in Wal-Mart Supercenter, and other categories (e.g., meat) in Albertson's. In other words, Jane is, in fact, loyal to different stores in different product categories. Not understanding this aspect of Jane's shopping behavior may lead one to spuriously conclude that her lack of overall store loyalty implies her lack of store loyalty to the store for *any product category*.[1]

Our focus in this study, therefore, is to examine store loyalty as a category-specific trait. Unlike previous research on store loyalty, which model *overall* store loyalties of consumers (and answer questions like "Which grocery store is Jane Smith loyal to while shopping for groceries?"), we model store loyalty as a *category-specific consumer trait* (and address questions

[1] Alternatively, consider John Doe who does his grocery shopping most of the time at Costco, but buys cheese and beer always at Safeway because it offers a larger and more diverse product assortment. In that case, modeling the overall store loyalty of John Doe to Costco, as in the existing literature, will still miss out on capturing the important fact that John Doe is loyal to Safeway in some product categories.

like "Which grocery store is Jane Smith loyal to while shopping for milk? How about when shopping for wine?"). We call this *Store-Category Loyalty* (SCL).

To the best of our knowledge, there is only one paper that treats store loyalty as a category specific trait of a consumer. Dreze and Hoch (1998) classify grocery products into two types: (1) Type I, for which consumers are loyal to a specific retailer and, as far as possible, always shop at that retailer for those products, and (2) Type II, that are not associated with any retailer and are bought at whichever retailer consumers happen to shop when they plan or remember to buy the products. Using a controlled store experiment, the authors show that a store can successfully transform Type 2 products into Type 1 products using cross-merchandising programs. While Dreze and Hoch (1998) distinguish between categories where a consumer is store loyal and categories where the consumer is not, the authors do not study whether and why a consumer could be loyal to different stores in different product categories. This is the focus of our study. While some models on store choices (Aaker and Jones 1971, Blattberg, Peacock and Sen 1976, Keng and Ehrenberg 1984, Uncles and Ehrenberg 1990, Bucklin and Lattin 1992) have been developed at the category level, a category-level view of, and basis for, store loyalty has not been provided so far. Our study contributes to the literature in this regard. In doing this, we are able to shed light, for the first time in the marketing literature, on why a consumer is loyal to different stores in different categories.

Obtaining a nuanced understanding of store loyalty as a category-specific trait will be of great value to retailers. For example, if Safeway realizes that it has very high consumer loyalty in a few product categories, even though it does not command their overall store loyalty, understanding the drivers of such loyalty in those categories will assist Safeway in better managing consumers' loyalties in the remaining categories (where its loyalty among consumers is currently low). Instead, if Safeway focuses only on the overall store loyalty metric, it will be difficult for Safeway to discern the reasons for its low overall loyalty among consumers, which, in turn, will make it difficult for Safeway to improve customer patronage for their stores.[2]

We use an in-home scanning panel dataset that tracks 1321 households in 284 grocery categories across 16 stores over a 53-week period. We use a Hierarchical Bayes Multinomial Logit (HB-MNL) model at the level of each household[3] to explain the observed share-of-category purchase incidences of each store for the household over the study period We include 10 store-category characteristics (relating to stores' product assortments, prices and category characteristics), as well as household characteristics (i.e., demographics), as explanatory variables in the HB-MNL. The results show that most of the explanatory variables affect SCL in line with our predictions. We illustrate the managerial implications of our findings, for example, by deriving revenue consequences to stores from changing some of the marketing levers, i.e., variables related to product assortments and prices, which are in their control.

The rest of the paper is organized as follows. In section 2, we describe our unique panel dataset involving 284 product categories and 16 stores. This section also provides strong motivating evidence for the existence of SCL. In section 3, we conceptually develop predictions for the impact of various store-category and household characteristics on SCL that can be tested using our panel dataset. Section 4 presents a statistical model of SCL that is estimated on our panel dataset in order to test the predictions in section 3. The empirical findings are presented in section 5. Managerial implications are discussed in Section 6. Section 7 summarizes and concludes the paper.

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[2] Dhar and Hoch (1997) observe that retailers develop special expertise in particular categories, with some retailers excelling in their presentation of meat and produce, and others excelling in ethnic products. Dhar and Hoch (1997) also note that once developed, category expertise becomes part of the organization's intellectual capital.
[3] We use the terms "household" and "consumer" interchangeably in this paper.

2. DATA DESCRIPTION AND MOTIVATING EMPIRICAL EVIDENCE FOR SCL

We use in-home scanning data on longitudinal purchases of 1321 metropolitan households in a large southwestern city. The data contain the detailed purchase information of these households in 284 grocery categories across 16 stores over a 53-week period dated from September, 2002 to September, 2003. The 16 stores belong to 3 types of store formats: traditional supermarkets, supercenters, and warehouse club stores. There are 10 traditional supermarkets (Albertson's, Bashas', Food 4 Less, Food City, Fry Food Store, I.G.A., Safeway, Trader Joe's, Unlisted Chain and Wild Oats Market), 2 supercenters (Kmart Supercenter and Wal-Mart Supercenter), and 4 warehouse club stores (Costco, Sam's Club, Smart & Final and Unlisted Club Store). Moreover, two of the traditional supermarkets (Trader Joe's and Wild Oats Market) are specialty stores that specialize in organic and exotic foods.

In Figure 1, we present the relative positions of the 16 stores in the data in a price-assortment map. The x-axis tracks the breadth of the brand assortment available at the store, on average, across all categories. The y-axis tracks the price advantage of products available at the store, on average, across all categories.[4] From this map, one can see that Wal-Mart Supercenter offers the best prices, on average, among all 16 stores. Kmart Supercenter offers the next best prices, while the 4 warehouse club stores – Costco, Sam's Club, Smart & Final and Unlisted Club Store – are third best (Note: These 4 stores are also clustered in the left part of the map, which indicates that they have the worst brand assortments among the 16 stores). Safeway appears to be the most expensive store in the market, while the Unlisted Grocery Chain and Fry Food Store both offer good brand assortments.

[INSERT FIGURE 1 HERE]

[4] Price and assortment measures at the category-level are unit-free indices that are averaged across categories. Mathematical operationalizations of these measures are explained in Table 1 later. We also use other assortment and price variables in our empirical analysis. We only report 2 measures in this map for expositional convenience.

Next, we demonstrate the existence of SCL using our data. In Figure 2 we report the histogram of number of stores at which a household shops, over all 1321 households in the sample. We see that only 12 out of the 1321 households shop at a single store (i.e., have exclusive store loyalty) throughout the study period. Among the remaining 1309 households, the modal value is 6, which shows that households typically divide their grocery shopping among many stores. There are 3 households that shop at as many as 13 stores over the study period. This shows that based on the traditional view of store loyalty, there appears to be little store loyalty in this market.

[INSERT FIGURE 2 HERE]

Next, for each household we identify its favorite store, i.e., the store at which the household makes the largest number of shopping trips over the study period. We then calculate the proportion of shopping trips made by each household at its favorite store over its total number of shopping trips. In Figure 3, we report the probability density for all 1321 households in the sample. We see that about 50.2% of the households do not visit their favorite store on 50% or more of their shopping trips, which reiterates the finding in Figure 2 that households divide their grocery shopping among many stores and store loyalty from the traditional view appears to be low.

[INSERT FIGURE 3 HERE]

Next, we add the category dimension into the picture, and something interesting emerges. We find that each of the 1321 households, including those that shop at multiple stores, makes all of its purchases exclusively at the same store, for at least one regularly purchased product category in its shopping basket.[5] In Figure 4, we report the histogram of the number of categories

[5] We define a regularly purchased product category for a household as one in which the household makes at least two purchases over the study period.

in which a household is observed to have exclusive SCL, across all 1321 households. It is clear that many households are store loyal in a large number of categories. In other words, despite the seeming lack of store loyalty uncovered in Figures 2 and 3, store-category loyalty emerges in Figure 4. This is reminiscent of the "polygamous loyalty" findings documented in the literature on customer loyalty programs (see, for example, Dowling and Uncles 1997).

[INSERT FIGURE 4 HERE]

One may argue that the finding in Figure 4 could be attributed to the fact that each household makes its purchases of all its SCL categories exclusively at one store -- its favorite store. In order to test whether this is the case, for each of the households that have SCL in at least one category (in this case, all 1321 households), we first count the number of stores to which the household has SCL across all categories. We then plot a probability density of this count, over all SCL households, in Figure 5. We see that only about 10.2% of the SCL households purchase their SCL categories over time at one store. In fact, 24.5%, 29.3%, 22.4%, 9.6%, 3.3% and 0.7% of households purchase their SCL categories at 2, 3, 4, 5, 6 and 7+ stores, respectively. This strongly underscores the fact that SCL households are not loyal to their favorite store in all SCL categories. Instead, SCL households are loyal to many different stores across their SCL categories.

[INSERT FIGURE 5 HERE]

It is possible that Figure 5 may camouflage the fact that an SCL household may still be buying most of its SCL categories at its favorite store, while only buying a small number of its SCL categories at non-favorite stores. In order to test whether this is the case, for each of the SCL households, we calculate the proportion of the household's SCL categories that are purchased at its favorite stores. We report the probability density of this proportion, over all SCL households, in Figure 6. It is clear that the histogram has a fat left tail, which shows that many households buy a significant proportion of their SCL categories at non-favorite stores.

[INSERT FIGURE 6 HERE]

Taking Figures 2-6 together, we can conclude that (at least for this dataset): (1) households, while showing little *overall* store loyalty for their grocery shopping, show high SCL, i.e., are store loyal in many categories; (2) these households are loyal to different stores in different categories; and (3) the presence of SCL is not trivial, and is worth further investigation. The purpose of this research is to obtain an understanding of the key drivers of such SCL. Next, we lay out a conceptual framework for this purpose.

3. CONCEPTUAL FRAMEWORK

We conceptualize a household's SCL by the household's share-of-category attracted by the store, i.e., the share of category purchase incidences that the household makes at the store. Households may become loyal to a store for a product category if that store delivers a value proposition in that category that exceeds the value proposition at any competing store in the market. Factors that positively enhance the category's value proposition at a store, therefore, would lead to an increase in households' SCL toward that store. We posit that these factors include both store-category characteristics and household characteristics. We describe these factors, as well as specific predictions for these factors, below.

3.1 Key Drivers (Store-Category Characteristics) of SCL

3.1.1 Product Assortment Variables

Several studies based on surveys and lab experiments have revealed that product assortments are very important factors in driving consumers' store evaluations and/or store choice decisions (Meyer and Eagle 1982, Arnold, Oum and Tigert 1983, Craig, Ghosh and McLafferty 1984, Louviere and Gaeth 1987). It has further been shown that consumers' perceptions of product assortments are multi-dimensional in that consumers pay attention to both assortment breadth and assortment quality (Broniarczyk, Hoyer and McAlister 1998, Chernev and Hamilton 2009). Therefore, we identify product assortment variables that relate to both the breadth, as well as the quality, of the assortments. We explain this below.

Conventional wisdom holds that shoppers prefer larger assortments. One explanation is that larger assortments offer a greater variety of options which, in turn, increase the likelihood that consumers can find options matching their preferences (Baumol and Ide 1956, Hotelling 1929, Lancaster 1990, Kahneman, Wakker and Sarin 1997). Another explanation is that larger assortments offer option value and create a perception of freedom of choice (Brehm 1972, Reibstein, Youngblood and Fromkin 1975). However, the available empirical evidence on whether increasing the assortment breadth in a product category benefits category sales is not positive. Some studies find no effect (Dreze, Hoch and Purk 1994, Broniarczyk, Hoyer and McAlister 1998), while others find a negative effect (Boatwright and Nunes 2001, Borle, Boatwright, Kadane, Nunes and Schmueli 2005). Notwithstanding the lack of a positive effect on category sales, assortment breadth has been shown to have a positive effect on store patronage behavior (Fox, Montgomery and Lodish 2004, Borle, Boatwright, Kadane, Nunes and Schmueli 2005, Briesch, Chintagunta and Fox 2009). Since store patronage is closer to our outcome of interest (i.e., SCL), we expect variables that are related to assortment breadth to positively impact SCL. Toward this end, we identify three assortment breadth variables, which have been not only shown to influence consumer perceptions of assortment breadth (Hoch, Bradlow and Wansink 1999, Boatwright and Nunes 2001), but also found to be significant predictors of households' store choice probabilities (Briesch, Chintagunta and Fox 2009). The three assortment breadth variables are listed below (subscripts *s* and *c* refer to store and category, respectively):[6]

Assortment Breadth Variables

1. *Number of Brands in the Category at the Store* ($BRAND_{sc}$).
2. *Number of SKUs per Brand in the Category at the Store* (SKU_{sc}).
3. *Number of Sizes per Brand in the Category at the Store* ($SIZE_{sc}$).

We expect assortment size variables – $BRANDS_{sc}$, SKU_{sc}, $SIZE_{sc}$ – to have a positive effect on SCL.

Laboratory studies have shown that a consumer's evaluation of an alternative depends on the valence of the alternative's unique features and that the consumer focuses differentially more on unique as opposed to common features (Houston and Sherman 1995, Dhar and Sherman 1996). Stores vary on the number of private labels that they carry within their product assortments. To the extent that a private label is unique to a store, this measure can serve as a proxy for the uniqueness of the store's product assortment. Corstjens and Lal (2000) argue that the availability of private label items in a store's product assortment has an effect on store loyalty. Therefore, we expect the number of private labels in a store's category assortment to positively impact SCL. Toward this end, we identify the following assortment uniqueness

[6] The detailed mathematical operationalizations of these variables, as well as all other variables discussed in this section, as used in the empirical analysis, are provided in Table 1.

variable, which has been found to be a significant predictor of households' store choice probabilities (Briesch, Chintagunta and Fox 2009), as a predictor of SCL.

Assortment Uniqueness Variable

4. *Number of Private Labels in the Category at the Store* ($PVTLABEL_{sc}$).

We expect the assortment uniqueness variable – $PVTLABEL_{sc}$ – to have a positive effect on SCL.

Stores vary on not only the breadth and uniqueness of the product assortments that they carry, but also the attractiveness of the items that they carry within these assortments. For example, assortments that carry best-selling SKUs, which are likely to appeal to a majority of buyers, may be perceived as more attractive than assortments containing less popular items (Chernev and Hamilton 2009). In addition, assortments that better match the individual preferences of the store's customers may be perceived as more attractive (Broniarczyk, Hoyer and McAlister 1998). Therefore, we expect variables that are related to assortment attractiveness to positively impact SCL. Toward this end, we identify the following two assortment attractiveness variables, the second of which has been found to be a significant predictor of households' store choice probabilities (Briesch, Chintagunta and Fox 2009), as predictors of SCL.

Assortment Attractiveness Variables

5. *Market Popularity of SKUs in the Category at the Store* ($POPULARITY_{sc}$).

6. *Household Preference-Matching SKUs in the Category at the Store* ($PREFMATCH_{sch}$).[7]

We expect assortment attractiveness variables – $POPULARITY_{sc}$, $PREFMATCH_{sch}$ – to have a positive effect on SCL.

3.1.2 Price Variables

[7] It is useful to note that this store-category variable, unlike the others listed earlier, is household-specific (since SKU preferences are household-specific). Its mathematical operationalization is made clear in Table 1.

One of the robust findings in store patronage research is that low prices are an important factor in driving positive consumer evaluations of stores (Baumol and Ide 1956, Brown 1978, Meyer and Eagle 1982, Arnold, Oum and Tigert 1983, Bell and Lattin 1998, Bell, Ho and Tang 1998). Therefore, we include the following price variable as a predictor of SCL.

7. *Price Advantage of the Store in the Category to the Household (PRICEADV$_{sch}$).* [8]

We expect *PRICEADV$_{sch}$* to have a positive effect on SCL.

Given the same level of average prices at two stores, the store with lower price variability over time may be interpreted as a consistent and dependable provider of good value in the category, which may increase consumers' loyalties to that store in the category. Conversely, a store with greater price variability over time may encourage consumers to shop at that store only when low prices are offered in the category, and drive consumers during periods of high prices to search for lower prices among other stores. In other words, greater price variability in a category at a store would reduce consumer loyalty to that store in the category. For this reason, we include the following price variable as a predictor of SCL.

8. *Price Variability of the Store in the Category (PRICEVAR$_{sc}$).*

We expect *PRICEVAR$_{sc}$* to have a negative effect on SCL. While previous research has quantified the adverse effect of temporal price variability on consumers' brand loyalties (Farley 1964, Bell, Chiang and Padmanabhan 1999), ours is the first to investigate the effect on SCL.

3.1.3 Category Characteristics

Thus far, we have motivated the importance of variables relating to product assortments and prices in driving consumers' loyalties to different stores in different categories. An additional driver of SCL could be category characteristics. For example, consumers may be less

[8] It is useful to note that this store-category variable, like PREFMATCH$_{sch}$, is also household-specific (since the price advantage of a category depends on which SKUs' prices are relevant to the household).

likely to be loyal to warehouse club stores, such as Sam's Club and Costco, in frequently purchased product categories (such as milk or produce), because warehouse club stores are typically located in inconvenient locations that are difficult to visit on a regular basis. For this reason, we include the following category variable as a predictor of SCL.

9. *Average Purchase Frequency in the Category ($PURCHFREQ_c$).*

We expect $PURCHFREQ_c$ to have a negative effect on SCL for warehouse club stores. While previous research has shown that higher category purchase frequency is associated with lower brand loyalty within the category (Narasimhan, Neslin and Sen 1996), ours is the first to investigate its effect on SCL for specific stores in a market.

Another relevant category characteristic is the household's budget share of a category. Consumers may be more likely to be loyal to warehouse club stores in product categories which command a higher share of their grocery shopping budget, because of the significant price savings that would accrue in the long run. On the other hand, consumers may also be more likely to be loyal to high-quality stores in high budget share categories since the adverse consequences of choosing a poor quality product are greater in such a category.

10. *Budget Share of Household in the Category ($BUDGSHARE_{ch}$).*

We expect $BUDGSHARE_{ch}$ to have a positive effect on SCL for warehouse club stores or/and high-quality stores. While previous research has shown that higher category budget share is associated with lower loyalty within a category (Raju 1992), ours is the first to investigate its effect on SCL for specific stores in a market.

To summarize, we have identified 10 key drivers that are expected to impact SCL, 3 of which pertain to assortment breadth ($BRANDS_{sc}$, SKU_{sc}, $SIZE_{sc}$), 2 each pertain to assortment attractiveness ($POPULARITY_{sc}$, $PREFMATCH_{sch}$), prices ($PRICEADV_{sch}$, $PRICEVAR_{sc}$) and category characteristics ($PURCHFREQ_c$, $BUDGSHARE_{ch}$), and 1 pertains to assortment uniqueness ($PVTLABEL_{sc}$). Next, we identify pertinent household characteristics.

3.2 Household Characteristics

Aspects of households themselves may influence their SCL. We identify two household demographics – family size ($FAMSIZE_h$) and income ($INCOME_h$) – and include them as moderating influences on the effects of the 10 key drivers (identified in section 3.1) on SCL. In other words, demographic variables are expected to increase or decrease the effect of each key driver on SCL. We conceptualize these demographic influences next.

Family size is related to a household's preference for large assortments. All else being equal, larger family sizes imply preference for larger assortments. This is because the needs and desires of larger families tend to be more diverse (Blattberg, Buesing, Peacock and Sen 1978, Inman, Winer and Ferraro 2009). Therefore, we expect the effects of assortment sizes ($BRANDS_{sc}$, SKU_{sc}, $SIZE_{sc}$), as well as assortment attractiveness ($POPULARITY_{sc}$, $PREFMATCH_{sch}$), to be stronger for larger families, and weaker for smaller families. Bell, Ho and Tang (1998) find that larger families are more likely to be store-loyal. Since our measure of store loyalty is category-specific, we can study, for the first time, whether the effect of family size on SCL is differently signed for different types of stores.

Income is related to a household's opportunity cost of time (Becker 1965, Blattberg, Eppen and Leiberman 1978). All else being equal, higher incomes imply higher opportunity costs of time and, therefore, lower sensitivity to price (Douglas and Isherwood 1979, McCracken 1990, Dhar and Hoch 1997, Ainslie and Rossi 1998, Seetharaman, Ainslie and Chintagunta 1999). Therefore, we expect the effects of price advantage ($PRICEADV_{sch}$) and price variability

($PRICEVAR_{sc}$) to be weaker for higher income households, and stronger for lower income households. Higher opportunity costs of time also imply higher travel costs. Therefore, we expect higher income households to have weaker SCL toward warehouse club stores such as Costco and Sam's Club that are typically located in inconvenient locations that are more difficult to visit.

We present the detailed mathematical operationalizations of the 10 key drivers plus the two demographic variables in Table 1. It is clear that all 10 key drivers are operationalized to be unit-free and scale-free indices, which makes the constructed measures comparable across categories. In Table 2, we also provide descriptive statistics pertaining to these variables in our dataset, which show that all variables have comparable scales in the data.

[INSERT TABLES 1 AND 2 HERE]

We summarize the expected signs of both the effects of the 10 key drivers on SCL, as well as the moderating effects of the 2 demographic variables on the effects of the key drivers, in Table 3. These predictions will be tested using our statistical model, described next.

[INSERT TABLE 3 HERE]

4. MODEL AND ESTIMATION

We propose a model of store loyalty for a household in a category. Consider a household *h* that is choosing among *S* stores while buying category *c* over time. We use an *S*-dimensional multinomial share vector $y_{ch} = (y_{1ch}, y_{2ch}, \ldots, y_{Sch})'$, to capture the household's loyalty – share of category purchase incidences – to each of the *S* stores in category *c*. Our goal is to model y_{ch} on the basis of a *P*-dimensional vector of explanatory variables X_{sch}, representing the 10 key drivers identified earlier (i.e., sections 3.1). We employ the familiar Multinomial Logit (MNL) model specification (McFadden 1974) for this purpose, as shown below.

$$y_{sch} = \frac{e^{\beta'_{ch} X_{sch}}}{\sum_{r=1}^{S} e^{\beta'_{ch} X_{rch}}} \ (s = 1, \ldots, S), \tag{1}$$

where β_{ch} is a *P*-dimensional vector of parameters, which captures the effects of drivers on household *h*'s SCL outcome in category *c*. We observe household *h*'s purchase frequencies at store *s* in category *c*, N_{sch}. Following Zenor and Srivastava (1993), the likelihood function associated with the observed purchase frequencies, under the Multinomial Logit specification for SCL shares (as in equation (1)) can be written as follows.

$$L_{sch} = \prod_{s \in S} \left(\frac{\exp(x_{sch}\beta_h)}{\sum_{j \in S} \exp(x_{jch}\beta_h)} \right)^{N_{sch}} \tag{2}$$

We extend the proposed single-category store loyalty model, as represented above in equation (1), to multiple categories by recognizing that category characteristics are included as explanatory variables within the vector X_{sch} (which captures cross-category differences) and dropping the subscript *c* from the parameter vector β_{ch}, which yields a single set of household parameters, β_h, that is assumed to be common across *C* categories. Further assuming that households' category purchase decisions are independent across categories[9] yields the following MNL model for store loyalty at the household level.

$$y_{sch} = \frac{e^{\beta'_{h} X_{sch}}}{\sum_{r=1}^{S} e^{\beta'_{h} X_{rch}}} \ (s = 1, \ldots, S) \ (c = 1, \ldots, C), \tag{3}$$

where X_{sch} includes characteristics pertaining to store *s* and category *c*.

[9] We acknowledge that this may be a restrictive assumption for complementary categories such as bacon and egg. Relaxing this assumption (see, for example, Chib, Seetharaman and Strijnev 2002) is beyond the scope of this research.

In order to allow for unobserved heterogeneity across households in the sample, we assume that the parameter vector is distributed across households as follows.

$$\beta_h = \delta ' Z_h + \upsilon_h , \tag{4}$$

where Z_h is a K-dimensional row vector of household demographics (i.e., family size and income, as listed in section 3.2), δ is the corresponding K-dimensional vector of parameters (representing the effects of observed heterogeneity across households), and $\upsilon_h \sim N_P(0, \Sigma)$ represents stochastic variation in model parameters across households on account of unobserved heterogeneity.[10]

In order to estimate model parameters, we use Hierarchical Bayes estimation methodology, specifically, Markov Chain Monte Carlo (MCMC) sampling. More details about the estimation approach are provided in the Appendix. This completes the exposition of our proposed Hierarchical Bayes Multinomial Logit (HB-MNL) model of SCL outcomes.

It is useful to reiterate that the vector of explanatory variables (X_{sch}) in equation (2) includes the following 10 key drivers: (1) $BRANDS_{sc}$, (2) SKU_{sc}, (3) $SIZE_{sc}$, (4) $PVTLABEL_{sc}$, (5) $POPULARITY_{sc}$, (6) $PREFMATCH_{sch}$, (7) $PRICEADV_{sch}$, (8) $PRICEVAR_{sc}$, (9) $PURCHFREQ_c$, *(10)* $BUDGSHARE_{ch}$. Given the predictions developed in sections 3.1, we expect the effects of (1)-(7) and (10) on SCL to be +, and the effects of (8) and (9) on SCL to be -.

It is also useful to note that the vector of household demographics (Z_h) includes the following 2 variables (as identified in section 3.2): (A) $FAMSIZE_h$ and (B) $INCOME_h$. Given the predictions developed in section 3.2, we expect the moderating effects of (A) on the effects of key drivers (1)-(3) and (5)-(6) on SCL to be +, and the moderating effect of (B) on the effect of

[10] To keep a flexible specification, we allow the covariance matrix Σ to be unrestricted.

key driver (7) on SCL to be -, and the moderating effect of (B) on the effect of key driver (8) on SCL to be +. We present our empirical results next.

5. EMPIRICAL RESULTS

We estimate our model on the data described in section 2 using the MCMC procedure described in the Appendix. We also estimate a benchmark model that allows for store intercepts only (i.e., no explanatory variables). The within-sample log-likelihood for the proposed model is -829463, while that for the benchmark model is -975577, suggesting that the proposed model fits the data very well (yielding a 15% improvement in model fit in terms of log-likelihood). We discuss the parameter estimates from our proposed model below.

5.1 Effects of Key Drivers on SCL

5.1.1 Assortment and Price Effects

The estimated effects of the 6 assortment variables, as well as the 2 price variables, are reported in Table 4. Consistent with our predictions, we find that 5 out of the 6 assortment variables – 3 assortment size variables ($BRANDS_{sc}$, SKU_{sc}, $SIZE_{sc}$), 1 assortment uniqueness variable ($PVTLABEL_{sc}$), and 1 assortment attractiveness variable ($PREFMATCH_{sch}$) – have significant + effects on SCL ([0.179, 0.082, 0.106]; [0.055]; [1.109]). These estimates strongly support our hypotheses regarding the importance of category assortment breadth and quality variables in driving positive consumer perceptions of stores and, therefore, their SCL in specific product categories. The only assortment variable that has a counter-intuitively signed – effect (-0.063) on SCL is $POPULARITY_{sc}$. One interpretation of this finding, taken together with our finding that $PREFMATCH_{sch}$ has the expected + effect on SCL, could be that carrying popular

SKUs creates the perception among consumers that the store is not unique and it simply stocks popular SKUs without paying attention to its customers' idiosyncratic or unique preferences. On the other hand, carrying less popular SKUs may create the perception that the store addresses niche preferences, which increases loyalty to the store in that category.

Consistent with our predictions, we find that the estimated effects of the 2 price variables – $PRICEADV_{sch}$, $PRICEVAR_{sc}$ – on SCL have the expected signs, i.e., + and -, respectively (1.943 and -0.179). These estimates strongly support our hypotheses that low prices, and temporally consistent prices, improve consumer SCL to stores.

[Insert Table 4 HERE]

5.1.2 Category Effects

The estimated effects of category purchase frequency ($PURCHFREQ_c$), which are relative to the excluded store (Safeway), are reported in Table 5. Consistent with our prediction, we find that the estimated effect of $PURCHFREQ_c$ on SCL is most negative for a warehouse club store (-7.501 for Unlisted Club Store). However, we also notice that the effect is negative and significant for all stores except Albertson's and Fry Food Store. In fact, the only store that *gains* consumer loyalty (relative to Safeway) as category purchase frequency increases is Fry Food Store (0.030). This can be rationalized using the fact that Fry Food Store is the largest store in this market, which means that it attracts the highest frequency of shopping which, in turn, makes it easier for consumers to consistently buy their most frequently purchased categories at Fry Food Store than at other stores.

[INSERT TABLE 5 HERE]

The estimated effects of the household's budget share ($BUDGSHARE_{ch}$), which are relative to the excluded store (Safeway), are reported in Table 6. Contrary to our predictions, we find that the estimated effect of $BUDGSHARE_{ch}$ on SCL is mostly negative, including for warehouse clubs and specialty stores. In fact, the only store for which its effect is significantly + is Wal-Mart Supercenter (0.028). This could be taken as perhaps indicating that EDLP stores (such as Wal-Mart Supercenter) may gain consumer loyalty for high budget share categories.[11]

[INSERT TABLE 6 HERE]

5.2 Moderating Effects of Consumer Demographics on the Effects of Key Drivers on SCL

Moderating effects of family size and family income are reported within columns titled, "FAMILY SIZE" and "INCOME" respectively, in Tables 4-6. We discuss the key results next.

In Table 4, consistent with our predictions, we find that for 2 out of the 5 assortment variables ($BRANDS_{sc}$, $SIZE_{sc}$), family size increases their estimated positive effect on SCL. However, for $PREFMATCH_{sch}$, family size decreases its estimated positive effect on SCL, i.e., preference matching becomes a less important driver of SCL for larger families. One reason for this could be that as the family size increases, it becomes more difficult for the family members who are responsible for shopping to account for the preferences of all members in the family, which makes the aspect of whether a store assortment matches the household's preferences less important in driving such family members' choice of store in the category.

Also in Table 4, we find that household income decreases the estimated positive effect of $SIZE_{sc}$ (-0.015) and $PVTLABEL_{sc}$ (-0.003). That is, higher-income households are not as sensitive as lower-income households when it comes to how much the number of product sizes available per brand in the category, or the number of private labels in the category, positively influence SCL. This makes sense considering that higher-income households may not be as willing as lower-income households to buy either heterogeneous package sizes (to redeem lower unit prices

[11] For readability, we suppress the reporting of the estimated store intercepts. These are available from the authors.

over time) or private label brands (which is usually perceived as inferior to national brands on quality).

We find that for the price variable $PRICEVAR_{sc}$, income accentuates (i.e., makes less negative) its estimated negative effect on SCL (-0.010). This indicates that higher-income households are less tolerant than lower-income households of category price variability at a store. One reason for this could be that higher-income households take (high) product prices to be a signal of (high) product quality in the store's service environment, so that when prices fluctuate between high and low prices, such higher-income households become more skeptical about the store's quality.

For the category effects, in Table 5, we find that family size decreases (i.e., makes more positive) the estimated negative effect of $PURCHFREQ_c$ on SCL for Costco (0.027), Sam's Club (0.021) and Wal-Mart Supercenter (0.019). That is, larger families are less unwilling than smaller families to be loyal to warehouse club stores for more frequently purchased categories. This may be because larger families may save more money in the long run by buying frequently purchased categories in low-price warehouse club stores, albeit their inconvenient locations and bulky purchase amounts.

5.3 Estimated Heterogeneity in Household Preferences

Given the large number of variances and covariances, we cannot report the estimated heterogeneity distribution in full (which is available from the authors). Instead, we discuss a few salient findings here. The largest pair-wise correlation (0.64) is estimated between a household's sensitivity to $BRAND_{sc}$ and SKU_{sc}, which shows that a household whose SCL is very sensitive to the number of brands in the category, is also very sensitive to the number of SKUs per brand in the category. This makes intuitive sense. The correlations between a household's sensitivity to $PRICEADV_{sch}$ and its sensitivity to 3 assortment variables, $BRAND_{sc}$, SKU_{sc} and $PREFMATCH_{sch}$ are negative (-0.24, -0.23, and -0.19 respectively). This implies that for households whose SCL is more sensitive to a store's price advantage, their SCL is also less sensitive to the store's category assortment (i.e., breadth and preference matching). This suggests an aggregate trade-off between how consumers view category price level versus category assortment in driving their SCL. A large negative correlation (-0.24) is estimated between a household's sensitivity to $POPULARITY_{sc}$ and $PREFMATCH_{sch}$, which means that for households whose SCL is more negatively related to the market popularity of the products in the assortment, their SCL is more positively related to how closely matched those products are to their own preferences. This implies that consumers who are concerned about how well the store matches their individual preferences, also care about whether the store has a niche position in the category.

6. MANAGERIAL IMPLICATIONS

We next conduct some managerial exercises to demonstrate the substantive usefulness of our estimation results to retailers.

First off, a retailer would be greatly interested in identifying product categories in which they enjoy high store loyalties across all households in the market. Coupling this information with the retailer's internal understanding of what marketing strategies they have employed in those high loyalty categories would guide the retailers' efforts in boosting store loyalty in other (low loyalty) categories. Therefore, for each of the 16 stores in our dataset, we calculate the posterior SCL mean for each household in each category. We then average the values of these posterior SCL means across all households in each category. In Table 7, we report the top 5 categories (i.e., the 5 categories with the highest average posterior SCL mean, referred to as "flagship" categories henceforth) for each of the 16 stores. Suppose we consider the stores with the highest annual turnover in the market, i.e., Fry Food Store and Safeway, we see that their "flagship" categories are primarily refrigerated/frozen food categories (4 out of 5 categories). Among the other 8 supermarkets, excluding I.G.A. and Trader Joe's, the remaining 6 supermarkets have both food and non-food items among their flagship categories. Interestingly, although they additionally carry food items, both Supercenters – Kmart Supercenter and Wal-Mart Supercenter in our dataset – have only general merchandise items (the historical core of their business) as their flagship categories. Among the club stores in our dataset, both Costco and Sam's Club have 3 health-related product categories among their 5 flagship categories. Curiously, these club stores also attract high store loyalty for tobacco products (with Costco simultaneously attracting high store loyalty for anti-smoking products as well).

[INSERT TABLE 7 HERE]

While Table 7 enables retailers to identify their top 5 categories (in terms of households' store loyalties), it does not tell them how they are faring, in a relative sense, in these (or other) categories against their competitors. A retailer would be interested in also knowing how close its competitors are, in terms of the average SCL that they attract, in any given category. For this purpose, we rank-order the 16 stores, from highest to lowest values of the average posterior SCL mean, for each category. In Table 8, we report the 5 highest loyalty stores for the top 20 categories (i.e., categories with the highest sales revenue). The first thing to note is that Fry Food Store enjoys the first rank across all top 20 categories. The second thing to note is that Safeway enjoys the second rank in 18 out of the top 20 categories (being challenged by Costco in the Spirits/Liquor category, and by Wal-Mart Supercenter in the Dog Food category). As far as ranks 3, 4 and 5 are concerned, there appears to be competition between Bashas', Albertson's and Wal-Mart Supercenter, with Bashas' having an edge over the other two stores (enjoying the third rank in 11 out of the top 20 categories). Overall, therefore, across the top 20 categories, 5 stores – Fry Food Store, Safeway, Bashas', Albertson's, Wal-Mart Supercenter – are dominant in attracting households' store loyalties in the market.

[INSERT TABLE 8 HERE]

While our estimation results shed light on the effects of 10 store-category drivers on SCL, in order to better interpret the implications of our results, we systematically select a set of 6 product categories where each category has a different store as the one with the highest posterior SCL mean ("winning store" henceforth). These categories, along with the names of the "winning stores" are given in Table 9. We also report the average values of 8 store-category drivers – 6 assortment variables, and 2 price variables – at these "winning stores" and the corresponding average values averaged across the remaining 15 stores (within parentheses) in Table 9. It is interesting to see that the "winning" store has an overwhelming advantage, i.e., substantially "better" value of the assortment or price variable, over the 15 remaining stores for all 8 store-category drivers in each of the 6 categories. For example, in the baby accessories category, Wal-Mart Supercenter (the store with the highest posterior SCL mean) has more than 3 times the number of brands (BRAND index of 2.71), more than 3 times the amount of preference matching (PREFMATCH index of 0.87), about 3 times the category price advantage (PRICEADV index of 0.74), and about 8 times the number of private labels (PVTLABEL index of 2.45), compared to the counterpart values in competing stores (0.79, 0.24, 0.26 and 0.32, respectively). This managerial illustration also lends strong face validity to our estimation results in section 5.

Substantive findings such as the above will be of enormous practical value to retailers in terms of enabling their management of SCL in different product categories.

[INSERT TABLE 9 HERE]

Next, we cluster the 284 product categories in terms of the average values of posterior SCL means across households for the 16 stores. We use the k-Means clustering algorithm for this purpose and identify a 6-cluster solution as managerially optimal.[12] This reveals the presence of the following 6 clusters of product categories:

1. A set of 35 categories that are mostly *bulky household products* (e.g. laundry detergent, dish detergent, bleach, mouthwash, household lubricants etc.); loyalty is mainly distributed among 4 stores - Fry Food Store (26%), Costco (16%), Safeway (12%) and Wal-Mart Supercenter (12%),[13]
2. A set of 52 categories that are mostly *personal care products* (soap, shampoo, toothpaste, deodorant, sanitary napkins, hair conditioner, razors, shaving cream, facial cosmetics, contraceptives etc.); loyalty is primarily to 2 stores - Fry Food Store (35%) and Wal-Mart Supercenter (23%),
3. A set of 80 categories that are mostly *frequently purchased food products* (e.g., bread, milk, soup, eggs, crackers, bottled juices, bottled water, coffee, butter etc.); loyalty is primarily to 2 stores - Fry Food Store (33%) and Safeway (19%).[14]
4. A set of 78 categories that are mostly *less frequently purchased (but common) food products* (e.g., carbonated beverages, frozen dinners, yogurt, cold cereals, ice cream,

[12] Detailed results of the cluster analysis are available from the authors.
[13] Given the bulkiness associated the package sizes commonly seen in these categories, it is not surprising to see high loyalty to a club store such as Costco, as well as to Wal-Mart Supercenter.
[14] Given that Fry Food Store and Safeway are the two largest supermarket stores in this market, it is not surprising that they attract high loyalty in frequently purchased food products.

cookies, pasta, frozen pizza etc.); Fry Food Store commands disproportionately high (40%) loyalty,

5. A set of 26 categories that are mostly *infrequently purchased household products* (pet supplies, office products, pest control, lighters, vacuum bags etc.); loyalty is primarily to 2 stores – Wal-Mart Supercenter (33%) and Fry Food Store (22%),
6. A set of 13 *rarely purchased household products* (e.g., socks, motor oil, flashlights, computer disks etc.); Wal-Mart Supercenter commands disproportionately (62%) high loyalty.

Cluster analysis results, such as the above, can help retailers identify the product categories that can be grouped together in managing store category loyalty. These results also provide retailers with useful information regarding their overall positions relative to their competitors in different types of products.

To the extent that we estimate the impact of various drivers of households' store-category loyalties, retailers can use our study to figure out which marketing levers to push to achieve desired levels of store-category loyalties in chosen categories. To illustrate this, we perform a managerial simulation for Safeway, the second largest retailer in the market, in the carbonated beverages category, which is the largest category in the market (based on revenue), by assuming that Safeway changes one marketing lever among the following: (1) Number of Brands, (2) Number of SKUs per Brand, (3) Number of Sizes per Brand, (4) Number of Private Labels, (5) Market Popularity of SKUs, (6) Price Variability. We quantify the revenue consequences of this change for Safeway, as well as its competitors, by first simulating each consumer's share of purchase incidences for each of the 16 stores (based on our individual-level posterior estimates of consumer preferences), and then transforming the share measure to a revenue measure, and finally aggregating individual revenues over all consumers in the sample for each store. We report the own- and cross-revenue elasticities for all stores in Table 10, where each column corresponds to a different simulation (for one of the above-mentioned marketing levers). The magnitude of the change that we assume is that Safeway increases the value of the corresponding marketing lever from the value observed in our sample to the maximum value observed across all 16 stores.[15,16]

[INSERT TABLE 10 HERE]

The own-revenue elasticity associated with the Number of Brands at (17%) is the highest, followed by the own-revenue elasticity associated with the Number of SKUs per Brand (13.8%). The number can be interpreted as follows: For a 1% increase in the number of brands (or the number of SKUs per brand) carried in the Safeway store, its store revenues increase by 17% (or 13.8%). The magnitude of the own-revenue elasticities associated with the Number of Sizes per Brand (2.1%) is lower, but still substantively significant. Decreasing the temporal price variance within the category by 1% is also observed to increase own-store revenues by 3.3%.

The cross-revenue elasticity associated with the Number of Brands / Number of SKUs per Brand at Safeway is the highest for Costco (-13.9% / -14%), suggesting that the improvement by Safeway on assortment breadth has the greatest negative impact on Costco. Moreover, we see that a decrease in the temporal price variance at Safeway also hurts Costco the most (3.2%) among all competing retailers.

[15] For Market Popularity of the SKUs, it is assumed that Safeway changes to carrying all SKUs in the market, i.e., POPULARITY=1. For Price Variability, it is assumed that Safeway changes to having no price variability, i.e., PRICEVAR = 0.

[16] We assume that competitors do not react to Safeway's moves, as is usually done while running demand simulations such as ours. Understanding competitive reactions would warrant the estimation of additional statistical models, which are beyond the scope of this research.

7. SUMMARY AND CONCLUSIONS

The marketing literature views store loyalty as a behavioral trait that applies at the level of households' shopping patronage decisions, in terms of explaining which stores are most frequently visited by households for their overall grocery shopping needs. However, a household that is observed to shop at many grocery stores over time, thus appearing to be not store loyal overall, may still purchase different product categories from different stores in a loyal manner over time. We call this *store-category loyalty* (SCL).

Using purchase data from 1321 households in 284 grocery categories across 16 stores in a large southwestern city, we show that there is strong empirical evidence of SCL in the data (although overall store loyalty based on the traditional view is low). We develop predictions regarding the key drivers of such SCL, which are related to product assortments and prices at the store, as well as category characteristics. We also develop predictions regarding consumer demographics, which are expected to moderate the effects of the key drivers on SCL. We test these predictions by estimating a Hierarchical-Bayes Multinomial Logit (HB-MNL) model of households' share-of-category across stores. Most of the predictions are validated in the empirical analysis.

To our knowledge, our study is the first that empirically shows store loyalty to be a category trait (i.e., consumers are loyal to different stores in different categories), while at the same time identifying its key drivers. Using our approach, retailers can study each product category systematically to understand the category's position within their stores, as well as the positions of their stores relative to their competitors in that category. Based on this "share of category" metric, retailers can then prioritize product categories for management, particularly by focusing on categories in which their share of category position is weak, thus improving the overall store patronage.

In this study, we do not model cross-category correlations such as due to complementary (Chib, Seetharaman, and Strijnev 2002), nor do we explicitly study the relationship between store-category loyalty and overall store loyalty. We hope that our work spurs further research on better modeling and understanding store-category loyalty behavior of households.

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Figure 1. Relative Positions of 16 Stores in a Price-Assortment Map

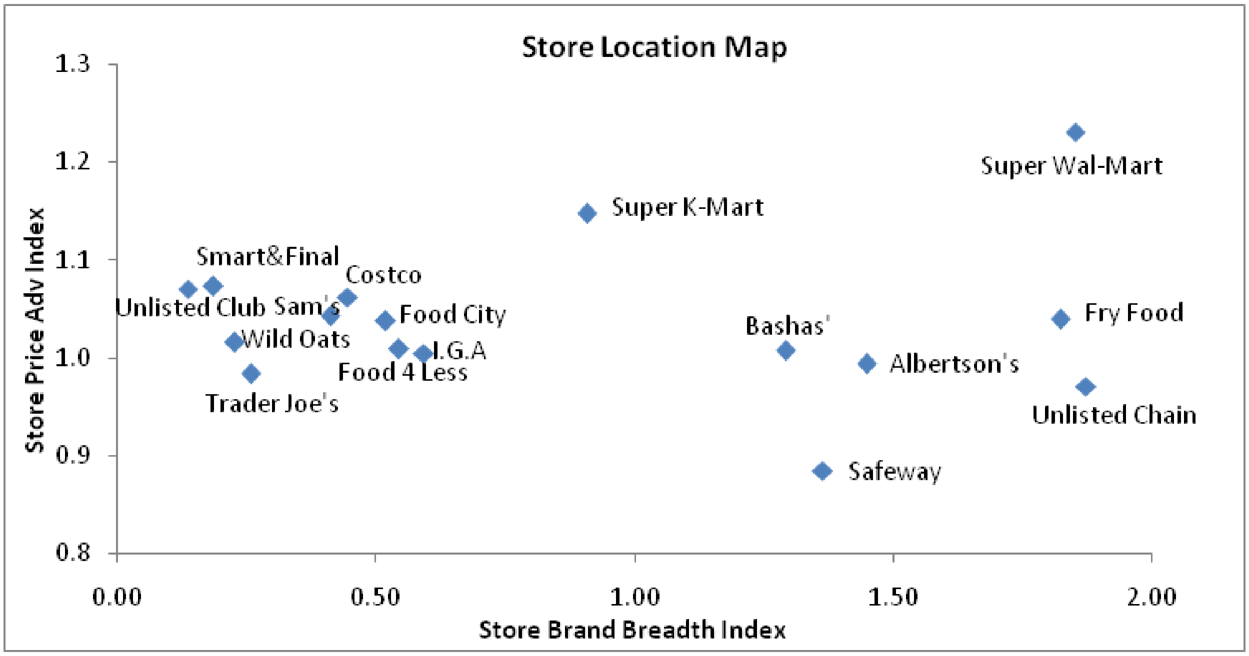

Figure 2. Histogram of Number of Stores at Which a Household Shops (Across Households)

Figure 3. Probability Density of Proportion of Shopping Trips Made at a Household's Favorite Store (Across Households)

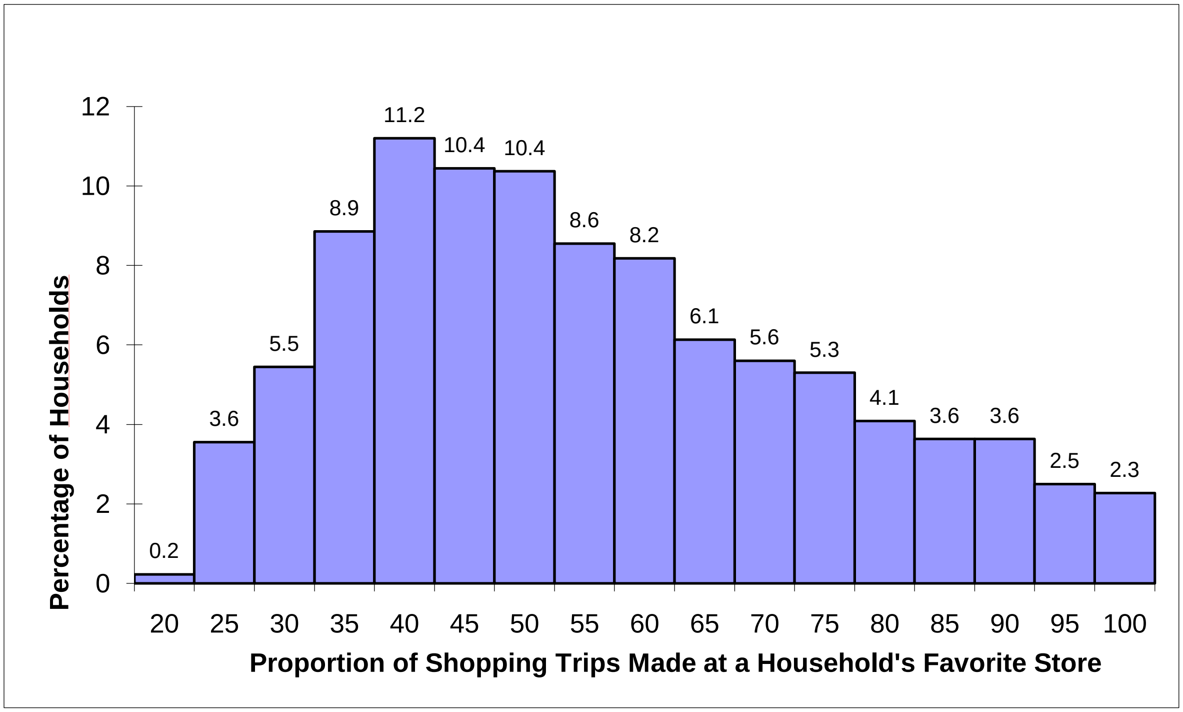

Figure 4: Histogram of Number of Categories in Which a Household has Exclusive SCL (Across Households)

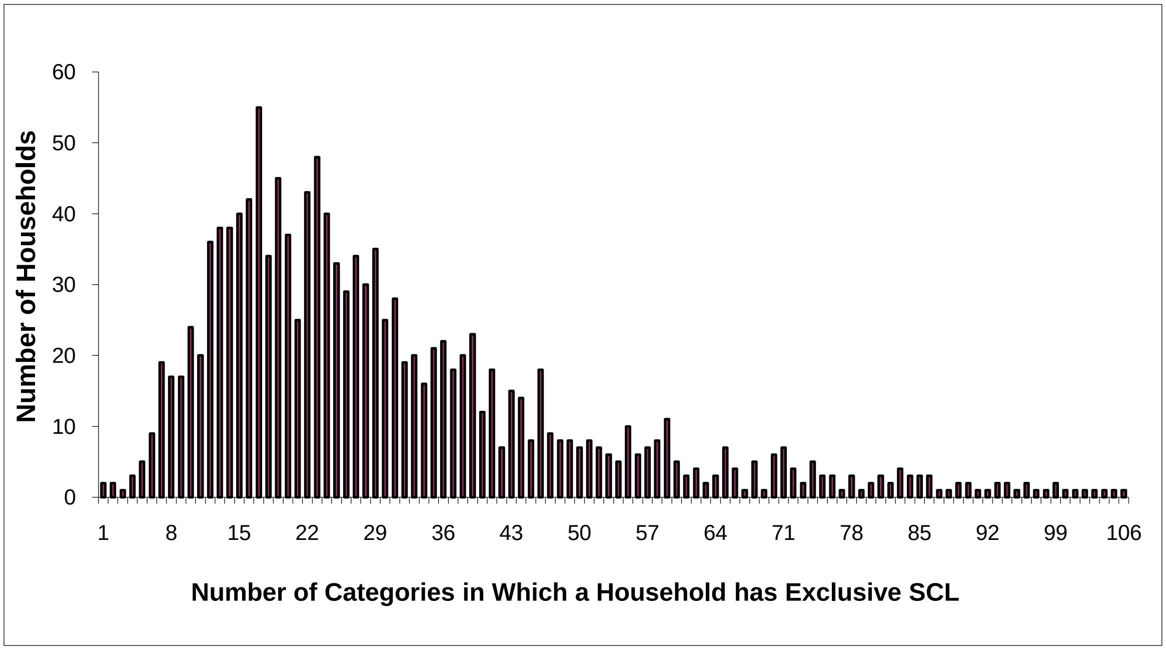

Figure 5: Probability Density of Number of Stores to Which an SCL Household has Exclusive SCL (Across SCL Households)

Figure 6: Probability Density of Proportion of a Household's SCL Categories Bought at its Favorite Store (Across Households)

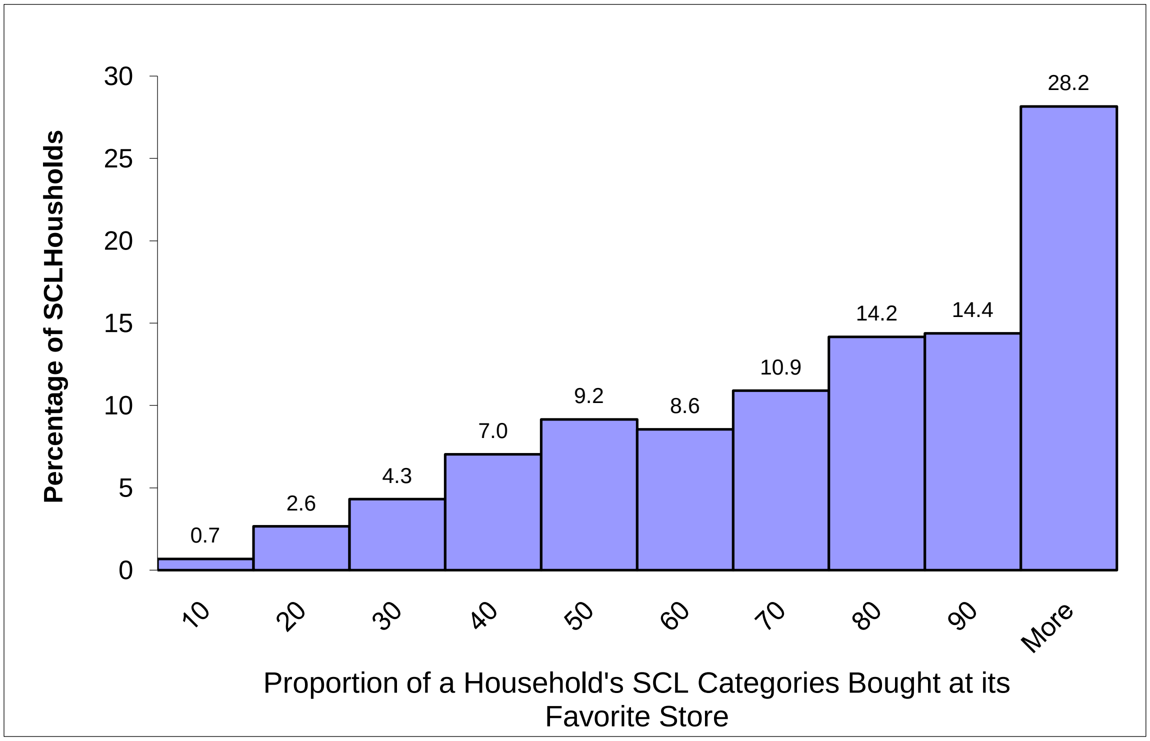

Table 1: Measures Used in the Empirical Analysis

Store-Category Characteristics (Key Drivers of SCL)

Assortment Size Variables

1. *BRAND*$_{sc}$ This is defined as $\mathrm{BRAND}_{sc} = \dfrac{\mathrm{BRANDS}_{sc}}{\left(\sum_{k=1}^{S} \mathrm{BRANDS}_{kc}\right) \Big/ S}$ where *BRANDS*$_{sc}$ stands for the number of brands in category *c* available at store *s*, and *S* is the total number of stores. In other words, this variable is the number of brands in the category at store *s* normalized by the average number of brands in the category over all stores.
2. *SKU*$_{sc}$ This is defined as $\mathrm{SKU}_{sc} = \dfrac{\mathrm{SKUS}_{sc}/\mathrm{BRANDS}_{sc}}{\left(\sum_{k=1}^{S} \mathrm{SKUS}_{kc}/\mathrm{BRANDS}_{kc}\right) \Big/ S}$ where *SKUS*$_{sc}$ stands for the number of SKUs in category *c* available at store *s*. In other words, this variable is the number of SKUs per brand in the category at store *s* normalized by the average number of SKUs per brand in the category over all stores.
3. *SIZE*$_{sc}$ This is defined as $\mathrm{SIZE}_{sc} = \dfrac{\mathrm{SIZES}_{sc}/\mathrm{BRANDS}_{sc}}{\left(\sum_{k=1}^{S} \mathrm{SIZES}_{kc}/\mathrm{BRANDS}_{kc}\right) \Big/ S}$ where *SIZES*$_{sc}$ stands for the number of product sizes in category *c* available at store *s*. In other words, this variable is the number of product sizes per brand in the category at store *s* normalized by the average number of product sizes per brand in the category over all stores.

Assortment Uniqueness Variable

4. *PVTLABEL*$_{sc}$ This is defined as $PVTLABEL_{sc} = \dfrac{\mathrm{PVTLABELS}_{sc}}{\left(\sum_{k=1}^{S} \mathrm{PVTLABELS}_{kc}\right) \Big/ S}$ where *PVTLABELS*$_{sc}$ stands for the number of private labels in category *c* available at store *s*. In other words, this variable is the number of private labels in the category at store *s* normalized by the average number of private labels in the category over all stores.

Assortment Attractiveness Variables

5. *POPULARITY*$_{sc}$ This is defined as $POPULARITY_{sc} = \sum_{u=1}^{N_{sc}} \mathrm{MS}_{scu}$ where *MS*$_{scu}$ stands for the market share of SKU *u*, which is available at store *s*, in category *c*, and N_{sc} stands for the total

number of SKUs available in category *c* at store *s*. This variable represents the collective market share of the category SKUs that are available in store *s*.

6. *PREFMATCH$_{sch}$* This is defined as $\mathrm{PREFMATCH}_{\mathrm{sch}} = \dfrac{\sum_{u=1}^{N_{sc}} \mathrm{AVAIL}_{scu} \cdot \mathrm{W}_{hcu}}{\left(\sum_{k=1}^{S} \sum_{u=1}^{N_{kc}} \left(\mathrm{AVAIL}_{kcu} \cdot \mathrm{W}_{hcu} \right) \right) \Big/ S}$,

   where *AVAIL$_{scu}$* is an indicator variable that takes the value *1* if SKU *u* is available in category *c* at store *s*, and 0 otherwise, *W$_{hcu}$* is household *h*'s purchase quantity share for SKU *u* in category *c* over the study period. The numerator of this variable represents the weighted average availability of the category SKUs at the store, where the weights are household-specific preferences for SKUs. The denominator is the corresponding average of the same weighted average availability over all stores.

Price Variables

7. *PRICEADV$_{sch}$* This is defined as $\mathrm{PRICEADV}_{\mathrm{sch}} = \dfrac{\sum_{u=1}^{N_{sc}} \left(\dfrac{\mathrm{W}_{hcu}}{\left(\sum_{t=1}^{T} \left(\dfrac{\mathrm{P}_{scut}}{\mathrm{AvgP}_{cu}} \right) \right) \Big/ T} \right)}{\sum_{u=1}^{N_{sc}} \mathrm{W}_{hcu}}$ where P_{scut} stands for the price of SKU *u* in category *c* in store *s* at time *t*, and *AvgP$_{cu}$* is the average price of SKU *u* in category *c* over time across all stores. When constructing this price variable, we consider the following issues: (1) we eliminate the effects of different magnitudes of prices across different SKUs within the category on account of heterogeneous package sizes, qualities etc. (through the SKU price normalization, i.e., divide the SKU prices by average prices); (2) if a SKU is not available in a store during the study period, the contribution of this SKU to the category price advantage at this store is 0 (through the inversion of normalized SKU prices); (3) we account for household heterogeneity in their preferences to different SKUs (through the weight, *W$_{hcu}$*).

8. *PRICEVAR$_{sc}$* This is defined as $\mathrm{PRICEVAR}_{\mathrm{sc}} = \dfrac{\mathrm{CV}_{sc}}{\left(\sum_{k=1}^{S} \mathrm{CV}_{kc} \right) \Big/ S}$, where *CV$_{sc}$* stands for the coefficient of (temporal) variation of prices in category *c* at store *s* over the study period, where the price in category *c* at store *s* at time *t*, in turn, is defined as $\mathrm{Cat\_Price}_{sct} = \dfrac{\sum_{u=1}^{N_{sc}} \left(\dfrac{\mathrm{P}_{scut}}{\mathrm{AvgP}_{cu}} \right)}{N_{sc}}$.

Category Variables

9. *PURCHFREQ*$_c$ This is defined as $\mathrm{PURCHFREQ}_c = \dfrac{\mathrm{TP}_c}{\left(\sum_{k=1}^{C} \mathrm{TP}_k\right) \Big/ C}$ where TP_c stands for the total number of purchases observed in category c over the study period and C is the total number of categories. In other words, this variable is the category purchase frequency for category c normalized by the average category purchase frequency across all categories.

10. *BUDGSHARE*$_{ch}$ This is defined as $\mathrm{BUDGSHARE}_{ch} = \dfrac{\mathrm{EXPEND}_{ch}}{\sum_{k=1}^{C} \mathrm{EXPEND}_{kh}}$ where $EXPEND_{ch}$ stands for the total expenditure made by household h in category c over the study period. In other words, this variable is the household's expenditure share in category c of the household's total expenditure across all categories.

Household Characteristics (Moderating Variables)

11. *FAMSIZE*$_h$ This is defined as the number of individuals within household h.
12. *INCOME*$_h$ This is defined as the annual income (in \$) of household h.

Table 2. Descriptive Statistics of Assortment and Price Variables

	MIN	MAX	MEAN	STD DEVIATION
BRAND	0.018	4.857	1	0.759
SKU	0.106	4.391	1	0.448
SIZE	0.269	2.612	1	0.274
PVTLABEL	0	8.640	0.625	1.150
POPULARITY	2.699e-08	1	0.378	0.338
PREFMATCH	0.001	9.155	1	0.511
PRICEADV	0.293	98.944	1.032	0.294
PRICEVAR	0	4.815	0.890	0.584

Table 3: Expected Signs of Effects of Explanatory Variables

Expected Signs of Effects of Store Category Characteristics (Key Driers) on SCL

<u>Assortment Size Variables</u>

1. $BRAND_{sc}$	+	
2. SKU_{sc}	+	
3. $SIZE_{sc}$	+	

<u>Assortment Uniqueness Variable</u>

4. $PVTLABEL_{sc}$	+	

<u>Assortment Attractiveness Variables</u>

5. $POPULARITY_{sc}$	+	
6. $PREFMATCH_{sch}$	+	

<u>Price Variables</u>

7. $PRICEADV_{sch}$	+	
8. $PRICEVAR_{sc}$	-	

<u>Category Variables</u>

9. $PURCHFREQ_{c}$	-	for warehouse club stores
10. $BUDGSHARE_{ch}$	+	for warehouse club / Specialty stores

<u>Moderating Effects of Household Characteristics on Effects of Key Drivers</u>

11. $FAMSIZE_{h}$	+	$BRAND_{sc}$, SKU_{sc}, $SIZE_{sc}$, $POPULARITY_{sc}$, $PREFMATCH_{sch}$
12. $INCOME_{h}$	-	$PRICEADV_{sch}$
	+	$PRICEVAR_{sc}$

Table 4. Estimated Effects of Assortment and Price Variables [a]

	MEAN	FAMSIZE	INCOME	VARIANCE
BRAND	0.179 (0.010)	0.020 (0.007)	-0.001 (0.004)	0.090 (0.005)
SKU	0.082 (0.014)	0.003[b] (0.008)	0.008[b] (0.005)	0.105 (0.006)
SIZE	0.106 (0.012)	0.015 (0.007)	-0.015 (0.004)	0.063 (0.004)
PVTLABEL	0.055 (0.003)	2.754e-5[b] (0.002)	-0.003 (0.001)	0.004 (0.000)
POPULARITY	-0.063 (0.021)	-0.043 (0.014)	0.007[b] (0.008)	0.329 (0.022)
PREFMATCH	1.109 (0.010)	-0.024 (0.008)	-0.001[b] (0.004)	0.104 (0.006)
PRICEADV	1.943 (0.024)	-0.013[b] (0.018)	0.010[b] (0.010)	0.587 (0.028)
PRICEVAR	-0.179 (0.011)	0.015[b] (0.010)	-0.010 (0.004)	0.072 (0.005)

[a] Posterior means of model parameters are reported in the table. The standard errors are reported within parentheses.

[b] Estimate is not significant at the 0.05 level.

Table 5. Estimated Effects of Category Variable 1: Purchase Frequency [a]

Store Format	PURCHFREQ	MEAN	FAMSIZE	INCOME	VARIANCE
Supermarket	Albertson's	0.007[b] (0.004)	0.005[b] (0.003)	0.001[b] (0.002)	0.014 (0.001)
Supermarket	Bashas'	-0.011 (0.004)	0.001[b] (0.003)	0.001[b] (0.002)	0.012 (0.001)
Supermarket	Food 4 Less	-5.795 (0.151)	-0.118[b] (0.102)	0.037[b] (0.056)	19.580 (1.055)
Supermarket	Food City	-1.474 (0.057)	0.027[b] (0.026)	-0.047 (0.015)	1.009 (0.075)
Supermarket	Fry Food Store	0.030 (0.004)	0.002[b] (0.003)	-0.001[b] (0.001)	0.011 (0.001)
Supermarket	I.G.A.	-1.558 (0.053)	-0.005[b] (0.035)	-0.095 (0.018)	1.853 (0.118)
Supermarket	Safeway	-	-	-	-
Supermarket	Trader Joe's	-0.549 (0.047)	-0.094 (0.017)	-0.006[b] (0.010)	0.488 (0.047)
Supermarket	Unlisted Chain	-0.281 (0.014)	-0.018[b] (0.010)	0.011 (0.005)	0.139 (0.009)
Supermarket	Wild Oats Market	-3.063 (0.093)	-0.024[b] (0.058)	0.024[b] (0.031)	5.382 (0.285)
Supercenter	Kmart Supercenter	-0.475 (0.024)	0.007[b] (0.012)	-0.035 (0.006)	0.220 (0.020)
Supercenter	Wal-Mart Supercenter	-0.149 (0.008)	0.019 (0.005)	-0.002[b] (0.003)	0.046 (0.003)
Club Store	Costco	-0.539 (0.019)	0.027 (0.012)	0.032 (0.007)	0.301 (0.018)
Club Store	Sam's Club	-0.240 (0.009)	0.021 (0.006)	-0.002[b] (0.003)	0.071 (0.004)
Club Store	Smart & Final	-0.663 (0.024)	0.005[b] (0.014)	-0.001[b] (0.008)	0.333 (0.020)
Club Store	Unlisted Club Store	-7.501 (0.168)	-0.181[b] (0.121)	0.148 (0.064)	27.364 (1.326)

[a] Posterior means of model parameters are reported in the table. The standard errors are reported within parentheses.
[b] Estimate is not significant at the 0.05 level.

Table 6. Estimated Effects of Category Variable 2: Budget Share [a]

Store Format	BUDGSHARE	MEAN	FAMSIZE	INCOME	VARIANCE
Supermarket	Albertson's	-0.006[b] (0.008)	0.002[b] (0.004)	0.001[b] (0.002)	0.021 (0.002)
Supermarket	Bashas'	-0.004[b] (0.008)	0.008 (0.004)	-0.003[b] (0.002)	0.021 (0.002)
Supermarket	Food 4 Less	-2.546 (0.058)	0.051[b] (0.041)	-0.025[b] (0.022)	3.050 (0.148)
Supermarket	Food City	-1.667 (0.059)	0.103 (0.038)	-0.066 (0.021)	2.273 (0.113)
Supermarket	Fry Food Store	0.003[b] (0.007)	0.001[b] (0.004)	-0.002[b] (0.002)	0.019 (0.002)
Supermarket	I.G.A.	-2.329 (0.074)	-0.124 (0.046)	-0.018[b] (0.026)	4.136 (0.242)
Supermarket	Safeway	-	-	-	-
Supermarket	Trader Joe's	-1.362 (0.041)	-0.095 (0.029)	0.026[b] (0.015)	1.520 (0.085)
Supermarket	Unlisted Chain	-0.453 (0.029)	-0.039 (0.014)	0.012[b] (0.007)	0.315 (0.025)
Supermarket	Wild Oats Market	-0.289 (0.011)	-0.012[b] (0.008)	-0.004[b] (0.004)	0.109 (0.007)
Supercenter	Kmart Supercenter	-0.798 (0.027)	0.013[b] (0.020)	-0.048 (0.011)	0.555 (0.044)
Supercenter	Wal-Mart Supercenter	0.028 (0.009)	-0.009[b] (0.005)	-0.003[b] (0.003)	0.033 (0.003)
Club Store	Costco	-0.118 (0.011)	-0.007[b] (0.007)	0.011 (0.004)	0.076 (0.005)
Club Store	Sam's Club	-1.542 (0.059)	0.004[b] (0.039)	0.022[b] (0.021)	2.598 (0.165)
Club Store	Smart & Final	-0.787 (0.019)	-0.009[b] (0.013)	-0.014[b] (0.007)	0.299 (0.018)
Club Store	Unlisted Club Store	-1.097 (0.029)	0.002[b] (0.018)	-0.002[b] (0.010)	0.613 (0.036)

[a] Posterior means of model parameters are reported in the table. The standard errors are reported within parentheses.
[b] Estimate is not significant at the 0.05 level.

Table 7. Top 5 Categories by Average SCL across Households for Each Store

Store	Cat_SCL_Rank_1	Cat_SCL_Rank_2	Cat_SCL_Rank_3	Cat_SCL_Rank_4	Cat_SCL_Rank_5
Albertson's	Breath Freshener Sprays/Drops	Personal Thermometers	Contraceptives	Refrigerated Entrees	Cloth Dye
Bashas'	Breath Freshener Sprays/Drops	Refrigerated Teas/Coffee	Non-Fruit Drinks	Energy Drinks	Household Lubricants
Food 4 Less	Fruits & Vegetables	Soap Dishes	Personal Thermometers	Baking Cups/Paper	Cough Syrup
Food City	Charcoal Lighter Fluids	Refrigerated Pizza	Multi-Task Sheets	Cheesecakes	Charcoal
Fry Food Store	Refrigerated Meat/Poultry Products	Pies & Cakes	Refrigerated Side Dishes	Ice Cream Cones/Mixes	Refrigerated Baked Goods
I.G.A.	Flour/Meal	Refrigerated Teas/Coffee	Glazed Fruit	Energy Drinks	Cheesecakes
Safeway	Frozen Pet Foods	Refrigerated Pizza	Glazed Fruit	Refrigerated Salad Dressing	Refrigerated Spreads
Trader Joe's	Juice/Drink Concentrate	Other Frozen Foods	Wine	Non-Fruit Drinks	Frozen Side Dishes
Unlisted Chain	Frozen Coffee Creamer	Multi-Task Sheets	Soap Dishes	Other Frozen Foods	Floor Cleaners/Wax Removers
Wild Oats Market	Other Frozen Foods	Frozen Coffee Creamer	Non-Fruit Drinks	Cosmetic Storage	Bath Products
Kmart Supercenter	Cosmetic Storage	Tights/Socks	Personal Thermometers	Multi-Task Sheets	Family Planning
Wal-Mart Supercenter	Computer Disks	Toothbrush Holders	Home Permanent/ Relaxer Kits	Flashlights	Automobile Waxes/Polishes
Costco	Contact Lens Care Product	Water Softeners/ Treatment	Blank Audio/Video Media	Tobacco Products	Anti-Smoking Products
Sam's Club	Family Planning	Home Health Care/Kits	Weight Control Candy/Tablets	Tobacco Products	Charcoal Lighter Fluids
Smart & Final	Juice/Drink Concentrate	Household Plastics	Soap Dishes	Coffee Creamer	Frozen Coffee Creamer
Unlisted Club Store	Personal Thermometers	Multi-Task Sheets	Playing Cards	Soap Dishes	Home Permanent/Relaxer Kits

Table 8. Top 5 Stores for Top 20 Categories by Average SCL across Households

Category	Revenue Rank	SCL_Rank_1	SCL_Rank_2	SCL_Rank_3	SCL_Rank_4	SCL_Rank_5
Carbonated Beverages	1	Fry Food Store	Safeway	Bashas'	Albertson's	Wal-Mart Supercenter
Milk	2	Fry Food Store	Safeway	Bashas'	Albertson's	Wal-Mart Supercenter
Frozen Dinners /Entrees	3	Fry Food Store	Safeway	Bashas'	Wal-Mart Supercenter	Albertson's
Cold Cereal	4	Fry Food Store	Safeway	Bashas'	Wal-Mart Supercenter	Albertson's
Fresh Bread & Rolls	5	Fry Food Store	Safeway	Bashas'	Albertson's	Wal-Mart Supercenter
Salty Snacks	6	Fry Food Store	Safeway	Bashas'	Wal-Mart Supercenter	Albertson's
Natural Cheese	7	Fry Food Store	Safeway	Albertson's	Bashas'	Wal-Mart Supercenter
Beer/Ale /Alcoholic Cider	8	Fry Food Store	Safeway	Bashas'	Albertson's	Wal-Mart Supercenter
Ice Cream/Sherbet	9	Fry Food Store	Safeway	Bashas'	Albertson's	Wal-Mart Supercenter
Wine	10	Fry Food Store	Safeway	Costco	Bashas'	Albertson's
Spirits/Liquor	11	Fry Food Store	Costco	Safeway	Albertson's	Bashas'
Dog Food	12	Fry Food Store	Wal-Mart Supercenter	Safeway	Costco	Bashas'
Soup	13	Fry Food Store	Safeway	Bashas'	Albertson's	Wal-Mart Supercenter
Luncheon Meats	14	Fry Food Store	Safeway	Bashas'	Wal-Mart Supercenter	Albertson's
Chocolate Candy	15	Fry Food Store	Safeway	Wal-Mart Supercenter	Bashas'	Albertson's
Frozen Poultry	16	Fry Food Store	Costco	Safeway	Wal-Mart Supercenter	Bashas'
Crackers	17	Fry Food Store	Safeway	Wal-Mart Supercenter	Bashas'	Albertson's
Yogurt	18	Fry Food Store	Safeway	Bashas'	Albertson's	Wal-Mart Supercenter
Cookies	19	Fry Food Store	Safeway	Wal-Mart Supercenter	Bashas'	Albertson's
Toilet Tissues	20	Fry Food Store	Safeway	Wal-Mart Supercenter	Bashas'	Albertson's

Table 9. Comparisons of Assortment and Price Variables between Store with the Highest Average Posterior SCL Mean and other Stores (for a few selected categories)[17]

CATEGORY	STORE WITH THE HIGHEST AVERAGE POSTERIOR SCL	BRAND	SKU	SIZE	PVTLABEL	POPULARITY	PREFMATCH	PRICEADV	PRICEVAR
Carbonated Beverages	Fry Food Store	1.78 (0.95)	1.83 (0.94)	1.56 (0.96)	5.86 (0.41)	0.98 (0.62)	1.62 (0.72)	1.16 (0.79)	0.52 (0.97)
Baby Accessories	Wal-Mart Supercenter	2.71 (0.79)	1.76 (0.91)	1.28 (0.97)	2.45 (0.32)	0.57 (0.18)	0.87 (0.24)	0.74 (0.26)	0.93 (1.01)
Misc. Snacks	Safeway	1.90 (0.94)	1.46 (0.97)	1.17 (0.99)	0.86 (0.65)	0.40 (0.24)	0.73 (0.32)	0.60 (0.34)	0.59 (0.96)
Energy Drinks	Bashas'	2.15 (0.89)	1.24 (0.98)	0.94 (1.01)	1.00 (1.00)	0.70 (0.36)	0.70 (0.33)	0.57 (0.34)	1.08 (0.69)
Cosmetic Storage	Kmart Supercenter	1.11 (0.97)	0.77 (1.06)	0.95 (1.01)	1.00 (1.00)	0.17 (0.21)	1.00 (0.00)	1.00 (0.00)	1.00 (0.00)
FZ Coffee Creamer	Unlisted Chain	1.50 (0.75)	1.00 (1.00)	1.00 (1.00)	1.00 (1.00)	0.83 (0.42)	1.33 (0.67)	1.00 (1.00)	1.00 (0.50)

[17] The focal store's variables are presented in the Table, along with the average values of the variables at competing stores within parentheses.

Table 10. Estimated Revenue Elasticities for Changes in Safeway's Retail Instruments

	BRAND	SKU	SIZE	PVTLABEL	POPULARITY	PRICEVAR
Safeway	17.0%	13.8%	2.1%	7.3%	-0.2%	-3.3%
Albertson's	-4.4%	-4.1%	-0.1%	-1.6%	-0.2%	0.9%
Bashas'	-4.4%	-3.7%	0.0%	-2.0%	0.7%	0.8%
Food 4 Less	-4.9%	-1.8%	-1.5%	-1.8%	-1.8%	0.6%
Food City	-3.3%	-2.9%	-1.1%	-1.8%	1.7%	0.0%
Fry Food Store	-3.8%	-3.1%	-0.4%	-1.7%	-0.1%	0.8%
I.G.A.	-4.6%	-4.9%	-1.7%	-2.1%	3.4%	0.6%
Trader Joe's	-9.7%	-11.2%	0.0%	-3.5%	-3.5%	1.7%
Unlisted Chain	-0.4%	0.1%	-0.8%	-0.9%	-1.9%	0.6%
Wild Oats Market	-3.8%	-7.0%	0.8%	-3.0%	-2.9%	1.3%
Kmart Supercenter	-8.5%	-8.1%	1.4%	-3.8%	-0.8%	1.1%
Wal-Mart Supercenter	-4.9%	-3.1%	-2.5%	-1.8%	0.6%	0.9%
Costco	-13.9%	-14.0%	0.7%	-4.8%	-6.1%	3.2%
Sam's Club	-3.3%	-1.0%	-0.3%	-2.3%	3.4%	-0.4%
Smart & Final	-3.8%	-4.0%	1.4%	-2.1%	4.8%	1.0%
Unlisted Club Store	-3.2%	-3.3%	1.3%	-1.2%	-1.4%	-0.4%

Appendix: Details of the MCMC Procedure Used for Hierarchical Bayes Estimation

We use a Bayesian estimation algorithm, specifically, Markov Chain Monte Carlo (MCMC) sampling. We are interested in simulating from the posterior distribution of (β,Σ, $\{\beta_h\}|D_h, N_{sch}, X_{sch}$). While it is possible to sample from the joint posterior directly, it is efficient to simulate from the conditional posteriors of the parameters (Rossi, Allenby and McCulloch 2005, Train 2003). For computational simplicity, we assume diffuse conjugate priors for β and Σ. We assume that β is distributed normally with mean β_0 and variance covariance matrix B_0. We also assume that Σ is distributed Wishart with degrees of freedom ν_0 and scale matrix S_0.

$$\beta \sim Mvn(\beta_0, B_0)$$
$$\Sigma \sim Wishart(\nu_0, S_0)$$

For given priors, the MCMC sampling algorithm for conditional posteriors is described below.

step 0: intialize β_h to $\beta_h^{(0)}$ and Σ to $\Sigma^{(0)}$

step 1: draw $\beta^{(g)}$ from

$$\Pi(\beta^{(g)} \,|\, \bullet) \sim Mvn\left(\frac{\left(\sum_h D_h^{'} \Sigma^{-1(g)} \beta_h^{(g)} + B_0^{-1} \beta_0 \right)}{\left(B_0^{-1} + \sum_h D_h^{'} \Sigma^{-1(g)} D_h \right)}, B_0^{-1} + \sum_h D_h^{'} \Sigma^{-1(g)} D_h \right)$$

step 2: draw $\Sigma^{-1(g)}$ from

$$\Pi(\Sigma^{-1(g)} \,|\, \bullet) \sim Wis\left(\nu_0 + H,\ \left[S_0^{-1} + (\beta_h^{(g)} - D_h \beta^{(g)})(\beta_h^{(g)} - D_h \beta^{(g)})' \right]^{-1} \right)$$

step 3: draw $\beta_h^{(g)}$ by Metropolis-Hastings

$$\Pi(\beta_h^{(g)} \,|\, \bullet) \sim \prod_{c \in C_h} \prod_{s \in S} \left(\frac{\exp\left(x_{sch} \beta_h^{(g)} \right)}{\sum_{j \in S} \exp\left(x_{jch} \beta_h^{(g)} \right)} \right)^{N_{sch}} * \exp\left(-\frac{1}{2} \left(\beta_h^{(g)} - D_h \beta^{(g)} \right)' \Sigma^{-1(g)} \left(\beta_h^{(g)} - D_h \beta^{(g)} \right) \right)$$

step 4: go to step 1

The above-mentioned steps are repeated 100,000 times. After discarding the initial 50,000 draws for burn-in, in order to let the MCMC chain stabilize, we use the remaining 50,000 draws for the posterior distribution. Once we have the full posterior distribution, we compute mean and variance of different parameters of interest as reported in Table 4, 5 and 6.