An Empirical Analysis of Store Competition[1]

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Abstract

Supermarkets typically rely on high store traffic and product turnover to compensate for razor thin margins in the industry. For store managers, understanding the fundamental drivers of consumer's store choice is critical. In this paper we develop a comprehensive model of consumer store choice that incorporates many elements of retailer's long-term strategic decisions such as location and investment in private label program, as well short-term decisions such as price promotion. A novel feature of our modeling approach compared to the previous literature is how we capture the four key constructs of households' store choice decisions: (i) time-varying consumption needs for different products; (ii) search for price information; (iii) trade-offs between fixed costs and expected savings on the basket; (iv) interactions between effectiveness of store promotion policies and time-varying consumption needs. The model is calibrated on a rich scanner panel data and parameter estimates are used to conduct a variety of policy simulations for optimal pricing/promotion decisions. Results show that several factors affecting the fixed utility such as availability of private labels, larger assortment (when the planned basket size is large), and distance to the store are important determinants of store choice. High penetration product categories such as carbonated soft drinks are found to be more effective in generating store traffic and revenues. In addition, our results show the importance of accounting for consumers time-varying consumption needs since the drawing power of a brand or category in generating traffic varies significantly across time periods due to seasonal demand differences. Implications of our model and results for store managers are discussed.

1. Introduction

It is well known that consumers make periodic visits to supermarkets (stores) to satisfy their consumption needs in many categories. Consumers' decision to shop at a supermarket is in general based on location, assortment and quality of the merchandise, service, price image and promotions. On the supply side supermarkets compete in an increasingly competitive environment. Growth in alternate retail formats such as warehouse stores, price clubs, and supercenters has added tremendous pressure on an already competitive industry. Given the value dimensions or drivers behind consumers' store choice decisions, stores tend to compete on these drivers week in and week out. Stores tend to achieve a differential positioning from their competitors through long-term strategic variables such as location, assortment, service and perhaps a general price image. In the short term, mostly week-to-week, the competition among stores is based on advertised specials, coupons and in store activities. To understand the effectiveness of such short-term strategies it is important to quantify the relative importance of the primary drivers of consumer store patronage. This is particularly important considering that fact that supermarkets operate on the basis of an after tax net income of less than 1% (Food Marketing Institute, Facts and Figures, 2004). Not surprisingly, many of the retailer's short-term activities such as promotions on traffic building categories (loss-leader pricing), as well as long term strategies such as adding ancillary services to provide one-stop-shopping are dictated by a desire to influence consumer store choice and build store traffic. Our objective in this paper is to understand the dynamics of store competition and how the drivers behind consumers' choice of stores influence the weekly patterns of competition that we observe. To achieve this we develop a comprehensive model of store choice that incorporates many elements of retailer's long-term strategic decisions such as location and investment in private label program, as well short-term factors such as price promotions due to consumer's time varying consumptions needs. The model is calibrated on a rich scanner panel data and parameter estimates are used to conduct a variety of policy simulations for optimal pricing/promotion decisions.

Early research on store choice focused on gravitational attraction theories that predict that store patronage primarily depends on consumer's distance to the store (Huff 1964, Brown 1969). More recently, researchers have explored factors besides locations that could influence consumer store choices. These include aspects related to preference for a particular pricing format, EDLP vs. Hi-Lo (Bell and Lattin 1998, Bell, Ho and Tang 1998), breath of product assortment and consumer desire for one-stop-shopping (Messinger and Narasimhan 1997), depth of product assortment within a category (Broniarczyk et al. 1998, Hoch et al. 1999, Briesch et a. 2004), role of store brands in creating store loyalty (Corstjens and Lal 2000) and so forth. Besides these long-term factors, a number of researchers have studied the impact of price promotions in individual product categories on store switching (Walters and Rinne 1986, Kumar and Leone 1988, Walters and MacKenzie 1988, Bucklin and Lattin 1992) and impact on store sales due to a temporary change in pricing policy from Hi-Lo to EDLP (Hoch et al. 1994).

In general, these papers have reported conflicting findings on the impact of these factors on consumers store patronage. For instance, Bell and Lattin (1998) find that pricing format is quite important in determining store choice and that large basket shoppers are primarily attracted to EDLP stores. Hoch et al. (1994) on the other hand conducted a series of field experiments and found that a change in pricing policy from Hi-Lo to EDLP had a muted consumer response, suggesting that these pricing policies are more long-term positioning strategies (Lal and Rao 1997). Similarly, Broniarczyk et al. (1998) and Boatwright and Nunes (2001) find limited (or negative) impact of product assortment on category sales while Fox et al. (2004) find product assortment to be significant predictor (even more important than price, and location) on consumer store choice. There is also mixed evidence with regards to the impact of short-term price promotions on store switching. For instance, Kumar and Leone (1988) find that consumers switch stores in response to temporary price promotion in a category while others (e.g. Bucklin and Lattin 1992) find no effect of short-term marketing activities on store choice. Finally, Lal and Matutes (1994) study pricing and advertising strategies for multi-product retailers and show that firm’s advertise products below costs (loss-leader pricing) to attract consumers to the store. Chevalier et al. (2003) find empirical evidence that supermarkets systematically reduced margins at seasonal demand peaks, which is consistent with loss leaders pricing strategy. On the other hand, Walters and McKenzie (1988) studied weekly price promotions at two supermarkets and concluded that loss leaders do not affect store profit and have little impact on store traffic.

Several important conclusions emerge from past literature:

(i) Consumers, certainly on major shopping trips, buy a basket of items.

(ii) The attractiveness of shopping at a store depends on the category a consumer intends to buy which could vary from period to period.

(iii) Consumers may not know the prices of all items they plan to buy. They may use available stimuli such as feature advertising to become informed about prices but residual uncertainty might still exist.

(iv) Assortment and travel distance affect the utility consumers might assign to shopping at a store.

This leads to the following research questions that we propose to address in this paper:

1. What is the impact of short-term decisions, such as price promotions, relative to long term decisions, such as location of a store and other services, on a consumer's store choice decision?
2. Which categories and brands are the best candidates for price promotion to increase the likelihood of a consumer's visit? What is the impact of short-term promotions on brand, category, and aggregate store revenue, and how does this vary due to seasonal factors?
3. What is the cross-substitution pattern across stores? If a retail chain can price differently among its stores, how should this vary systematically?

Answers to this question is predicated upon building a comprehensive store choice model that explicitly takes into account the generalizations from the extant analytical and empirical work listed in items (i)-(iv) above. This leads to the following additional research questions that we address.

4. How does households' *time-varying* consumption needs, involving several categories, affect their store choices over time?
5. How effective is feature advertising in influencing consumers' search for price information? What are the potential biases in our understanding of consumer shopping behavior if we ignore the fact that consumers only have imperfect price information when they decide which store to visit?

To address these questions we develop a comprehensive model of consumer store choice. We postulate that on any shopping occasion consumers form expectations about the cost and benefit of shopping at each store with limited information. Building on the past literature (Bell, Ho, and Tang 1998), we model the total utility (or disutility) from a given shopping trip as consisting of a fixed and a variable component. The fixed component of the utility consists of time invariant (in the short-run) factors such as distance to the store, breadth and depth of product assortment, quality and availability of store brands, and other ancillary services offered at the store. The variable component is the sum of the expected utility generated from all products in consumer's shopping list, which depends on their *time-varying* consumption needs and *a priori* price information at various stores. A novel feature of our modeling approach compared to the previous literature is how we capture the four key constructs of household store choice decision: (i) consumers' time-varying consumption needs for different products; (ii) search for price information; (iii) trade-offs between fixed costs and expected savings on the basket; (iv) interactions between effectiveness of store promotion policies and time-varying consumption needs.[3]

The model is applied to a scanner panel data that consists of detailed purchase history information of over 1,000 households. The data is available for a two year period from January 1993 to April 1995 and covers purchases from 32 packaged good categories. These categories cover a broad spectrum of products including essentials (e.g., milk), food (e.g., pasta) and non-food (e.g., detergents) that are typically found in a consumer basket. The dataset is quite unique in that it covers 31 grocery stores, belonging to four major competing chains, in a small geographical area. The data also includes detailed household demographics including the location of each household and store. We are therefore able to compute household's traveling distances to all stores as well as pair wise distances between competing stores. Finally we use store level data to compute measures on product assortment and availability of store brands in various categories.

Our results show the following

- Fixed factors such as availability of private labels, assortment and distance to the store are important determinants of store choice. There is an interaction effect

[3] Bodapati and Srinivasan (2001) was the closest to this paper. They used a nested logit approach to model households' store choices, and found a strong impact of featured advertising. As a comparison, we explicitly address the impacts from both short term promotional activities and long term strategic factors. We also explicitly consider the interaction between time varying consumption needs and promotional activities.

between the assortments carried in a store and the expected basket size of a consumer on the attractiveness of shopping at the store. In addition, consumers on average are willing to travel an extra mile to save (approximately) $3.00 in total spending, although there is considerable heterogeneity across consumers.

- Inter store distance moderates cross-store substitutability that arises due to short-term price promotions with stores located in competitive neighborhoods more vulnerable to price cuts by competitors. We find, from policy experiment that we conduct, that adopting differential pricing across stores such as a zone pricing policy may generate higher store revenues.
- High penetration categories such as carbonated soft drinks are more effective in generating store traffic and revenues than lower penetration categories such as canned soup. There is a significant spillover effect on the sales of other categories since consumers buy a basket of items. Therefore categories such as carbonated soft drinks may be useful as a loss-leader.
- Time varying consumption needs moderate effectiveness of promotion policy in generating store traffic and revenues. For example a 20% price cut on Coke is found to increase store traffic by 1.3% in summer compared with a 0.6% increase in winter, ceteris paribus.
- Ignoring the fact that consumers may not be fully informed about prices prior to their visits to stores leads to estimated price elasticities that are downward-biased.

The rest of the paper is organized as follows. In the next section we describe our model of household store choice process. The data used in the study is discussed in Section 3 and in Section 4 we outline the estimation procedure. We present the results in Section 5 and in Section 6 we discuss the results from various simulations on optimal pricing/promotion policies. Section 7 concludes with a discussion on the limitation of the current study and directions for future research.

2. A Store Choice Model

A household's[4] store choice decision process is described in Figure 1. At the beginning of each period, consumption needs (as a function of exogenous factors such as

[4] "Consumers" and "households" are used as equivalent hereafter in the paper.

household size and demand shocks due to holiday and seasonality) arise. This leads to the formation of a shopping basket. Households then form expectations about the cost of this basket at different stores either through a price search via feature advertising, or through their past experiences. Traveling costs, general store preference due to assortment, availability of private labels, store services etc., and expected expenditures on all products are combined to evaluate the total attractiveness of each store on each shopping trip. Once in a store, households are exposed to in-store promotions and they make the final decisions on what brands to buy. The model allows each of these factors (consumption needs, probability of price search, disutility of travel, etc.) to vary across households due to observed (demographics) and unobserved factors.

Thus, compared with traditional brand choice models in marketing, there are at least three important issues that we have to address when modeling the store choice decision: (1) Households incur travel cost to visit a particular store and households might, due to the various services and shopping experiences provided by the stores, have different preferences for different stores. Note that the fixed cost and the general preference for a store are both invariant to what is bought at the store. (2) Stores sell multiple categories and multiple brands within each category and households usually buy baskets consisting of various categories. (3) Unlike in standard models where choice is modeled conditional on store visit, here households do not know the actual prices when deciding which store to shop at. Hence, they have to use past shopping experiences and other informational sources such as store advertisements to form expectations about prices at stores. The major challenge in this paper is to account for these issues in the store choice model.

We note that the above process may not apply to every shopping trip. In particular, this may only apply to "major" shopping trips with relatively larger baskets and higher expenditures. We will further explore this aspect later in the paper. Furthermore, our model ignores the possible dynamic planning over shopping trips in different stores. A very price sensitive household (e.g., cherry-pickers) may shop in different stores within a period to maximize its savings on grocery shopping. Though this could be an important topic to explore, it is outside the scope of this paper.

We assume a linear additive utility function for household *h* visiting store *s* at time *t* as:

$$U(Q_{ht})_{hst} = fu_{hs} + vu_{hst} + e_{hst}, \quad (1)$$

where fu_{hs} is the household-specific and time-invariant fixed utility (or disutility) from visiting store *s* (corresponding to issue (1) above), vu_{hst} is the household-specific time-varying *expected* utility or consumer surplus generated from the shopping basket (corresponding to issues (2) and (3) above), and e_{hst} represents a stochastic component observed by the household but unobserved by researcher, which may include the utility generated from purchasing other categories not included in our data.[5] Figure 1 below provides an illustration of the store choice decision.

Before making its store choice decision, a household forms expectation about prices based on several sources ((b) in Figure 1). Since different products have different expected prices, the household evaluates the expected purchase quantity ((d) in Figure 1) and its category and brand preferences ((e) in Figure 1) to form the expected utility of purchasing each category (c) in Figure 1). The expected utility from a shopping basket ((f) in Figure 1) is the sum of the utilities from all the categories. This, together with the fixed utility ((a) in Figure 1) discussed above, forms the expected utility of visiting stores ((g) in Figure 1). The household chooses that store with the highest expected utility. We next discuss how to model each of the boxes in Figure 1.[6]

a. Fixed Utility of Visiting

We first describe a household's expected fixed utility and disutility of visiting a store denoted by fu_{hs} in equation (1). This includes cost of traveling to the store, utility the household gains from services and other in-store experiences. We would expect distance from a store to have a negative impact while higher level of service and positive experiences to enhance utility from visiting a store. We therefore model the fixed utility from shopping fu_{hs} as:

[5] Our data only has 32 product categories. We do not observe purchase data from other categories or the total expenditure on each shopping trip.

[6] Note that for the ease of exposition, we first discuss the expected utility from purchasing a category (c), the lower part of the diagram, then the quantity purchase decisions (d) and category and brand preferences (e), the upper parts.

$$fu_{hs} = f(store\_envir_s, \text{distance}_{hs}; \upsilon_{hs}) \quad (2)$$

where *store_envir*$_s$ is a vector that captures customer intrinsic preference and loyalty to a store, store size, product assortment, and availability of private labels. The variable *distance*$_{hs}$ is the travel distance between the household's home to the store, and υ_{hs} is a vector of parameters to be estimated.

b. Household Price Information

Since household's price expectations constitute an important determinant of the expected cost of the shopping basket and consequently its decision to visit a store, stores have an incentive to inform consumers if their prices are lower such as when on promotion. A common practice in the supermarket industry is to use flyers or newspapers to advertise the promoted items. A household's price information will depend on whether or not it is exposed to these advertised specials in a particular week. We assume that a household, before deciding which store to visit, constructs the price information either from these advertisements or from its past shopping experiences. In addition, we may expect households to vary in the way they search for the price information. For instance, price sensitive households may seek out to be informed of the advertised specials at different stores, while higher income or otherwise time-constrained households may not exert the effort to become informed.

We assume that if a household is exposed to these specials, it knows the *actual* prices for the advertised products. For the unadvertised products, we assume that a household will expect the stores to charge *regular* prices (see Lal and Matutes (1994)). In equilibrium, stores charge the reservation prices on unadvertised products, and a rational household will fully anticipate this pricing behavior. If the household does not read the newspaper, it will form *expectations* about that prices at a store based on its past shopping experience. We provide more details about how the price expectation is constructed later in the paper.

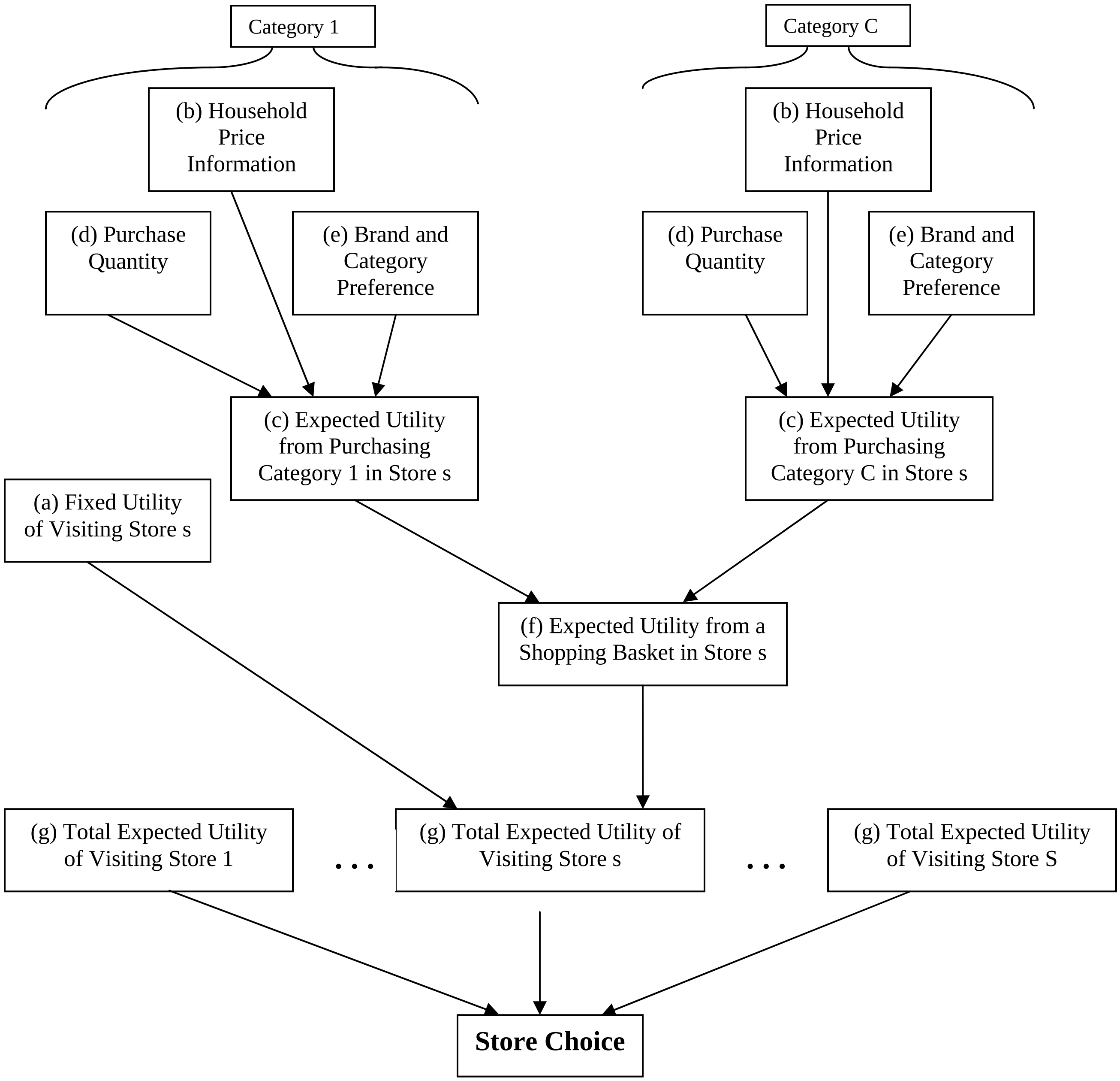

Figure 1: Households' Store Choice Decision Process

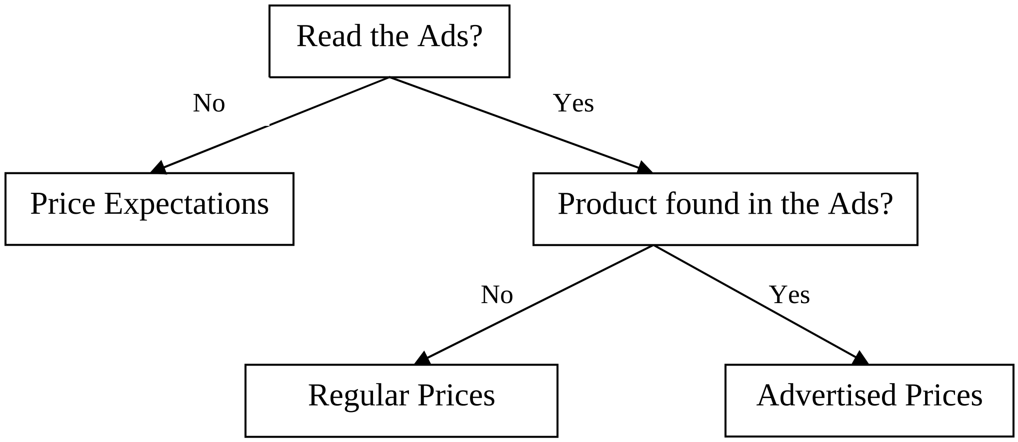

Figure 2: Construction of Price Information

Figure 2 illustrates our model of how a household constructs its price information. Since the actual decision of reading the advertised specials is unobserved, we model household's probability of reading store flyers. Let $\Pr(ADs)_{hst}$ denote the probability that household *h* reads advertisements from store *s* at time *t*. This is also the probability that the household knows the actual prices (of the advertised items), and $1-\Pr(ADs)_{hst}$ is the probability that the household infers prices from its past experiences. We model $\Pr(ADs)_{hst}$ as:

$$\Pr(ADs)_{hst} = g(chain_s, basketspend_{ht}, demographics_h; \rho_{hs}). \qquad (3)$$

where $chain_s$ is a vector of dummies to capture chain level fixed effects, $basketspend_{ht}$ household *h*'s expected expenditure in period *t*, and $demographics_h$ is a vector of demographic variables that includes household income, education level, female employment status and so forth. Finally ρ_{hs} is a vector of parameters to be estimated[7].

c. Expected Utility from Purchasing a Category

[7] The assumption that households, if they read store newspapers, will know all advertised prices may be too restrictive. A potential extension is to further assume that households only read some sections of the whole advertisements. We can model the probability of reading advertisements for category c in store s $\Pr(ADs)_{hsct}$ conditional on the probability of reading store *s*'s advertisements $\Pr(ADs)_{hst}$.

Let $1_{ht}\{ADs\}$ be an indicator variable which equals 1 if household *h* reads the advertisement of store *s* at time *t*, and 0 otherwise and let vu_{hsct} be the household-specific and time-varying expected utility of purchasing in category *c* (we provide details on its specification below). We use $E[vu_{hsct} \mid \Theta_{hct}, 1_{hst}\{ADs\}]$ to denote the expected utility generated from purchasing in category *c*, conditional on $1_{hst}\{ADs\}$ and the set of random coefficients in the utility function Θ_{hct}. According to Figure 2, if the household does not read the advertisement, it expects the actual prices to follow the distribution, $F(p^0_{hsct} \mid \Omega_{hst})$, where Ω_{hst} is the household's information set at time *t* based on its past shopping experience. The superscript 0 implies that $1_{hst}\{ADs\} = 0$. The expected utility from purchasing category *c* is specified as the following:

$$\begin{aligned} &E[vu_{hsct} \mid \Theta_{hct}, 1_{hst}\{ADs\} = 0] \\ &= \int vu_{hsct}(\Theta_{hct}, p^0_{hsct}) \cdot dF(p^0_{hsct} \mid \Omega_{hst}) \end{aligned} \tag{4}$$

When the household reads the advertisement, we assume that the expected price of a product is the advertised price if the product is advertised or the regular price if the product is not advertised. In this case the expected utility is specified as follows:

$$\begin{aligned} &E[vu_{hsct} \mid \Theta_{hct}, 1_{hst}\{ADs\} = 1] \\ &= vu_{hsct}(\Theta_{hct}, p^1_{sct}) \end{aligned} \tag{5}$$

Prices p^1_{sct} are the advertised prices (equal to the observed prices in data p_{sct}) if the corresponding products are advertised, or the regular prices p^r_{sct} if the corresponding products are not advertised. Note that there is no uncertainty in prices p^1_{sct} in (5), whereas p^0_{hsct} in (4) follows a distribution.

To model vu_{hsct} conditional on prices p^l_{sct}, where *l = 0* (equation (4)) *or 1* (equation (5)), we make some simplifying assumptions: First, we specify the expected utility of purchasing brand *j* in category *c* as the following:

$$vu_{hscjt}(\Theta_{hct}, p^l_{sct}) = [u_{hscjt} \cdot Q_{hsct}](\Theta_{hct}, p^l_{sct}) \tag{6}$$

where Q_{hsct} is the quantity purchased, and u_{hscjt} is the *constant* marginal utility generated from each unit of consumption.

To simplify the analysis we assume that each household chooses at most one brand in a category during a shopping trip. That is, households are assumed to be making discrete brand choices, which is largely consistent with our empirical data. Under this assumption, household *h* will choose the brand that maximizes the expected utility of purchasing in category *c*:

$$vu_{hsct}(\Theta_{hct}, p^l_{sct}) = \max_{j \in c}\{[u_{hscjt} \cdot Q_{hscjt}](\Theta_{hct}, p^l_{sct})\} \quad (7)$$

Finally, we assume that the marginal utility u_{hscjt} is independent of Q_{hscjt} and its conditional expectation function can be separated from Q_{hscjt}:

$$[u_{hscjt} \cdot Q_{hsct}](\Theta_{hct}, p^l_{sct}) = u_{hscjt}(\Theta_{hct}, p^l_{sct}) \cdot Q_{hsct}(\Theta_{hct}, p^l_{sct}) \quad (8)$$

d. Purchase Quantity Decisions

Let's turn to the purchase quantity decisions Q_{hscjt} in (8) above. We do not observe the quantity a household *expects* to buy before its visit to a store. If we were to model the *expected* purchase quantity before store visit as a latent variable then we have to simultaneously estimate the store choice, brand choice, and the quantity purchase decisions. Doing so creates a heavy computational burden since we have to literally estimate hundreds of parameters across all categories in a non-linear simultaneous equation system that involves complicated simulation procedures (we provide the technical details in section 4).

To solve this problem, we make a simplifying assumption that the *expected* purchase quantity decisions are independent of household's store and brand preferences and use the *observed* purchase quantity, Q_{hscjt}, to proxy for the *expected* purchase quantity, for all stores *s*, and all brands *j* in *c*, in every period[8]. For some product categories, Q_{hscjt} may provide a good approximation for the *expected* purchase quantity: If household inventory-holding cost is high, a household may buy the exact amount to satisfy its expected consumption need, which is likely to be independent from its store and brand preferences as well as in-store promotional activities. This assumption is perhaps potentially restrictive for some categories. To model and estimate simultaneously

[8] Therefore we have $Q_{hsct}(\Theta_{hct}, p^l_{sct}) = Q_{hsct}(\Theta_{hct})$ in (8) and if there is no purchase in period *t*, $Q_{hscjt} = 0$ for all categories *c*, brands *j* and stores *s*.

the decisions of which store to visit, what (multiple) categories and brands, and how much to buy decisions, will be an important future development along this line of research.[9]

e. Brand Preferences

We model the marginal utility function in (8) as:

$$u_{hscjt}(\Theta_{hcjt}, p^{l}_{hscjt}) = \kappa_{hc} + b_{hcj} + d_{hc} disp_{scjt} - \lambda_h p^{l}_{hscjt} + \varepsilon_{hscjt}, \qquad (9)$$

where $disp_{scjt}$ is an indicator variable that equals 1 if the product is on display and 0 otherwise, and d_{hc} is the corresponding parameter. κ_{hct}, b_{hcj}, and λ_h are household specific parameters to capture category consumption preferences[10], brand preferences (for model identification we normalize the preference for one of the brands in each category to *0*), and marginal disutility of price that is constant across categories, respectively. Finally ε_{hscjt} is a random brand preference shock unobserved by researchers that is assumed to be *i.i.d. Gumbel(0,1)*.

Since the purchase quantity is assumed to be independent of brand preferences and store prices, we may infer the brand preference parameters (up to κ_{hct}) from the *observed* brand choices among households. Once inside a store, a consumer observes all prices, and will choose the brand that maximizes the expected consumption utility in the category if her consumption need is positive. That is, she will choose brand *j** if

$$j^{*}_{hsct} = \arg\max_{j \in c}[b_{hcj} + d_{hc} disp_{scjt} - \lambda_h p_{scjt} + \varepsilon_{hscjt}] \qquad (10)$$

Note that κ_{hct} is omitted from (10) because this is common for all brands in category *c*. We assume that product displays may change households' brand choice only inside the store. Prior to visiting stores households assume that it is unlikely that any product would be on display, i.e., $E[disp_{scjt}] = 0$, in forming expected shopping utility. Given the small number of items, among the tens and thousands of SKUs, that are on display in any given week at a supermarket, this assumptions seems reasonable. Also note that p_{scjt} in (10)

[9] Most of the previous studies on "where, what, and how much to buy" decisions have only focused on single category purchases. For examples see Chiang (1991) and Chintagunta (1993).

[10] κ_{hct} is uncorrelated with the *quantity* needed. Instead, it implies the cost to household *h* if it needs to give up consuming category *c*.

are the observed store prices, but it will be the expected prices when households are making store choice decisions, and j^* will be the expected chosen brands.

f. Expected Utility from a Shopping Basket

Based on the above discussion, we can model the expected utility from a shopping basket at store *s*. We use a linear separable specification for the utility function, vu_{hst}, by assuming that it is the sum of the expected utility generated from each of the categories $vu_{hsct}(\Theta_{hct}, p^l_{sct})$. Therefore, we can write down the expected utility function, conditional on $1_{hst}\{ADs\}$ and the household consumption preference parameters Θ_{ht} as:

$$E[vu_{hst} \mid \Theta_{ht}, 1_{hst}\{ADs\}] = \sum_{c=1}^{C} E[vu_{hsct} \mid \Theta_{hct}, 1_{hst}\{ADs\}].$$[11]

Similar to our discussion before if $1_{hst}\{ADs\} = 0$, we have

$$\begin{aligned} &E[vu_{hst} \mid \Theta_{ht}, 1_{hst}\{ADs\} = 0] \\ &= \sum_{c=1}^{C} \left[\int vu_{hsct}(\Theta_{hct}, p^0_{hsct}) \cdot dF(p^0_{hsct} \mid \Omega_{hst}) \right] \end{aligned} \tag{11}$$

and if $1_{hst}\{ADs\} = 1$, we have

$$\begin{aligned} &E[vu_{hst} \mid \Theta_{ht}, 1_{hst}\{ADs\} = 1] \\ &= \sum_{c=1}^{C} \left[vu_{hsct}(\Theta_{hct}, p^1_{sct}) \right] \end{aligned} \tag{12}$$

Conditional on prices $p^l_{sct},\ l = 0,1,$ we have

$$vu_{hsct}(\Theta_{hct}, p^1_{sct}) = (\kappa_{hct} + \max_{j \in c}\{b_{hcj} + d_{hc} disp_{scjt} - \lambda_h p^l_{scjt} + \varepsilon_{hscjt}; \forall j \in c\}) \cdot Q_{hct} \tag{13}$$

where Q_{hct} is the observed quantity purchased of category *c* of household *h* in period *t*.

g. Total Expected Utility of Visiting Store and Store Choice

With the fixed utility of visiting stores and the expected utility from a shopping basket we can compute the total expected utility of visiting a store based on equation (1). As discussed before, e_{hst} represents an unobserved state variable which may include the utility generated from purchasing other categories not included in our data. We are

[11] This linear separability assumption implies that there are no substitutability or complementarity relationships across categories in the utility function. Though this may be restrictive for some categories, computation burden is reduced. More importantly, these interactions in the utility function are difficult to identify given that we do not model quantity purchase decisions.

concerned that e_{hst} may not be *i.i.d.* across households. For example, households may have different consumption needs for other categories and hence their preferences for visiting the stores in our data *vs. outside* options can be systematically different. As a partial solution, we use a set of demographic variables Z_{ht} [12], such as household income and size, to control for the differences in unobserved consumption needs across households. That is, we assume

$$e_{hst} = Z_{ht}\delta + \omega_{hst}, \tag{14}$$

After controlling for this household heterogeneity, we assume that the stochastic part ω_{hst} is *i.i.d.* across *h, s,* and *t*.

With all of the above specifications, we assume that consumers will choose the store that will generate the highest total expected utility of visiting, that is,

$$s^*_{ht} = \underset{\{s=1,\ldots,S\}}{\arg\max}\{ fu_{hs} + vu_{hst} + Z_{ht}\delta + \omega_{hst}\} \tag{15}$$

3. The Data

We calibrate the model on a scanner panel data from a large metropolitan area. The data contains purchase histories of 2,100 households in 32 categories and spans over 98 weeks starting from Jan 1st 1993. Some of these categories are narrowly defined so we combine several closely related categories that leaves with 25 broad categories (e.g., we combine apple juice and grape juice as the fruit juice category.) These categories cover a broad spectrum of products including food (e.g. pasta), non-food (e.g. detergents), snacks (e.g. crackers), beverages (e.g. soft drinks), and essentials (e.g. milk) that are typically found in a consumer basket.[13] Each category is composed of several (and sometimes hundreds) of individual SKUs. For tractability we aggregate all the SKUs of a brand into one. We retain between two to five large (in terms of market shares) brands in every category and combine the rest into the "other" brand. We use the average price, product displays, and features of all SKUs within a brand; weighted by their relative market share, as the marketing mix variables at the brand level.

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[12] Household demographics are reported every year. We observe significant changes for some households over time. Therefore, demographic variables are described with a time subscript.
[13] Like most scanner panel data, out dataset does not have perishables like meat and produce.

There are altogether 256 stores in the data. These include grocery stores as well as smaller convenient stores and gas stations. We observe pricing and other promotion activities, including product displays and features, for 31 stores that belong to four major grocery chains. However, store level merchandising files are missing for the smaller retailers and hence we are not able to construct the weekly marketing mix variables for these stores. Fortunately, majority of the shopping trips in our data are made at one of the 31 grocery stores and we combine all other outlets as the outside option in the store choice model.

Besides the standard demographics, our dataset also includes distance between every pair of households and stores. This enables us to model the effect of location on competitive behavior by modeling consumer’s travel cost. However, most of the households and stores are concentrated in a small geographical area, while the rest of the consumers and stores are dispersed away from this cluster. Since we are concerned that there may be many non grocery stores in the far flung areas and thus contaminate our results, we decided to focus on the area where most households and stores are located. Furthermore, to reduce computational burden we randomly pick 300 households that belong to the selected area and are active shoppers. Figure 3 shows the geographic distribution of stores and households used in our estimation of brand preference, quantity purchased, and store choices. The selected households altogether made 46,727 shopping visits in the 98 weeks. Column 3 in Table 1 reports the market share (in revenue) of the four major chains and the outside stores. Since households may make multiple trips in a week, we also consider only the major shopping trips: one with the largest shopping basket in each week. There are altogether 25,291 major trips in the data. Comparing all trips vs. major trips we see that the overall shares are fairly similar. Chain 3 has the largest number of stores and the highest market share, but chain 4 has the largest per store market share. Chains 1 and 2 are less successful in attracting households and although chain 2 has a large number of stores, its per store market share is less than half compared with chain 3. Finally note that while there are 104 stores in the outside option, their total market share is only about 25%.

Figure 4 shows the distribution of the total number of shopping trips across stores. Most households made between 100 and 200 trips in the sample period of 98 weeks.

Table 2 contains the number of different stores these consumers visited during the 98 weeks. Majority of the households visit between 3 and 6 stores and we observe significant store switching. For instance, if we define the "most preferred" store for a household as the store it visited most frequently, we find that approximately 25% (60%) of households shopped at stores outside of their "most preferred" option more than 50% (30%) of times.

Table 3 provides summary statistics of the shopping pattern in the 25 categories for the 300 households in our sample. Column 2 reports the percent of total expenditure in the sample period for each category: overall households spend much more on some categories such as cereal, carbonated and non-carbonated soft drinks, milk and beer than other categories such as frosting, cake mix, and cookies. Column 3 reports the average dollar amount spent on each category (conditional on purchase) while the last column reports the percent of shopping trips that the category was purchased. We observe significant differences across categories on both dimensions. Cereal, coffee, beer, and detergent are the categories with high expenditures while cereal, carbonated and non-carbonated soft drinks and milk are bought most frequently. It is important to note that from a retailer's perspective understanding the value of a whole shopping basket may be more critical than expenditures on individual categories. For example, the average basket size containing detergent is approximately 30% larger than baskets containing beer. Thus, while beer may generate high revenue as a single category its impact on the total store profitability may be less than categories such as detergent since heavy buyers in this category are more likely to have larger families and spend more.

To see the impact of seasonality and holidays on demand, in Figure 5 we report the aggregate weekly sales for canned soup. Sales from September to February (fall and winter) are observed to be significantly higher than from March to August, demonstrating a strong seasonality effect. In contrast, the aggregate weekly sales for milk in Figure 6 show a much smaller seasonality effect. Although not reported to conserve space, other categories such as beer and carbonated and non-carbonated soft drinks demonstrate strong holiday effects.

Table 4 summarizes the average basket size and from expenditures in the 25 categories on our dataset. Though the values are rather small compared with a typical shopping basket size, we note that they include many fill-in trips that typically consist of smaller number of items. If we only look at the largest shopping trip in each week, the mean basket size is \$16.1, with a standard deviation of \$17.9. Still, we acknowledge that the lack of purchase data from some categories, such as meat and vegetables, is a limitation of our data.

To summarize, the major advantages of the data are that it covers a relatively complete set of stores and their marketing mix variables within an area. It also provides a data on travel distances between households and stores. The major limitation is that the data does not cover some of the important product categories such as meat and vegetables; hence, we are not able to study store competition among some categories that may be important in store choice decisions (e.g., turkey during Thanksgiving.)

4. Model Estimation

In this section we develop specification for each element in the store choice equation (15) and outline the main aspects of the estimation procedure. Finally we will discuss endogeneity and identification issues in model estimation.

Model Details

We model the fixed utility from shopping, fu_{hs}, identified in (2) as:

$$fu_{hs} = chain_s \upsilon_{1,h} + \upsilon_2 \cdot assort_s + \upsilon_3 \cdot private_s + \upsilon_4 \cdot distance_{hs}, \qquad (16)$$

where $\upsilon_{1,h}$ represents a vector of chain-specific fixed effect for household *h* (to capture a household's intrinsic preference for a chain), $chain_s$ is a vector of dummy variables for chain *s* whose *m-th* element equals 1 if store *s* belongs to chain *m*, and 0 otherwise. We use the (log of) total number of assortments inside the store, $assort_s$, to proxy for the store size and product availability. The variable $private_s$ is the number of categories with private labels. Since private labels are exclusive to a store, this variable is used as a proxy for the uniqueness of products offered in that store and can be a tool for generating store loyalty (Corstjens and Lal 2000). Note that $assort_s$ and $private_s$ are store specific since we find significant differences across stores within the same chain, probably driven by store size. Finally, $distance_{hs}$ is the travel distance between the household h and store s.[14] As discussed in the introduction, these variables cannot be changed within a short time period, but in general $assort_s$ and $private_s$ are likely to be more flexible than $distance_{hs}$.

To reduce the computational burden we model heterogeneity in the coefficients for the chain-specific fixed effects, $\upsilon_{1,h}$. We assume that, $\upsilon_{1,h} = \upsilon_1 + e_{\upsilon,h}$, where $e_{\upsilon,h} \sim normal(0, \Sigma_\upsilon)$ is a vector of stochastic variables, and Σ_υ is a variance-covariance matrix, which is assumed to be diagonal for simplicity.

Corresponding to equation (3), we specify the probability of reading an advertisement from a store as:

$$\begin{aligned} W_{hst} &= chain_s \rho_1 + \rho_2 \cdot basketspend_{ht} + \rho_3 \cdot income_h + \rho_4 \cdot fedu_h + \rho_5 \cdot femploy_h + \varsigma_{hs} \\ &= \hat{W}_{hst} + \varsigma_{hs}, \end{aligned} \tag{17}$$

where $income_h$ is the (log of) household income level; $fedu_h$ is a dummy variable that equals 1 if the female head of the household has college education or above, and 0 otherwise; $femploy_h$ is a dummy variable that equals 1 if the female head of the household is employed, and 0 otherwise. Other variables are defined as before. To compute the variable $basketspend_{ht}$ we use the average category prices weighted by market share of brands within the category, multiplied by observed purchases Q_{ht} in each period. The stochastic variable ς_{hst} is assumed to be *i.i.d.* over households and stores, with a *Gumbel(0,1)* distribution. The variable $\hat{W}_{hst}$ in the second equality is the deterministic part of the function. This implies that $\Pr(ADs)_{hst} = \exp(\hat{W}_{hst}) / (1 + \exp(\hat{W}_{hst}))$.[15]

We also assume that, for each category c in the brand preference function in (9), $\kappa_{hc} = \kappa_c + e_{\kappa,hc}$, and $e_{\kappa,hc} \sim normal(0, \sigma_\kappa^2)$. Parameters κ_c, $c=1,\ldots,C$, and σ_κ are to be estimated from data.[16]

[14] We can also include a quadratic term in (16) if the effect of travel cost is nonlinear.

[15] The parameters in (17) are restricted to be homogeneous across households. We also estimated an alternative random coefficient model which allows for the unobserved heterogeneity, but the estimates are highly imprecise. The main reason is that we do not observe whether a household reads advertisements or not; hence, this type of the household heterogeneity is difficult to identify from our data.

[16] Again for the sake of simplicity we assume σ_κ to be the same for all categories.

Assuming that ε_{hscjt} in (9) and (10) follow a Gumbel distribution, we arrive at the familiar multinomial logit brand choice model conditional on category purchase $Q_{hsct} > 0$, as:

$$\Pr\{j_{hsct} \mid Q_{hsct} > 0\} = \frac{\exp(b_{hcj} + d_{hc} disp_{scjt} - \lambda_h p_{scjt})}{\sum_{k=1}^{K_c} \exp(b_{hck} + d_{hc} disp_{sckt} - \lambda_h p_{sckt})} \tag{18}$$

Heterogeneity across households in (18) is specified as follows:

$$\begin{aligned} & b_{hcj} = b_{cj} + \sigma_{b,c} \cdot e_{b,hcj}, \\ & d_{hc} = d_{0,c} + d_{1,c} \cdot hhsize_h + d_{2,c} \cdot income_h + \sigma_{d,c} \cdot e_{d,hc}, \\ & \lambda_h = \lambda_0 + \lambda_1 \cdot hhsize_h + \lambda_2 \cdot income_h + \sigma_\lambda e_{\lambda,h}, \\ & e_{b,hcj}, e_{d,hc}, e_{\lambda,h} \sim_{i.i.d.} normal(0,1). \end{aligned} \tag{19}$$

where $hhsize_h$ is the size of household h, and $income_h$ is the (log of) household income.

Let Θ be the full set of model parameters to be estimated from the data. We partition Θ into two parts: $\Theta = \{\Theta^b, \Theta^s\}$, where

$$\Theta^b = \{b_{cj}, \sigma_{b,cj}, \forall c, \forall j; d_{0,c}, d_{1,c}, d_{2,c}, \sigma_{d,c}, \forall c; \lambda_0, \lambda_1, \lambda_2, \sigma_\lambda\}$$

is the set of parameters related to household brand choice to be estimated in (19), and

$$\Theta^s = \{\upsilon_{1m}, \rho_{1m}, m = 1,...,4, \Sigma_{\upsilon\rho}; \upsilon_2, \upsilon_3, \upsilon_4; \rho_2, \rho_3, \rho_4, \rho_5; \delta; \kappa_c, c = 1,...,C, \sigma_\kappa\}$$

is the set of other parameters related to household store choice in the model. Let X_{ht} be the set of explanatory variables in brand and store choice models. The probability function for brand and store choices $\{j_{hst}, s_{ht}\}$ can be written as $\Pr\{j_{hst}, s_{ht} \mid \mathrm{X}_{ht}; \Theta^b, \Theta^s\}$.

Estimation Procedures

We observe from the data both j_{hsct} and s_{ht}, for all *h, s, c*, and *t*. Since brand preferences in (10) are implicitly assumed to be independent of store preferences, and the fact that category preference coefficients κ_{hc} in (9) are the same for every brand in category *c* (and hence will not affect brand choices), we can first directly estimate a brand choice model conditional on category purchases $Q_{hsct} > 0$, i.e., $\Pr\{j_{hst} \mid Q_{hst} > 0\}$ in (18), to obtain consistent estimates for Θ^b. Note that parameters $\{\lambda_0, \lambda_1, \lambda_2, \sigma_\lambda\}$ are assumed to be same across categories. Therefore, we have to estimate the brand choice model in

(18) across all categories simultaneously. Since we assumed that brand choice and store choice decisions are independent the computation burden is reduced.

Since the brand choice model is estimated conditional on purchase, category preference parameter κ_c is not identifiable from that model. Instead, the identification of κ_c comes from the store choice (hence $\kappa_c \in \Theta^s$). All else equal, suppose that promotion on category *c* in one store attracts more households compared with promotion for another category *c'*. We will infer that κ_c is higher than $\kappa_{c'}$ in general. In the second step in the estimation we plug in the consistent estimates $\hat{\Theta}^b$ into the store choice function in (15) to estimate the set of parameters Θ^s . Assuming ω_{hst} in (15) follows a Gumbel distribution we write down the store choice probability as:

$$\Pr_{ht}(s) = \frac{\exp\left(fu_{hs} + vu_{hst} + Z_{ht}\delta \right)}{1 + \sum_{s' \in S} \exp\left(fu_{hs'} + vu_{hs't} + Z_{ht}\delta \right)} \tag{20}$$

where *S* is the set of stores that a household can choose from. Note that the first term in the denominator is to account for the outside option which in our case represents the value of shopping in a store other than the ones in our data (the utility for which is normalized to zero).

Combined with previous discussions in the model section $1_{hst}\{ADs\}$ and expected shopping utility $E[vu_{hst} \mid \hat{\Theta}^b, \Theta^s, 1_{hst}\{ADs\}]$ are probability distributions which have to be integrated in order to get the store choice probability in (20). Since purchase quantity decisions are assumed to be independent from store choices, we can simplify the estimation procedure by plugging in the observed Q_{ht} from the data. Let $\xi_h^b = \{e_{b,hcj}, e_{d,hc}, e_{\lambda,h}, \varepsilon_{ht}\}$ be the vector of stochastic components in the brand choice functions (see (19) and the distribution assumption for ε above) and $\xi_h^s = \{e_{\upsilon,h}, e_\kappa\}$ be the vector of stochastic components in the store choice function. We can now write down the conditional store choice model as:

$$\Pr_{ht}(s \mid Q_{ht}; \hat{\Theta}^b, \Theta^s) = \iint \frac{\exp\left(fu_{hs} + E[vu_{hst} \mid \hat{\Theta}^b, \Theta^s, 1_{hst}\{ADs\}] + Z_{ht}\delta \right)}{1 + \sum_{s' \in S} \exp\left(fu_{hs'} + E[vu_{hs't} \mid \hat{\Theta}^b, \Theta^s, 1_{hs't}\{ADs\}] + Z_{ht}\delta \right)} \times dF\left(\xi_h^b; \hat{\Theta}^b\right) \times dF\left(\xi_h^s; \Theta^s\right) \times dF\left(1_{ht}\{ADs\}\right) \tag{21}$$

where

$$E[vu_{hst} \mid \hat{\Theta}^b, \Theta^s, 1_{hst}\{ADs\}] = \sum_{c=1}^{C} \begin{bmatrix} \int vu_{hsct}(\hat{\Theta}^b, \Theta^s, p^0_{hsct}) \cdot dF(p^0_{hsct} \mid \Omega_{hst}) \cdot \{1_{hst}\{ADs\} = 0\} \\ + vu_{hsct}(\hat{\Theta}^b, \Theta^s, p^1_{sct}) \cdot \{1_{hst}\{ADs\} = 1\} \end{bmatrix},$$

and

$$vu_{hsct}(\hat{\Theta}^b, \Theta^s, p^l_{sct}) = (\kappa_{hc} + \max_{j \in c}\{\hat{b}_{hcj} - \hat{\lambda}_h p^l_{hscjt} + \varepsilon_{hscjt}\}) \cdot Q_{hct}, \quad l = 0,1.$$

where $\hat{b}_{hcj}$ and $\hat{\lambda}_h$ are the estimates obtained from the first-stage brand choice model. This is the store choice model that we estimate.

Simulated Likelihood

Since the advertised and unadvertised prices in stores within the same chain are similar to each other, we assume that store advertisements are set at the chain level. This implies that once a household is exposed to advertised prices at one store in a chain it knows that prices of such items at all stores belonging to that chain. Let Π (with a dimension of 2^4 = 16) be the set of all permutations of $\{1\{Ads\} = 0,1\}$ for the four chains. We can re-write (21) as follows:

$$\Pr_{ht}(s \mid Q_{ht}; \hat{\Theta}^b, \Theta^s) = \iint \left(\sum_{m \in \Pi} \frac{\exp\left(fu_{hs} + E[vu_{hst} \mid \hat{\Theta}^b, \Theta^s, 1^m_{hst}\{ADs\}] + Z_{ht}\delta \right)}{1 + \sum_{s' \in S} \exp\left(fu_{hs'} + E[vu_{hs't} \mid \hat{\Theta}^b, \Theta^s, 1^m_{hs't}\{ADs\}] + Z_{ht}\delta \right)} \Pr(m \in \Pi) \right) \times dF\left(\xi^b_h; \hat{\Theta}^b\right) \times dF\left(\xi^s_h; \Theta^s\right) \tag{22}$$

where $\Pr(m \in \Pi_{AD})$ is the probability of a specific combination of reading newspaper of the four chains $\{1\{Ad_1\}, 1\{Ad_2\}, 1\{Ad_3\}, 1\{Ad_4\}\}$ such that $\sum_{m \in \Pi} \Pr(m \in \Pi) = 1$, and the probability function of each $1\{Ad_s\}$ is given in (17).

The computational challenge for us is that the integrals in (21) and (22) have no closed forms, so we resort to simulation procedures (see Hajivassiliou and Ruud (1994) for properties of simulated likelihood estimator). In particular, for each household *h*, we make NS_1 [17] draws for $\{\xi^b_h, \xi^s_h\}^n$, where $n=1,\ldots,NS_1$, from distribution functions

[17] NS_1 is equal to 100 in our model estimation.

$dF\left(\xi_h^b;\hat{\Theta}^b\right)\times dF\left(\xi_h^s;\Theta^s\right)$. Next we plug into the functions of fu_{hs} and $E[vu_{hst} \mid \hat{\Theta}^b,\Theta^s,1_{hst}^m\{ADs\}]$ in (22) to form the corresponding simulated parts $fu_{hs}{}^n$ and $E[vu_{hst} \mid \hat{\Theta}^b,\Theta^s,1_{hst}^m\{ADs\}]^n$. The simulated probability function can then be written as

$$\Pr_{ht}^{sim}(s \mid Q_{ht};\hat{\Theta}^b,\Theta^s)=\frac{1}{NS_1}\sum_{n=1}^{NS_1}\sum_{m\in\Pi}\frac{\exp\left(fu_{hs}{}^n+E[vu_{hst} \mid \hat{\Theta}^b,\Theta^s,1_{hst}^m\{ADs\}]^n+Z_{ht}\delta\right)}{1+\sum_{s'\in S}\exp\left(fu_{hs'}{}^n+E[vu_{hs't} \mid \hat{\Theta}^b,\Theta^s,1_{hs't}^m\{ADs\}]^n+Z_{ht}\delta\right)} \times\Pr(m\in\Pi) \tag{23}$$

Given that $vu_{hsct}(\hat{\Theta}^b,\Theta^s,p_{sct}^l)=(\kappa_{hc}+\max_{j\in c}\{\hat{b}_{hcj}-\hat{\lambda}_h p_{hscjt}^l+\varepsilon_{hscjt}\})\cdot Q_{hct}$, *l=0,1,* for each draw $\{\xi_h^b,\xi_h^s\}^n$, we will have the simulated $\{\kappa_{hc}^n,\hat{b}_{hcj}^n,\hat{\lambda}_h^n,\varepsilon_{hscjt}^n\}$. As discussed above, if $1_{hst}^m\{ADs\}=1$ households know that the prices in stores are either regular prices p_{st}^r or advertised prices p_{st}. However, if $1_{hst}^m\{ADs\}=0$, price expectations follow a distribution $F(p_{hsct}^0 \mid \Omega_{hst})$. This requires another level of simulations (draw prices from $F(p_{hsct}^0 \mid \Omega_{hst})$) to compute the value of $\int vu_{hsct}(\hat{\Theta}^b,\Theta^s,p_{hsct}^0)\cdot dF(p_{hsct}^0 \mid \Omega_{hst})\cdot\{1_{hst}\{ADs\}=0\}$, given each pair of draws $\{\xi_h^b,\xi_h^s\}^n$. To simulate these prices, we first use the observed empirical distributions of prices, of all brands in all categories in each store, from the data to represent $F(p_{hsct}^0 \mid \Omega_{hst})$.[18] Then we randomly draw prices from these empirical distributions, and plug in to compute the expected $E[vu_{hst} \mid \hat{\Theta}^b,\Theta^s,1_{hst}^m\{ADs\}=0]$. That is, given the draws $\{\xi_h^b,\xi_h^s\}^n$,

$$E[vu_{hst} \mid \hat{\Theta}^b,\Theta^s,1_{hst}^m\{ADs\}]^n = \sum_{c=1}^{C}\left[\begin{array}{l}\kappa_{hc}^n+\left\{1_{hst}^m\{ADs\}=1\right\}\cdot\max_{j\in C}(\hat{b}_{hcj}^n-\hat{\lambda}_h^n p_{hscjt}^1+\varepsilon_{hscjt}^n)+\\ \left\{1_{hst}^m\{ADs\}=0\right\}\cdot\frac{1}{NS_2}\sum_{k=1}^{NS_2}\max_{j\in C}(\hat{b}_{hcj}^n-\hat{\lambda}_h^n p_{hscjt}^{0,k}+\varepsilon_{hscjt}^n)\end{array}\right]\cdot Q_{hct} \tag{24}$$

[18] When simulating $F(p_{hsct}^0 \mid \Omega_{hst})$ we also account for the seasonality effects. Specifically, we break down our sample by quarters and use the observed prices during each quarter to compile the empirical price distributions.

where NS_2 is the number of simulated price draws.[19] As discussed above, we do not need to draw p^1_{hscjt} as they are assumed to be known with no uncertainty.

Finally, we can calculate the store choice probability function in (23), and compute the simulated likelihood function

$$L = \prod_{h=1}^{H} \prod_{s=1}^{S} \prod_{t=1}^{T} \Pr_{ht}^{sim}(s)^{1_{hst}} \tag{25}$$

where 1_{hst} is an indicator function that is equal to 1 is household h visits store s at time t, and 0 otherwise. We iterate the set of parameters:
$\Theta^s = \{\upsilon_{1m}, \rho_{1m}, m = 1,...,4, \Sigma_{\upsilon\rho}; \upsilon_2, \upsilon_3, \upsilon_4; \rho_2, \rho_3, \rho_4, \rho_5; \delta; \kappa_c, c = 1,..., C, \sigma_\kappa\}$ until the likelihood function L in (25) is maximized.

Endogeneity and Identification Issues

A potential concern in our analysis is that we treat prices and other marketing mix policies including product displays and features as exogenous. It is conceivable that stores adjust prices each period based on their expectation of consumer demand and competitive environment. For example, according to the loss-leader pricing literature, stores may tend to promote some categories with higher seasonal demand by cutting prices and advertising. It is difficult for us to find sufficient instruments for prices at all stores, categories, and brands for every period. Therefore, traditional IV method is infeasible. However, we have a better set of "control" variables in our store choice model than traditional choice models. First, we explicitly include the time-varying consumption needs through Q_{hct} . Hence, the correlations between changes in demand, due to seasonality or holiday factors, and store marketing mix variables are accounted for in our model. Second, a store could price more aggressively due to the proximity of competing stores than another store that is relatively more isolated. This is accounted for in our model since we explicitly include the travel distances between households and stores. By incorporating those variables in the model, we believe that the issue of price endogeneity has been controlled for though not completely addressed.

Regarding the identification issue, we will focus on the identification of the store choice probability function here as identification issues in the brand choice model are

[19] NS_2 is equal to 100 in model estimation. Note that we have to draw the price of every brand in every category in the store in each draw.

standard. Conditional on the variable utility of visiting stores, the identification of parameters δ's in equation (14) comes from the share of shopping trips at inside stores relative to the outside option (stores not included in estimation) since $Z_{ht}\delta$ changes the household utility equally for every inside store. The identification of parameters υ's in equation (16) that are related to household's store preference comes from the relative market share among inside stores. For example, conditional on other variables, a household who visits chain 3 more frequently implies that its preference for chain 3 in $\upsilon_{1,h}$ is higher than the others. If households are observed to visit stores with larger assortments or more private labels more frequently, it implies that, conditional on other variables, larger assortments or more private labels makes the store more attractive and hence υ_2 and υ_3 in equation (16) will be positive. Finally, if households frequent stores closer to their homes, it implies disutility from travel and hence υ_4 will be negative.

The major difficulty of model identification comes from the equation describing the probability of reading advertisements in equation (17). We estimate the parameters of the function W_{hst} but do not observe from data whether a household reads store newspapers or not. Instead, these parameters are inferred from households' observed shopping trips and stores' feature advertising activities. For example, if households in data are more responsive to feature advertising of chain 3 relative to other chains this implies that chain 3's feature advertising is read by more households and hence ρ_1 for chain 3 in equation (17) will be larger than that for other chains. Similarly, differences in responsiveness to feature advertisement by households with different shopping basket sizes or demographics help to infer other parameters. For example, if a household with high income is found to shop more often in stores that are more expensive compared to other nearby stores, we will infer that the coefficient ρ_3 is negative. Of course, this requires our data to have sufficient variations in featured items in different weeks across chains/stores.

5. Results

In the first step, we estimate the brand choice model in the 25 categories (simultaneously) to obtain consistent estimates of $\hat{\Theta}^b$. Since this step is only a vehicle for estimating the store choice model in which we are interested, we do not report $\hat{\Theta}^b$ in order to conserve space.[20] Most of the parameter estimates had correct sign and reasonable magnitude. The estimated price coefficient is -.34 (with std. error .02) and its magnitude is smaller for higher income households.

In the second step, we estimate the store choice model by substituting $\hat{\Theta}^b$ and using simulation methods as in equation (23). As discussed before, for some fill-in trips in which households only buy small quantity to satisfy some urgent needs, households may not fully evaluate the benefits and costs of shopping in all stores and their decisions may solely rely on convenience of traveling to stores from home or work place, or on past shopping choices. To address this issue, we estimate the store choice model based on two sets of data (i) all the shopping trips (46,727 trips) and (ii) only the major shopping trip within a week, i.e., the shopping trip with the largest shopping basket (25,291 trips).[21] In the appendix we compare the results from the two models. Comparing the two sets of results, most estimates are similar to each other and quite reasonable. However, the all-shopping trip model does not provide reasonable estimates for the reading advertising probability function. In particular, chain intercepts have large standard errors. In addition, reading rate for chain 1 is estimated to be the highest (31 percent), which seems counterintuitive considering that chain 1 is only a small player in the market. In what follows, we use the major shopping trips as the basis for our discussion of the estimation results and for conducting the policy experiments.

Parameter Estimates from the Store-Choice Model

Table 5 reports the estimation results from the major shopping trip model. We first discuss the fixed utility function (see equation (16)) estimates, and then the parameters representing the probability of reading feature advertisements (see equation (17)). Most results in the fixed utility function are reasonable. For example, chains 3 and 4, which have the largest per store sales in our data, are preferred more compared to chains 1 and 2. The coefficient for travel distance (*Distance*) is significantly negative,

[20] The results are available from the first author upon request.
[21] One may define a major shopping trip using other criteria such as shopping expenditure above the mean or median for each household. It is also possible to model whether a trip belongs to major shopping trip or others more structurally. However, this approach will complicate model estimation. We also suspect that this model is hard to identify from our data.

which is consistent with the general notion that proximity to stores plays an important role in store choice decisions. Assuming a price coefficient of -.34 (from the first-stage model), this result implies that a household is willing to travel one extra mile in order to save $3.1 on its shopping basket. This amount will be larger for higher income households. The relatively large standard deviations of the estimates imply that there is significant heterogeneity across households.

The coefficient for the total number of assortments in store (*# of Assortment*) is significantly negative, implying that a larger store with more products offered is less attractive to households. Though this result seems puzzling, note that the coefficient for the interaction term (*# of Assortment*# of expected purchase items)* is significantly positive. This implies that a large store will be more (less) attractive to households if the planned shopping basket is large (small). For example, store assortments will have a positive impact on the store choice when the number of the expected purchase items is 7 or above. The significantly positive coefficient for *Private Label* implies that consumers prefer stores with a larger number of categories with private label, perhaps because its availability increases the uniqueness of product offerings at the store. Finally, the coefficient for household size is significantly negative and the coefficient for household income is positive, suggesting that smaller and higher income households prefer to shop at the stores in our data compared with outside alternatives (stores not included in our sample).

Looking at the parameters representing the probability of reading feature advertisements, the coefficients for chains 2, 3, and 4 are all significantly larger than that for chain 1. Household income is not a significant factor in reading ad probability but the coefficient for Female Head Education (equals *1* if education level for the female head in a household is college or above) is significantly negative, implying that more educated female customers pay less attention to store feature advertising. Other estimates in the model also seem reasonable but are not statistically significant. We also compute the average reading rate of feature advertising over the sample period for all households based on these estimation results. The model predicts the highest reading rates for chains 3 and 4 (23 and 33 percent, respectively) and the lowest for chain 1 (3 percent).

Model Fit

In order to evaluate how good our model fits the observed data, we use the parameter estimates to predict household's store choice on each shopping trip and compute the hit rate by comparing these predictions with the observed choices. Overall the model achieves a high hit rate (47.8 percent), considering that we allow households to choose among 31 stores contained in our data

How much value does modeling reading advertising add to the store choice model? In order to address this issue, we re-estimate the model assuming that households know all store prices before their store visits (i.e., full price information), and feature advertising only affects brand choices. The log-likelihood for the full-information model is -174,777 compared with -101,122 in our model, indicating that our proposed model clearly dominates the model that assumes full price information in terms of sample fit. Although not reported to conserve space, we also found significant differences in some parameter estimates when comparing these two approaches. However, we discuss the implied differences in the cross-store substitution patterns from the two approaches below.

Marginal Effects

To understand the effects of various factors on store visit decisions, in Table 6 we compute the marginal effects on store visits when the value of a specific factor changes at the chain level. Each entry represents the marginal effect on a chain due to a 1% change in the row variable. For example, to compute the effects of chain prices changes, we assume that the price of every SKU inside all stores within same chain increases by 1 percent in all weeks. Results show that on average store traffic will reduce 0.04 to 0.17 percent. Price promotions by chain 3, the chain with the largest market share and most stores, have the largest negative impacts on its competitors. We also compute the marginal effect of travel distance by increasing the travel distance of all households to every store within the same chain by 1 percent. Results show that store visits will decrease by about 0.02 to 0.10 percent. It is interesting to note that for chains 1 and 4, the chains with fewer stores (see Table 1) and with more sparse geographic distribution (see Fig. 3), a one percent reduction in prices has similar effect on increasing store visits as a one percent decrease in travel distance, while for chains 2 and 3 (the chains with more stores), the former effect is stronger. This is an intuitive result: most stores that belong to chains 1 and 4 are located away from the densely populated areas (within our sample households); hence, shortening travel distance will have a stronger impact. The marginal effect for a 1 percent increase in reading advertising probability is much smaller, when compared with that of other factors, partly because the estimated proportion of households that read advertising is relatively small (3 to 33 percent from estimation results). Finally, it is also interesting to see that the impact of increasing private labels is next only to price cuts, suggesting the importance of using private label to attract store traffic. These results are generally consistent with findings from the previous literature on store choice (Bell and Lattin 1998, Bell, Ho, and Tang 1998, Briesch, Chintagunta, and Fox 2005).

6. Policy Experiments

In this section we use the estimates from the model to conduct a variety of policy experiments to understand cross-store substitutability as well as the effectiveness of price promotion at different time periods. In particular, we study the impact on store traffic and store revenues due to changes in (1) aggregate store-level prices, (2) prices for individual product categories, and (3) price for specific brands in a category. For changes at category and brand level (corresponding to 2 & 3), we also study the role of demand differences at different time periods due to seasonality. In Section 6.2 we study another issue that has received considerable interest in the recent retailing literature: *micromarketing* or firm's ability to charge different prices at different outlets.

6.1: Store Traffic and Revenues

In this section we carry out several counter-factual experiments to study the impact on total store traffic and revenues due to changes in pricing policies. In particular we address the following issues:

a. What is the cross-store substitution pattern due to an overall change in store prices? How does the pattern depend on the store location vis-à-vis its competitors and customers?

b. What is the cross-store substitution pattern due to category-specific price changes? Since household consumption needs are time-varying, how does the category-specific pattern depend on seasonality?

c. What is the impact on brand, category, and total store revenue when a store offers price promotion on a single brand (e.g., loss-leader item)? How does this impact vary at different price levels and during different time periods?

a. Cross-Store Substitution Patterns

To investigate the cross-store substitution relationship due to a store-wide change in prices, we select four stores from our sample (see Figure 3 for their geographical locations). Store A belongs to chain 2, stores B and C belong to chain 3, and store D belongs to chain 4. While stores B, C, and D are located close to each other and hence likely to compete head-to-head, store A is relatively far away. Our research question here is how, relative to other factors, store locations affect their substitution patterns. We assume that the price of every SKU at a store is increased by 1 percent for all weeks, and simulate the resulting store choice and purchase decisions for the 300 households over the 25 product categories in our data.[22] Since the price change is over the whole sample period, we adjust the advertised and expected regular prices if households read feature advertising, and the expected price distributions if households do not read, by 1 percent, correspondingly. The left-side panel in Table 7 reports the simulated cross-elasticities in store traffic and store revenue[23] for the four stores using the proposed model. As expected, stores B, C, and D are closer substitutes with each other than with store A, as shown by the larger magnitudes of store traffic and revenue cross-elasticities. The substitution between A and other stores is almost negligible. Stores B and C are the closest substitutes since they are located near each other and belong to the same chain. Households that have a high preference for the chain and informed of the prices are likely to switch between the two stores depending on which store offers better deal. This

[22] Since we only have 25 product categories in data, which do not cover the whole shopping basket, our results for store revenues can only be interpreted as the lower bound of the aggregate impacts. Similarly, since we do not observe shopping trips if households purchase products out of the 25 categories, the results for store visits should be interpreted as the lower bound.

[23] Note that cross-elasticities here are in store *revenue* change of the 25 product categories, which is different from the usual definition of demand elasticity that is based on *quantity* change.

exercise demonstrates how one can use the results to understand how location and chain characteristics affect inter store rivalry.

The right-side panel in Table 7 reports the cross-elasticities using the model that assumes perfect price information for households. While the substitution patterns are similar, the own-price elasticities are smaller in magnitude. For example, the own-price elasticities in store traffic and revenue for store C are -2.7 and -5.1, respectively, compared with -3.3 and -6.1 from the proposed model. Cross-store elasticities are also under-estimated. That, the perfect price information model is mis-specified and why the estimated price elasticities are downward-biased is easy to see. Since perfect price information is assumed, lack of switching is attributed to other factors such as location and chain characteristics leading to a downward bias in the estimated elasticities.

b. Category-Specific Price Changes

We next investigate the cross-store substitution pattern (again in terms of store visit and aggregate store revenue) due to category-specific price changes. Since household consumption needs for specific categories may change over time due to seasonality, this exercise helps us to answer an important managerial question: Which categories are more effective in increasing store visits and revenues using price promotion at different times? To address this issue, we need to understand not only the time-varying category-specific consumption needs but also the buyers' entire shopping baskets. For example, if households that purchase a specific category are those with a smaller shopping basket, price promotion for this category may not increase store revenue. In this exercise we choose two product categories: canned soup and carbonated soft drinks (CSD). Both these categories demonstrate a strong seasonality effect in the data: demand for canned soup is strong in winter (see Figure 5), and demand for CSD is stronger in summer. On average, canned soup is bought only about 4 percent of the time and is one of the smallest categories in terms of a household's total expenditure while CSD is the most frequently bought (about 32 percent) and is second largest in terms of expenditure (13 percent). Our question here is how does the effectiveness of price promotion, in terms of store traffic and revenue, vary by category and seasonality. We break down our sample periods by seasons, and assume that the price of every SKU in the CSD and soup categories, is increased by 1 percent in summer and winter, respectively. We then simulate the store choice and purchase decisions of the 300 households over the 25 product categories. We adjust the advertised and expected regular prices if households read feature advertising, and the expected price distributions if households do not read by 1 percent, correspondingly.

To study the impact of category level price changes we use the same four stores mentioned above. The upper panel in Table 8 reports the cross-store price elasticities in store traffic and aggregate revenue. Several key observations here: First, the cross-store substitution pattern is very similar to the results in the previous section, that is, stores B, C and D are closer substitutes with each other than with store A, and stores B and C are the closest substitutes. Second, correlated with the seasonal demand for these categories, elasticities are larger during summer for CSD but smaller for canned soup. Hence, from the store's perspective, CSD will be more attractive to be used as a category for price promotion in summer to generate store traffic, while canned soup will be more attractive during winter. Third, elasticities for CSD are much larger than canned soup in both summer and winter, reflecting the fact that CSD is a category that households purchase more frequently and spend more on. Therefore, it is not surprising to find in our data that CSD is more frequently promoted in all stores. Finally, the external benefits to store from price changes within a category are significant. For example, a one percent price cut for CSD in store C will generate a 0.8 percent increase in store traffic and a 1.8 percent increase in store revenue, reflecting the fact that households are buying multiple categories once they are inside the store.

The exercise above ignores the fact the two of the stores (stores B & C) belong to the same chain. It is possible that price changes have to be implemented at the chain level for administrative reasons. In our data, price changes at stores that belong to the same chain are highly correlated. We next conduct the same exercise as above but assuming that the prices of CSD and canned soup increase by 1 percent among all stores that belong to the same chain. The results are in the lower panel in Table 8. The substitution patterns are consistent with our findings above, though the magnitudes seem to be smaller probably due to cannibalization among promoting stores. Cross-elasticities of chain 3, the chain with the largest number of stores and the market share, with others are the largest, implying that chain 3 is the major competitor to other chains in the market.

c. Brand-Level Pricing Experiments

The two exercises above were based on price changes for all SKUs in a category or all SKUs in the store. Since our store choice model is built upon brand consumption preferences, we can also conduct pricing experiments at the brand level. For example, stores may be interested to know which brand should be used for promotion during different periods in order to attract more store traffic and how that will change aggregate store revenue. We do not conduct extensive pricing experiments that involve different combinations of price levels among different brands. Instead, we focus on a single brand – Coca-Cola in the CSD category. As discussed above, CSD is the category that is most frequently purchased (about 32 percent) and is second largest in terms of the household total expenditure (13 percent). Coca-Cola is the second largest brand with 21% of market share in the category (Pepsi is the largest with 31% of market share). For this exercise, we focus on price changes at store D (see Figure 3), which belongs to chain 4 and is one of the largest stores in our data. We choose two weeks for the exercise, one during summer where demand is at the peak, and one during winter when demand is low. We then compute the estimated revenue for store D when Coca-Cola is at the regular price. We break down the revenue at the brand (Coca-Cola), category (CSD), and store level. Next we compute the changes in these estimated revenues under 4 scenarios (see Table 11) price of Coca-Cola (i) decreases by 20%; (ii) decreases by 10%; (iii) increases by 10%; and (iv) increases by 20%.

Table 9 reports the results. Brand revenue increases when the price is cut, and decreases when the price increases, implying that demand for Coca-Cola is elastic. Interestingly, we find that category revenue also increases when price is cut, implying that the increase in store traffic is large enough to overcome any loss in revenue due to substitution. This occurs even during the low demand week in winter (e.g., store traffic increases by 1.3 percent in the summer week and 0.6 percent in the winter week when the price decreases by 20 percent). Finally, impact on aggregate store revenue is positive when store D lowers the price, and vice versa when it increases the price. Store revenue increase changes by 0.8 percent when price promotion goes deeper from 10 to 20 percent, implying that there is still room for the store to offer even bigger discount in order to attract more traffic.

The impact on store revenue in summer is more than twice the impact in winter though the differences on brand and category revenues are not that large. Although it is well recognized, our results quantify the spillover effects to store because of the price promotion on a single product, as customers attracted to the store will purchase other items in store. Finally, we find that most of the switching households are from those who would have shopped in other stores that belong to chain 4 and in store B, the main competitor whose location is close to store D.

6.2. Store-Level Pricing

In this section we address another managerial question. If a chain can set different prices at different stores what factors should drive such a decision? This is analogous to the zone pricing policy, i.e., setting prices differently for stores in different local areas depending on the demographics and competitive environment (Montgomery (1998), Chintagunta et al. (2002), and Khan and Jain (2005)). These authors use aggregate store-level data from a retail chain (Dominick's Finer Foods in Chicago) to study the impact on category profits by moving from a uniform pricing policy to a zonal or store-level pricing. We build and improve on these earlier papers in several ways. First, while these papers rely on distance measures to proxy for competition we use sales and price data from competing retailers. Similarly, these papers use a single category and thus they do not capture the spillover effects that arise when households, attracted to the store due to promotion in a category, spend on other categories as well. In contrast, in our framework store visit decisions and expenditures are linked to brand choice in a category. Thus we can use our results to analyze the competitive patterns either at the category or aggregate store level. Given the multi-product nature of retailing, we consider these issues to be important from a managerial perspective. As an extension to this literature, we also investigate the impact of short- vs. long-term changes in pricing policy. The major difference here is in the price information for most households: short-term price fluctuations are assumed to be unexpected for households if they do not read feature advertising, while long-term pricing policy change will be known by households since it is stable overtime.

We select two stores, B and E, both from chain 3 to conduct this store pricing experiment (see Figure 3). They are chosen because both are located in densely populated areas (for our sample households) and are the two stores with the largest market share (B about 13 percent higher than E in revenue). However, while store B is close to other competing stores and to another store (store C) belonging to the same chain, store E is relatively isolated from competition. Suppose chain 3 changes prices for B and/or E during the two weeks before and during Christmas (the two weeks with the highest total grocery spending in data). What is the impact of price changes on these two stores as well as for the chain? We do not conduct extensive pricing experiments that involve different levels of price changes for different categories in the two stores. Instead, we only analyze the changes in store and chain revenues in the two weeks before and during Christmas under the six scenarios (see Table 10):

(i) Prices of all SKUs in both stores decrease by 10 percent during these two weeks (B=0.9, E=0.9)

(ii) Prices of all SKUs in store B decrease by 10 percent while that of store E remain the same (B=0.9, E=1)

(iii) Prices of all SKUs in store E decrease by 10 percent while that of store B remain the same (B=1, E=0.9)

(iv) Prices of all SKUs in both stores increase by 10 percent (B=1.1, E=1.1)

(v) Prices of all SKUs in store B increase by 10 percent while that of store E remain the same (B=1.1, E=1)

(vi) Prices of all SKUs in store E increase by 10 percent while that of store B remain the same (B=1, E=1.1).

We also simulate the results under two different conditions: short-term pricing changes and long-term pricing changes. Under short-term pricing changes households are not aware of the new policy. They only understand the price changes if they read store advertising and find the items featured, otherwise their perceived regular prices (when they read store advertising and do not find the items promoted there) and the expected price distributions (when they do not read store advertising) remain the same as before the new policy change. In contrast, long-term pricing changes simulate the scenario that households are well-informed of the overall store price changes. Hence, their perceived regular prices and expected price distributions will change correspondingly.

The computed price elasticities of store and chain revenues are reported in table 10.[24] Since stores B and E are in separate markets the cross-store elasticities are low. We also find that though store E has larger price elasticity when its prices decrease, prices reduction in E generates a lower increase in chain revenue than that in B. On the other hand, prices increase in E will lower the chain revenue less than prices increase in B. This result is quite reasonable, considering that the local market area where E is located is less competitive than the area B is located. One of the major implications from these results is that chain 3 may choose store B if it decides to reduce price level for one of the two stores. However, if chain 3 decides to increase price level due to increase in costs, it may choose to increase price for store E.

When comparing the results between short- and long-term policy changes, it is interesting to see that the store level revenue changes for the latter are much larger than the former. This is because only a fraction of households who read the store advertising are aware of the price changes under short-term policies. However, the chain-level revenue changes under long-term policies are smaller than under short-term policies. This seemingly counter-intuitive result is mainly due to cannibalization of sales from other stores within chain 3. As all households are aware of the price changes in long run, most of them who would have shopped in other stores belonging to chain 3 will switch to B and/or E when there are price reductions (as these are households loyal to the chain) , and vice versa for price increases. Hence, the results show that, at least for the two weeks before and during Christmas, short-term price changes in either or both of the two stores are more beneficial to chain 3 than when customers are fully aware of the changes.

7. Conclusion

Supermarkets operate with low net margins and many of a retailer's short-term activities such as promotions on traffic building categories (loss-leader pricing), as well as long term strategies such as adding ancillary services to provide one-stop-shopping are dictated by a desire to influence consumer store choice to increase store traffic. For store managers understanding the fundamental drivers of consumers' store choice decisions is

[24] Estimated percentages of revenue changes are equal to the estimated elasticities multiplied by 0.1, the percent of price change.

critical. We develop a comprehensive model of store choice that incorporates many elements of retailer's long-term strategic decisions as well short-term price promotions. Building on the past literature, we model the total utility of a consumer from a shopping trip as consisting of a fixed and a variable component. The fixed component of the utility consists of time invariant factors such as distance to the store while the variable component is the sum of the expected utility generated from all products in consumer's shopping list. A novel feature of our modeling approach compared to the previous literature is how we capture consumer's desire to search for price information, consumers' time-varying consumption needs for different products and the interactions between effectiveness of store promotion policies and time-varying consumption needs.

The model is calibrated on a rich scanner panel data that covers a relatively complete list of stores and their marketing mix policies in the market. The parameter estimates are used to conduct a variety of policy simulations for optimal pricing/promotion decisions. Our proposed model is found to fit the observed data well. Results indicate that several factors affecting the fixed utility such as availability of private labels and distance to the store are important determinants of store choice. We also find high-penetration categories to be more influential in generating store traffic and revenues than lower penetration product categories. Our results show that it is important to take into account consumers' time-varying consumption needs as the ability of individual brands or product category in generating traffic and revenues varies systematically across time periods due to seasonal demand differences.

There are of course some caveats to our analysis and directions for future research. First, as discussed in the data section, we do not observe households' purchase histories from several key product categories such as meat, produce, and other perishables. In addition, availability and quality of products in departments such as deli, bakery and HMR (home meal replacement) can be an important source of differentiation and store loyalty that we do not have in our data. From a modeling perspective, it would be interesting to explicitly incorporate supply side retail competition as well consumer dynamics in the store choice model. Finally, we treat both the short-term marketing mix activities as well long-term investments such as store location, size, and private label program as exogenous. It would be interesting to endogenize some of these in future research.

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Chain	# of Stores	Market Share (All Trips)	Market Share (Major Trips)
1	5	6.91%	6.26%
2	11	16.45%	16.63%
3	12	39.25%	40.98%
4	3	11.54%	12.27%
Outside	104	25.85%	23.85%

Table 1: Market Share of Major Grocery Chains

Number of Different Stores Visited	# of Consumers	% of All Consumers
1	1	0.33%
2	19	6.33%
3	40	13.33%
4	83	27.67%
5	69	23.00%
6	54	18.00%
7	16	5.33%
8	11	3.67%
9	3	1.00%
10	1	0.33%
≥ 11	3	1.00%

Table 2: Number of Different Stores Visited over 98 weeks

Categories	% of total spending	Average expenditure per trip	% of trips with purchase
Fruit Juice	2.23	2.8	7.12
Pasta Sauce	1.85	2.42	6.84
Can Soup	3.97	2.5	14.19
Soup Mix	1.04	1.74	5.32
Pasta	1.42	1.84	6.88
Cereal	14.77	6.24	21.15
Crackers	2.26	2.36	8.57
Syrup	5.81	3.12	16.66
Frosting	0.39	1.99	1.73
Cake Mmix	0.45	1.56	2.6
Cookies	0.92	2.85	2.87
Jams and Jelly	0.41	2.28	1.6
Peanut Butter	1.2	2.82	3.8
Ice Tea	0.7	2.3	2.73
Coffee	4.55	4.74	8.58
CSD	13.27	3.69	32.13
Soft Drink	6.79	3.37	18.04
Waffles	1.1	2.72	3.62
Frozen OJ	4.08	2.83	12.89
Icecream	3.45	3.15	9.78
Margarine	2.31	1.58	13.09
Butter	0.93	2.31	3.59
Milk	12.51	2.74	40.87
Beer	7.9	9.61	7.35
Detergent	5.7	5.11	9.96

Table 3: Some Summary Statistics of Category Purchases

	Mean	Median	Std Dev	Minimum	Maximum
Shopping Basket $	$12.91	$7.70	$15.88	$0.18	$509.38
# of Categories	2.18	2.00	1.56	1	14

Table 4: Summary Statistics on Household Shopping Basket

	Estimate	Std Dev
Fixed Utility Function		
Intercept	-7.67	2.78
Chain 2	-6.30	1.09
Chain 3	10.43	0.90
Chain 4	8.08	0.91
Std Dev for Intercept	-13.96	0.79
Std Dev for Chain 2	30.63	0.44
Std Dev for Chain 3	5.42	0.43
Std Dev for Chain 4	5.44	0.38
Travel Distance	-1.06	0.02
Std dev for Travel Distance	0.44	0.01
log(# of upc)	-1.50	0.56
Log(# of upc) * # of expected purchase items	0.23	0.02
log(# of categories with private label)	3.69	0.27
Log(Income)	-0.22	0.13
HH Size	-0.53	0.07
Probability Function of Reading Ads		
Intercept	-2.14	2.82
Chain 2	2.15	1.27
Chain 3	2.48	1.22
Chain 4	3.00	1.21
Expected Basket Cost	-0.01	0.01
Log(Income)	-0.11	0.22
Female Head Education	-0.93	0.31
Female Head Employment	-0.37	0.27
# of Observations	25291	
Log-Likelihood	-101122	
Hit Rate	47.8%	

Table 5: Some Estimates from the Store Choice Model

Marginal Effects on Chain's Share of Store Visits	Chain 1	Chain 2	Chain 3	Chain 4
Travel distance for Chain 1	-0.0003	0.0000	0.0001	0.0000
Travel distance for Chain 2	0.0000	-0.0002	0.0001	0.0000
Travel distance for Chain 3	0.0001	0.0001	-0.0010	0.0002
Travel distance for Chain 4	0.0000	0.0000	0.0003	-0.0006
Assortment for Chain 1	-0.0001	0.0000	0.0000	0.0000
Assortment for Chain 2	0.0000	-0.0001	0.0000	0.0000
Assortment for Chain 3	0.0000	0.0000	-0.0004	0.0001
Assortment for Chain 4	0.0000	0.0000	0.0001	-0.0002
Private Label for Chain 1	0.0003	0.0000	-0.0001	0.0000
Private Label for Chain 2	0.0000	0.0003	-0.0002	0.0000
Private Label for Chain 3	-0.0001	-0.0002	0.0015	-0.0003
Private Label for Chain 4	0.0000	0.0000	-0.0003	0.0006
Price of Chain 1	-0.0004	0.0000	0.0002	0.0000
Price of Chain 2	0.0000	-0.0005	0.0002	0.0001
Price of Chain 3	0.0001	0.0002	-0.0017	0.0003
Price of Chain 4	0.0000	0.0000	0.0004	-0.0007
Prob for Reading AD Chain 1	0.00001	0.00000	0.00000	0.00000
Prob for Reading AD Chain 2	0.00000	0.00002	-0.00001	-0.00001
Prob for Reading AD Chain 3	0.00000	-0.00001	0.00000	-0.00004
Prob for Reading AD Chain 4	-0.00001	-0.00002	-0.00009	0.00016

Note: Entry in any cell is the elasticity of the column variable w.r.t the row factor

Table 6: Own- and Cross Marginal Effects of Various Factors on Store Visits

	Proposed Model					Perfect Price Information			
	Store A	Store B	Store C	Store D		Store A	Store B	Store C	Store D
Store A	-0.71	0.02	0.00	0.02	Store A	-0.58	0.02	0.00	0.01
	-1.57	0.05	0.00	0.04		-1.29	0.06	0.00	0.04
Store B	0.01	-0.98	0.31	0.13	Store B	0.01	-0.77	0.25	0.09
	0.01	-1.85	0.59	0.23		0.02	-1.58	0.49	0.18
Store C	0.00	2.19	-3.25	0.11	Store C	0.00	1.86	-2.72	0.08
	0.01	4.19	-6.05	0.20		0.01	3.53	-5.06	0.15
Store D	0.01	0.21	0.03	-0.88	Store D	0.01	0.21	0.02	-0.66
	0.02	0.35	0.04	-1.65		0.03	0.43	0.05	-1.40

Note; In each cell the first number refers to elasticity w.r.t store traffic and the number below w.r.t to store revenue.
These numbers are elasticities w.r.t the prices of all products in the 'row' store.

Table 7: Cross-Store Substitution Patterns under Different Price Information

A. Store-Level Cross-Substitution Patterns

	Summer					Winter			
Soup	**Store A**	**Store B**	**Store C**	**Store D**	***Soup***	**Store A**	**Store B**	**Store C**	**Store D**
Store A	-0.013	0.001	0.001	0.001	**Store A**	-0.025	0.001	0.000	0.000
	-0.024	0.001	0.000	0.001		-0.041	0.001	0.000	0.001
Store B	0.000	-0.023	0.007	0.003	**Store B**	0.000	-0.050	0.016	0.006
	0.000	-0.041	0.012	0.005		0.000	-0.087	0.031	0.010
Store C	0.000	0.046	-0.068	0.002	**Store C**	0.000	0.105	-0.167	0.006
	0.000	0.078	-0.114	0.004		0.000	0.200	-0.306	0.010
Store D	0.000	0.006	0.001	-0.020	**Store D**	0.000	0.013	0.002	-0.038
	0.000	0.009	0.001	-0.029		0.000	0.019	0.003	-0.054

CSD	**Store A**	**Store B**	**Store C**	**Store D**	***CSD***	**Store A**	**Store B**	**Store C**	**Store D**
Store A	-0.226	0.006	0.001	0.005	**Store A**	-0.193	0.005	0.000	0.005
	-0.640	0.015	0.001	0.012		-0.502	0.019	0.001	0.015
Store B	0.002	-0.253	0.080	0.036	**Store B**	0.002	-0.198	0.055	0.030
	0.005	-0.573	0.173	0.062		0.006	-0.434	0.110	0.049
Store C	0.001	0.553	-0.848	0.025	**Store C**	0.001	0.359	-0.564	0.022
	0.003	1.189	-1.820	0.042		0.003	0.735	-1.167	0.036
Store D	0.002	0.039	0.004	-0.265	**Store D**	0.002	0.029	0.003	-0.219
	0.005	0.079	0.008	-0.642		0.006	0.059	0.007	-0.484

B. Chain-Level Cross-Substitution Patterns

Soup	**Chain 1**	**Chain 2**	**Chain 3**	**Chain 4**	***Soup***	**Chain 1**	**Chain 2**	**Chain 3**	**Chain 4**
Chain 1	-0.009	0.001	0.004	0.001	**Chain 1**	-0.022	0.002	0.010	0.002
	-0.014	0.001	0.005	0.002		-0.035	0.003	0.015	0.003
Chain 2	0.000	-0.005	0.002	0.000	**Chain 2**	0.001	-0.011	0.005	0.001
	0.000	-0.010	0.002	0.001		0.001	-0.020	0.008	0.002
Chain 3	0.001	0.001	-0.010	0.002	**Chain 3**	0.002	0.003	-0.026	0.004
	0.001	0.001	-0.016	0.003		0.002	0.004	-0.041	0.007
Chain 4	0.001	0.001	0.009	-0.017	**Chain 4**	0.002	0.003	0.022	-0.038
	0.001	0.002	0.010	-0.020		0.002	0.004	0.030	-0.049

CSD	**Chain 1**	**Chain 2**	**Chain 3**	**Chain 4**	***CSD***	**Chain 1**	**Chain 2**	**Chain 3**	**Chain 4**
Chain 1	-0.172	0.015	0.047	0.015	**Chain 1**	-0.153	0.013	0.034	0.013
	-0.445	0.032	0.100	0.034		-0.392	0.030	0.081	0.030
Chain 2	0.005	-0.092	0.024	0.008	**Chain 2**	0.005	-0.072	0.019	0.007
	0.010	-0.278	0.055	0.017		0.010	-0.174	0.043	0.013
Chain 3	0.013	0.021	-0.115	0.027	**Chain 3**	0.011	0.017	-0.092	0.024
	0.020	0.036	-0.243	0.040		0.018	0.030	-0.175	0.036
Chain 4	0.010	0.017	0.066	-0.224	**Chain 4**	0.010	0.014	0.056	-0.204
	0.020	0.034	0.115	-0.458		0.020	0.027	0.104	-0.381

Note: The meaning of the entries are same as in Table 7 except we consider either prices of all soup sku's or CSD sku's

Table 8: Seasonal Substitution Patterns due to Category-Specific Price Changes

Pricing Experiments for Coca-Cola	Summer			Winter		
	Brand Revenue Change (%)	Category Revenue Change (%)	Store Revenue Change (%)	Brand Revenue Change (%)	Category Revenue Change (%)	Store Revenue Change (%)
Price Cut by 20%	5.7	3.2	1.8	5.1	2.2	0.9
Price Cut by 10%	3.8	1.8	1.0	3.0	1.2	0.5
Price Rise by 10%	-5.0	-1.9	-1.0	-1.5	-0.8	-0.3
Price Rise by 20%	-7.9	-3.2	-1.7	-4.4	-1.6	-0.7

Note: The pricing experiment is conducted for store D.

Table 9: Some Results of Coca-Cola Pricing Experiments

Pricing Experiments	Short-Term Revenue Elasticity			Long-Term Revenue Elasticity		
	Store B	Store E	Chain	Store B	Store E	Chain
B = 0.9; E = 0.9	-1.33	-1.52	-0.36	-1.77	-2.72	-0.30
B = 0.9; E = 1	-1.35	0.01	-0.19	-1.86	0.03	-0.16
B = 1; E = 0.9	0.01	-1.54	-0.17	0.03	-2.80	-0.15
B = 1.1; E = 1.1	-1.15	-1.10	-0.28	-1.84	-1.59	-0.23
B = 1.1; E = 1	-1.15	0.00	-0.15	-1.84	0.01	-0.13
B = 1; E = 1.1	0.00	-1.11	-0.13	0.01	-1.59	-0.11

Note: The zone pricing experiment is conducted for store B and Store E in Chain 3.

Table 10: Some Results of Store Pricing Experiments

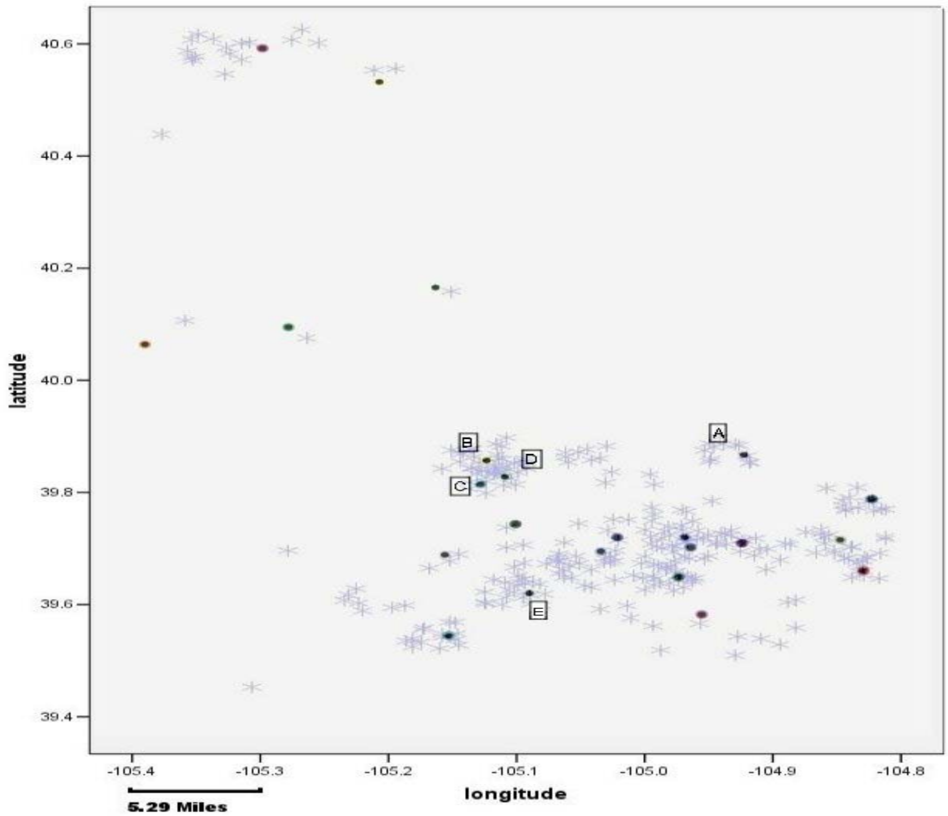

Figure 3: Geographic Distributions of Households and Stores

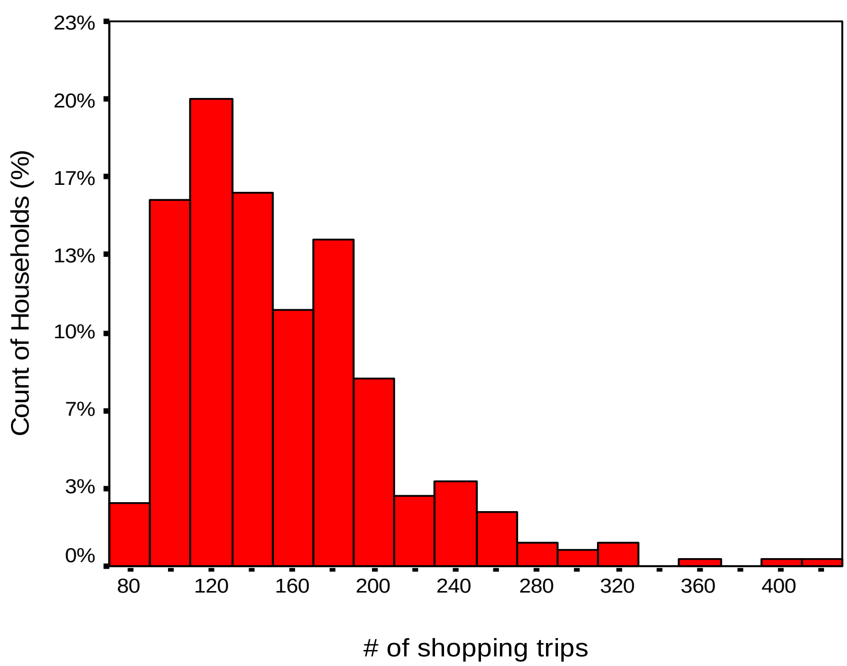

Figure 4: Distribution of the Household Shopping Trips

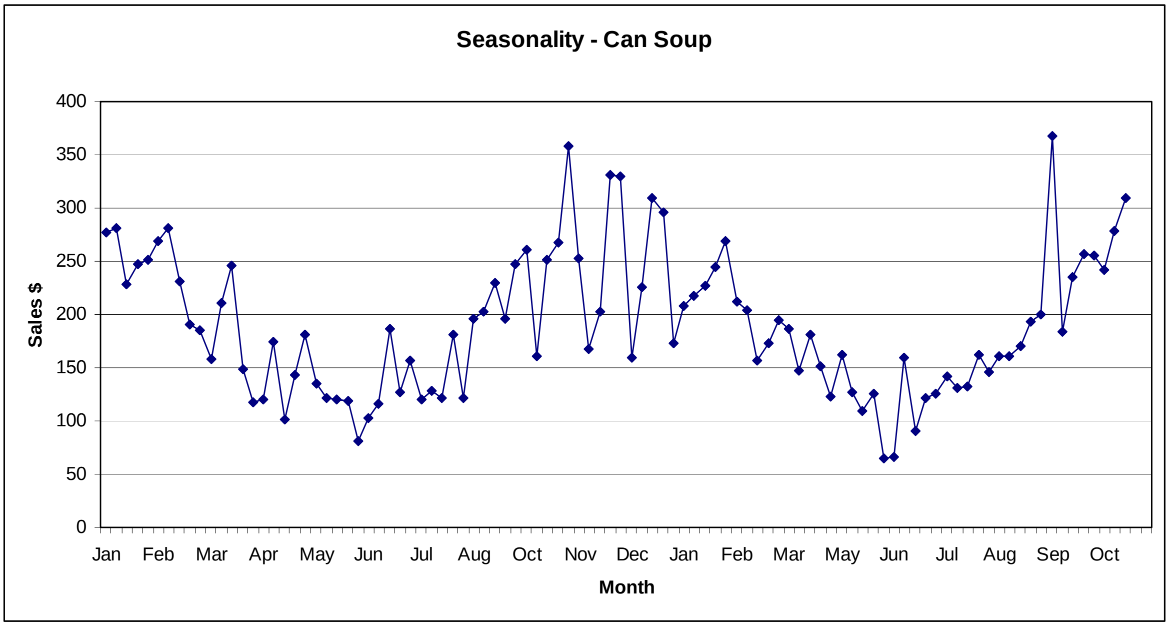

Figure 5: Aggregate Weekly Sales of Can Soup

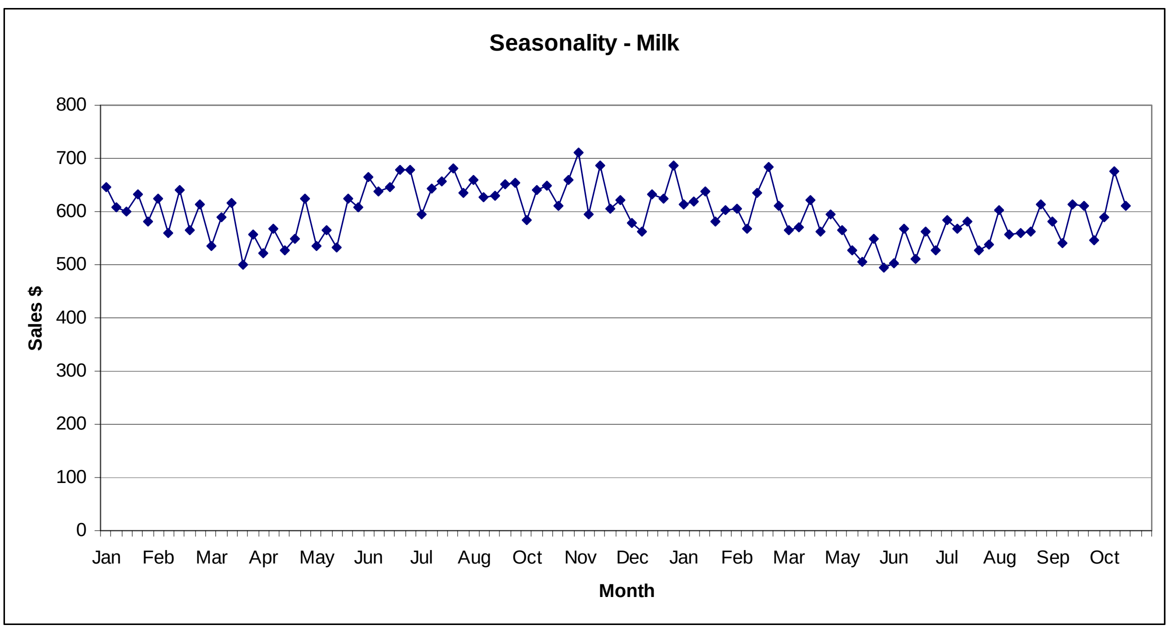

Figure 6: Aggregate Weekly Sales of Milk

Appendix

	All Shopping Trip Model		Major Shopping Trip Model	
	Estimate	***S. E.***	***Estimate***	***S. E.***
Fixed Utility Function				
Intercept	-8.54	2.01	-7.67	2.78
Chain 2	0.88	0.85	-6.30	1.09
Chain 3	7.54	0.54	10.43	0.90
Chain 4	7.05	0.55	8.08	0.91
Std Dev for Intercept	12.57	0.50	13.96	0.79
Std Dev for Chain 2	15.30	1.02	30.63	0.44
Std Dev for Chain 3	7.14	0.29	5.42	0.43
Std Dev for Chain 4	5.06	0.32	5.44	0.38
Travel Distance	-0.96	0.01	-1.06	0.02
Std dev for Travel Distance	0.41	0.01	0.44	0.01
Log(# of upc)	-1.43	0.38	-1.50	0.56
Log(# of upc) * # of expected purchase items	0.24	0.02	0.23	0.02
Log(# of categories with private label)	3.27	0.19	3.69	0.27
Log(Income)	0.00	0.10	-0.22	0.13
HH Size	-0.59	0.05	-0.53	0.07
Probability Function of Reading Ads				
Intercept	1.66	107.29	-2.14	2.82
Chain 2	-1.13	1.41	2.15	1.27
Chain 3	-2.95	1.55	2.48	1.22
Chain 4	-1.35	1.09	3.00	1.21
Expected Basket Cost	0.10	0.14	-0.01	0.01
Log(Income)	-2.21	1.08	-0.11	0.22
Female Head Education	-0.64	1.09	-0.93	0.31
Female Head Employment	22.13	106.79	-0.37	0.27
# of Observations	46727		25291	
Log-Likelihood	-148712		-101122	
Hit Rate	49.8%		47.8%	

Comparison of Estimates from Store Choice Models

All Shopping Trip Model				Major Shopping Trip Model			
Chain 1	Chain 2	Chain 3	Chain 4	Chain 1	Chain 2	Chain 3	Chain 4
30.5%	18.9%	5.8%	16.9%	2.5%	17.5%	22.6%	32.6%

Comparison of Estimated Read Ad Probability from Store Choice Models