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Consumer Shopping and Spending Across Retail Formats

by

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Abstract:

Grocery retailers increasingly view other retail formats, particularly mass merchandisers, as a competitive threat. We present an empirical study of household shopping and packaged goods spending across retail formats — grocery stores, mass merchandisers, and drug stores. Our study considers competition between these formats and explores how retailer assortment, pricing and promotional policies, as well as household demographics, affect shopping behavior and expenditures in these different formats. This research is made possible by a new panel dataset collected by Information Resources Inc. (IRI) which captures consumer packaged good purchases made at alternative retail outlets. These purchases have previously been missed by panels that use only purchases at supermarkets.

We estimate a hierarchical multivariate tobit model which captures consumer decisions about "where to shop" and "how much to buy." We find that shopping and spending vary much more across than within formats, and that the retailer's marketing mix explains more variation in shopping behavior than travel time. Of the marketing mix variables considered, we find that expenditures respond more to varying levels of assortment (in particular grocery stores) and promotion than price. This is surprising in light of the grocery industry's efforts to reduce retail assortments. Price sensitivity is most evident at grocers. Shoppers at drug stores are more sensitive to travel time than other formats, perhaps due to the convenience orientation of drug stores. We also find that households which shop more at mass merchandisers also shop more in all other formats, suggesting that visits to mass merchandisers do not substitute for trips to the grocery store.

Keywords: Store Formats, Retailing, Assortments, Multivariate Tobit

I. Introduction

Today, grocery stores operate in a competitive environment that includes other retail formats, in particular mass merchandisers. As a retail format mass, merchandisers grew rapidly throughout the 1980s and 1990s, and currently generate nearly as much revenue as supermarkets.[1] The sale of groceries has traditionally been the venue of supermarket retailers like Kroger, Safeway, and Albertsons. However, mass merchandisers such as Wal-Mart, Target, and Kmart now offer thousands of packaged goods products that are also found in grocery stores. Additionally, other retail formats like drug stores such as Walgreen's, CVS, and Eckerd also sell significant assortments of grocery items. The overlap in their product offerings raises a fundamental question about competition across retail formats – do grocers and mass merchandisers compete for packaged goods sales? The grocery industry believes itself to be in direct competition with mass merchandisers. According to the *Progressive Grocer* Report of the Grocery Industry (1999) Wal-Mart represents a "grave" threat to grocery retailers. Moreover, this perceived threat has prompted consolidation and strategic changes among grocery retail firms.

Our study of shopping across retail formats is made possible by a panel dataset collected by Information Resources Inc. (IRI) which is new to both industry and academic research. This dataset is different from other shopping panels in that the panelists use wand scanners in their homes to record purchases at *all* retail formats and outlets. In contrast, other panels that are commonly analyzed in marketing use only purchases scanned in-store at participating supermarkets. These more complete household purchase records enable us to analyze shopping and spending across grocery stores, mass merchandisers, and drug stores with a rich set of predictors. Our analysis addresses how factors within and outside the retailer's control affect store-level shopping decisions. We are also able to examine both intra- and inter-format competition. Our goal is to measure and characterize this competition, and also consider its importance to retail managers. This paper presents an exploratory analysis of consumer response across retail formats, which is intended to provide a foundation for future research in multi-format shopping behavior and retailer decision-making in non-grocery formats.

There has been very little empirical research on shopping at mass merchandisers and other non-grocery formats, despite their growing importance, due to the lack of data on cross-format purchases. Store choice research has focused exclusively on grocery stores (Barnard and Hensher, 1992; Bell and Lattin, 1998; Bell, Ho and Tang, 1998; Ho, Tang and Bell, 1998). It is problematic to generalize from this work to other retail formats because grocery stores differ systematically from other formats in their marketing policies. For example, mass merchandisers offer lower prices, more product categories (e.g., groceries, clothing, garden, automotive products, etc.), smaller assortments within categories (i.e., fewer product variants), and fewer promotional discounts than grocers.

In this paper, we estimate an econometric model to determine how marketing policies affect shopping and spending behaviors across retail formats. Our model incorporates consumer decisions about both "where to shop" and conditional on shopping, "how much to spend." The "where to shop" (patronage) decision is modeled as a binary choice for each store chain, where this choice is correlated across chains. The conditional spending decision at each store chain is modeled as a continuous variable, and also correlated across chains. In addition, we model differences between households due to known (i.e., demographic) and random factors with a Bayesian hierarchical specification. Thus, we develop and estimate a hierarchical, multivariate specification of the type 2 tobit model (using Amemiya's 1985 topology) for this application. To our knowledge this is the first such application of a multivariate type 2 tobit model, although univariate versions of the type 2 tobit and other forms of the multivariate tobit model have been published (Blundell and Smith, 1994, and Cornick, et al., 1994). The rationale for specifying the type 2 tobit model is that it allows predictors to have different effects on the censoring decision and the continuous relationship, which in our case are "where to shop" and "how much to spend."

The rest of this paper is organized as follows. We describe the data in Section II, and present our model in Section III. Section IV details our empirical analysis at both the store chain and format levels, and reports model fit and contribution of predictor variables. Section V considers the implications of our study for managers, and we conclude with a summary of our findings and opportunities for future research in Section VI.

II. Data Description

Before formally modeling shopping behavior across retail formats, we present a descriptive analysis of retailer marketing policies and consumer shopping behaviors across store chains in our dataset. We use a panel dataset which captures household-level shopping and spending across store chains and retail formats. This spending includes all items with uniform product codes (UPCs or bar codes) that can be scanned, as well as non-scannable items like perishables (e.g., produce, meats, and bakery goods). We model the shopping behavior of 96 households at six different store chains representing three retail formats — grocery stores, drug stores, and mass merchandisers — over a two-year period in a major US market.[2] Within each format, the store chain(s) selected are the largest and collectively account for the majority of the spending in that format.

Table 1 describes the marketing policies at each chain in our dataset — average prices paid and regular (i.e., non-promoted) shelf prices, promotional discounts, percentage of sales on promotion, within-category assortments, and travel times for shoppers.[3] Price and assortment indices reflect the relative price of a basket of the most commonly purchased products (1605 UPCs) and the relative number of products within the most commonly purchased categories (top 26 categories, or 10% of total), respectively. Formal definitions of these indices are given in §III. Promotional discounts are percent off the regular retail prices.

Differences in marketing policies across retail formats are clearly evident. In particular, product assortment is much greater at grocery chains. In common product categories, grocers offer far more product alternatives than mass merchandisers, which in turn offer more product alternatives than drug stores. Roughly speaking, grocers offer more than three times the assortment of mass merchandisers, and more than four times the assortment of drug stores. These extensive assortments are offered at a cost of either breadth of product variety (i.e., there are fewer, less diverse product categories at grocery stores than mass merchandisers) or larger stores (i.e., grocery stores have more floor space than drug stores).

Mass merchandisers are the lowest-priced format, offering prices that average 7% and 9% less than drug and grocery stores, respectively, and regular shelf prices that average 11% and 10% less than drug and grocery stores, respectively. Promotional discounts are deepest at the drug store chain, followed in order by grocers and mass merchandisers. Similarly, the highest percentage of promotional sales are made at drug stores, followed in order by grocers and mass merchandisers. Although regular shelf prices at drug stores are higher than other formats, drug store patrons still appear price sensitive as demonstrated by the higher percentage of sales on promotion. Clearly, drug store patrons make use of the deep promotional discounts provided.

Moreover, one should not conclude that price-sensitive consumers will patronize mass merchandisers, the lowest-priced format, inordinately. Even though average prices at grocery stores may be higher, their more extensive assortments and deeper discounts may provide more fertile ground for search than mass merchandisers, making them attractive to price-sensitive shoppers. Likewise, the even deeper discounts at the drug chain may also attract price-sensitive shoppers. We also note that grocers' larger assortments may increase shopping time, so time-constrained households may be willing to trade-off the convenience of drug stores for the higher prices. Finally, the larger number of drug stores results in the lowest average travel times from shoppers' households, followed in order by grocery stores and mass merchandisers.

Table 2 describes shopping behaviors at each chain in our dataset: the interval between shopping trips, spending per trip, and patronage at that chain. We define patronage as the percentage of households shopping at a store chain in a given month. Approximately a third of households frequent mass merchandisers each month, while almost half visit drug stores, and more than 70% visit grocers. The time interval between shopping trips follows a slightly different pattern. It is shortest for grocery chains, with an average shopping interval of just over one week (8.6 days), while visits to mass merchandisers or drug stores occur every two to three weeks. Households spend substantially more on trips to grocery stores ($87.18) and mass merchandisers ($81.11) than at drug stores ($36.36). Recall that all purchases, not only packaged goods, are reflected in these spending statistics. In summary, customers shop more frequently and spend more at grocery stores than other formats.

The relationships of marketing policies and shopping behaviors to retail format and are quite strong. Most of the variation is between formats, while variation within formats is relatively small. First, we consider marketing policies. An analysis of variation[4] reveals that 99%, 99%, 93%, 84%, and 76% of the variance for assortment, regular shelf price, actual price, travel time, and promotional discount (given in Table 1), respectively, are accounted for between formats, as opposed to within format. The strong relationships between marketing policies and retail format suggest that consumer response to marketing variables may differ by format, which we explore in subsequent analyses. Another analysis of variance shows that 99%, 83%, and 58% of the variation in shopping behaviors — spending per trip, patronage and the interval between trips, respectively (given in Table 2) — is explained by format. Overall then, we find that both marketing policies and shopping behaviors are format-specific. This implies that retail format is a good segmentation criterion for examining retailers.

III. The Model

In order to relate retailer marketing policies to shopper patronage and spending decisions, we develop relative measures of price, promotion, and assortments that incorporate the many products comprising shoppers' market baskets. These measures are constructed by averaging price, promotional status, and product availability over all packaged goods products, weighted by the household's long-term category consumption rate as measured by total consumption during a two-year period. This assumes that store-level (as opposed to product-level) shopping decisions depend on the relative price of the shopper's entire market basket at different stores (e.g., Bell, Ho and Tang, 1998; Bell, Bucklin, and Sismiero, 2000). We then use these price indices to predict monthly expenditures at each retail chain.

Perhaps the most controversial aspect of our modeling approach is temporal aggregation. The alternative would be to model shopping on a trip-by-trip basis or perhaps weekly. While a more disaggregate analysis may be generally preferred, we believe it is not practical using our dataset. We offer several reasons why temporal aggregation is desirable for this application.

First, a trip-level model would require the complete set of prices and promotions offered by each retailer. Unfortunately, this information is not available nor is it even possible to get such information from IRI, since key mass merchandisers forbid the distribution of this information by IRI on confidentiality grounds. Hence, the sparseness of marketing policy data for mass merchandisers is not conducive to trip-level modeling.[5] We are forced to piece together the causal data, as summarized in Table 1, from panelists' observed purchases (587,279 individual packaged goods purchases across 261 categories in the six store chains over two years, see endnote 3). Fortunately, we have determined that price variation is very robust to temporal aggregation from the weekly to monthly level (see Appendix A).[6]

Second, a trip-level model would require information about consumption, household inventory levels, and non-grocery items — information that we lack. While others have attempted to infer inventory as a parameter of a purchasing model (Bell, Ho, and Tang, 1998), the lack of full causal information in our model would likely make these estimates unstable. This problem is exacerbated in our dataset, since mass merchandising trips may be triggered by non-grocery purchases, for which we lack item-level data. For example, a consumer may buy clothing products (which are not tracked by UPC) and, while at the store, decide to purchase several grocery items that are either low in the household's inventory or a good value. Hence, in our dataset we would have difficulty explaining how consumers plan their mass merchandiser visits. Furthermore, we would expect that purchase (and consumption) will be more consistent at an aggregate level, since it is possible that week-to-week purchases could be quite volatile due to heavy workloads or vacations which might lead to more eating out and less grocery purchases. Therefore, without adequate information about consumption, inventory, and non-grocery items, an individual trip-level model would be difficult to estimate.

Third, our purpose is to predict consumer behavior at an aggregate level. When the true underlying generating model is unknown and nonlinear, temporal aggregation can result in a more linear model (Man 2002). It is quite likely that individual trip-level shopping behavior will depend nonlinearly upon inventory levels, price expectations, and planned consumption. Hence, temporal aggregation can help simplify the model structure. Diagnostics of our model's residuals do not show significant autocorrelation, hence our choice of monthly aggregation would seem to simplify the model.

There are disadvantages to estimating our model at an aggregate rather than a disaggregate level. Foremost, the interpretation of our variables is more difficult, since many tactical decisions are made at a weekly level. Aggregation can result in the loss of information when specifying and estimating the model; the predictions of aggregate models are not as good as aggregating predictions from a disaggregate model when the true generating process is known. Moreover, knowledge about structural properties of utility and demand could better be utilized at a disaggregate level. While we grant that a disaggregate model of cross-format retail shopping would be desirable, given the nascent state of research about retail formats, we believe it is better to propose a simpler model that makes weaker assumptions than a more complex one whose assumptions cannot be readily validated. Therefore, we believe the disadvantages are outweighed by the benefits of aggregation that we have detailed. We hope that the insights into the aggregate process will help future researchers in understanding the aggregate properties that disaggregate models of cross-shopping behavior must satisfy.

A. Model Specification

The household's spending decision at the store chain of interest is modeled as a regression model with the log of the household's monthly expenditures at that store chain as the continuous dependent variable. Our data consists of 13,824 observations (purchases of 96 households at six chains over 24 months). More than half of our expenditure observations, 7,227 out of 13,824, are zeros. Following Tobin (1958), we treat our continuous spending variable as censored, i.e., this regression is conditioned on a binary probit model for whether or not the chain was visited.

The variable of interest in our model, y_{hit}, is the expenditures made by household h (indexed $h = 1, \ldots, H$; H=96) at chain i ($i = 1, \ldots, S$; S=6) during month t ($t = 1, \ldots, T$; T=24). Expenditures are observed only when an indicator variable for household h's patronage at chain i at time t, z_{hit}, takes the value of 1. The observational equation for expenditures, y_{hit}, is:

$$y_{hit} = \begin{cases} y^*_{hit} & if\ z_{hit} = 1 \\ 0 & otherwise \end{cases} \tag{1}$$

where the model for the logarithm of the latent variable, y_{hit}^*, is:

$$\ln(y^*_{hit}) = \alpha_{hi} + \mathbf{x}'_{hit}\boldsymbol{\beta}_i + d_{hi}\gamma_i + \mathbf{s}'_t\lambda_i + \varepsilon_{hit} \tag{2}$$

Incidence of store patronage, z_{hit}, is a binary variable, and we use a probit model to describe its behavior:

$$z_{hit} = \begin{cases} 1 \; if \;\; z^*_{hit} \geq 0 \\ 0 \; otherwise \end{cases} \tag{3}$$

The latent variable, z_{hit}^*, is modeled through a linear model:

$$z^*_{hit} = \iota_{hi} + \mathbf{x}'_{hit}\boldsymbol{\theta}_i + d_{hi}\chi_i + \boldsymbol{s}'_t\boldsymbol{\kappa}_i + u_{hit} \tag{4}$$

The predictors $\mathbf{x}_{hit}$ and d_{hi} and $\mathbf{s}_t$ used in equations (2) and (4) are the same. However, these predictors may influence a shopper's patronage decision differently from her spending decision, so we allow for different coefficients in these two equations. Consider promotions as an example. Some retailers advertise everyday low prices, yet in fact offer substantial discounts in order to generate store traffic (i.e., shopper patronage). However, the increased patronage may come from opportunistic shoppers who will spend less than more loyal shoppers. The vector of marketing policy variables, $\mathbf{x}_{hit}$, that applies to household h during period t at chain i is comprised of price, promotional intensity, and product assortment. d_{hi} is the travel time for household h to the nearest store of chain i, and $\mathbf{s}_t$ is an 11×1 vector of indicator variables for the twelve months of the year, capturing seasonal effects.

As the subscripts of the intercept terms in equations (2) and (4) show, every household has an individual intercept coefficient for each store chain. In this way, the model incorporates individual differences in preference for retailers.[7] These preferences are modeled as a function of known and unknown (random) factors. This is accomplished by using a hierarchical specification for the intercept terms. Like Ainslie and Rossi's (1998) brand choice model, we specify household-level preferences to be systematically affected by household characteristics, i.e., demographics. For expenditure model intercepts:

$$\alpha_{hi} = \mathbf{w}'_h\boldsymbol{\delta}_i + \xi_{hi} \tag{5}$$

and for patronage model intercepts:

$$\iota_{hi} = \mathbf{w}'_h\boldsymbol{\psi}_i + \tau_{hi} \tag{6}$$

$\mathbf{w}_h$ is a vector of household demographics — family size, income, home ownership, working woman, education, and the presence of children under age 6. A detailed discussion of these predictors is presented in the next sub-section. $\boldsymbol{\delta}_i$ and $\boldsymbol{\psi}_i$ are parameter vectors relating household *h*'s demographics to its intrinsic preference for store chain *i* in the conditional spending and patronage models, respectively.

Our model incorporates both the binary choice of store patronage (i.e., will the household shop at Wal-Mart?) and the continuous decision of how much to spend at that store chain, given patronage. Note that the second decision is not spending per trip, but *total* spending during a given month at the chain. Thus, it may include multiple trips. Equations (1) through (4) define a type 2 tobit specification. Equations (5) and (6) define a hierarchical specification of individual preferences. We link the hierarchical type 2 tobit models for each chain in a multivariate framework by allowing errors to be correlated. The vector of household residuals from the log expenditure models, $\boldsymbol{\varepsilon}_{ht} = [\varepsilon_{h1t}\ \varepsilon_{h2t} \cdots \varepsilon_{hSt}]'$, is assumed to follow a multivariate normal distribution: $\boldsymbol{\varepsilon}_{ht} \sim \mathrm{MVN}(0,\boldsymbol{\Sigma})$. The vector of household residuals from the patronage models, $\mathbf{u}_{ht} = [u_{h1t}\ u_{h2t} \cdots u_{hSt}]'$, is also assumed to follow a multivariate normal distribution: $\mathbf{u}_h \sim \mathrm{MVN}(0,\boldsymbol{\Lambda})$. Because equations (2) and (4) use the same predictors, we must assume that $\boldsymbol{\varepsilon}_{ht}$ and $\mathbf{u}_{ht}$ are independent in order to identify the model.

The multivariate error distributions allow information from one chain to influence the conditional predictions of another (see Appendix B). We expect prediction errors for conditional spending models to be correlated across store chains, because excess expenditures in one store should result in less spending at other stores. If the total budget for groceries is fixed during a month, then any increase in expenditures in one chain should lead to a decrease in purchases at other chains, which in our model would be captured through a negative correlation. We also considered including cross-effects of the marketing mix variables directly in equations (2) and (4), but, due to the multicollinearity of this specification, we only allow cross-effects to enter through the error covariance matrix. One can think of our model specification as a cross-effects model in reduced form. Our specification of error correlations for equations (2) and (4) improves the efficiency of parameter estimation as in seemingly-unrelated regression (Zellner 1962).

We also allow for relationships in a household's intrinsic preferences for different store chains by specifying error correlations for the hierarchy — equations (5) and (6). The vector of residuals for equation

(5), which models household-level preferences for store spending, $\boldsymbol{\xi}_{ht} = [\xi_{h1t}\ \xi_{h2t} \cdots \xi_{hSt}]'$, is assumed to follow a multivariate normal distribution: $\boldsymbol{\xi}_{ht} \sim MVN(0,V_{\alpha})$. Similarly, the residual vector for equation (6), which models household-level preferences for store patronage, $\boldsymbol{\tau}_{ht} = [\tau_{h1t}\ \tau_{h2t} \cdots \tau_{hSt}]'$, is assumed to follow a multivariate normal distribution: $\boldsymbol{\tau}_{ht} \sim MVN(0,V_{\iota})$.

Only recently have Markov Chain Monte Carlo methods for estimating the posterior distributions of the parameters in high dimensional models become available (Gelfand and Smith, 1990; Casella and George 1992; also see Chib, 1993, for application to the tobit specification). A complete discussion of our estimation procedure is available as a technical report from the authors.

B. Predictors of Shopping Behavior

To predict expenditures across households and stores we have defined three sets of variables. First, we consider retailer marketing policies: pricing, promotion, and product assortment. These variables are firmly under the retailer's control and, with the exception of assortment, are easily manipulated in the short-term. Second, we measure the costs incurred by the shopper traveling to and from the store. This variable is also affected by the retailer, but only by its long-run store location decisions and market penetration. Third, demographic characteristics of the shopper's household (e.g., family size, income, home ownership), which are not affected by the retailer, are included in the hierarchy. All predictors are own effects. As noted, we are unable to incorporate cross-effects (i.e., marketing policies at one retailer are specified as predictors of shopping behavior at another) directly into the models due to multicollinearity.

1. *Retailer Marketing Policies:* Previous research on store choice and store sales have shown the importance of retailer prices and promotions on shopping behavior (Arnold, Ma and Tigert, 1978; Arnold and Tigert, 1982; Arnold, Oum and Tigert, 1983; Walters and Rinne, 1986; Kumar and Leone, 1988; Walters and MacKenzie, 1988; Walters, 1991; Barnard and Hensher, 1992; Bell and Lattin, 1998; Bell, Ho and Tang, 1998). Our *PRICE* variable is a price index weighted by the household's long-term consumption, which captures variation in expected prices across chains and individual households. This construction is similar to Dillon and Gupta (1996) who developed household-specific category price variables, weighting brand prices

by each household's long-term brand consumption. In our application, a price index is used to capture variation in the price of the household's average market basket across both stores and time. The composition of a household's average market basket is based on weighted-average category consumption over a two-year period, and so is unlikely to be affected by short-term price or promotional variation (Ainslie and Rossi, 1998).[8]

Formally, the price index, $PRICE_{hit}$, for household *h* at store *i* in period *t*, is the weighted average of category-level price indices at store *i* for category *c* at time *t*, which is denoted as p_{ict} (recall that these indices are based on observed panelist purchases). Category price indices are weighted by household *h*'s long-term consumption of products in each category *c*, denoted q_{hc}. Thus, we have:

$$PRICE_{hit} = \frac{1}{C}\sum_{c=1}^{C}\left(\frac{p_{ict}}{\overline{p}_{ct}}\frac{q_{hc}}{\sum_{c=1}^{C} q_{hc}}\right) \quad (7)$$

where $\overline{p}_{ct}$ is the average price of products in category *c* at time *t* across store chains.

As noted, different market baskets are used for each household, incorporating purchases across *all* stores and time periods. Thus, the market basket is specific to the household, but not to the month or store chain. This allows *PRICE* and other expenditure-weighted variables to reflect differences in long-term consumption between households. To illustrate, consider one household that has an infant child and buys diapers and baby food. A second household has no children and never purchases these categories. The prices of diapers and baby food will be reflected in the price indices applied to the first household at every store chain that offers them. Prices of these categories will be weighted in proportion to the first household's total expenditures on diapers and baby food. The prices of diapers and baby food will not be reflected in the price indices applied to the second household. In this way, the model captures variation in *PRICE* and other marketing policies across households based on differences in market baskets between households.

Retailer promotions are also well known to affect shopping behavior (see Blattberg, et.al., 1995, for a review). The *PROMO* variable summarizes the retailer's promotional policies. It is operationalized as the proportion of all purchases at a store chain that are made on promoted items, again weighted according to the household's average market basket. In this way, both the frequency and depth of retailer promotions are incorporated into a single variable.

Another marketing policy which has been shown to affect shopping behavior and patronage patterns is product assortment (Reilly, 1931; Huff, 1964; Brown, 1989).[9] *ASSORT* is an indexed measure of the number of products within each category, weighted by the household's average market basket. It therefore reflects diversity of the product offering within-category, not across categories. It is constructed like the other indexed variable, *PRICE*. Because assortment varies little over time, variation in *ASSORT* is virtually all cross-sectional.

2. *Travel Time:* Virtually all models of retail competition (Hotelling, 1929; Reilly, 1931; Huff, 1964, Hubbard, 1978; Brown, 1989) and shopping behavior (Barnard and Hensher, 1992; Arentze, Borgers, and Timmermans, 1993; Dellaert, et al. 1998; Bell, Ho, and Tang, 1998) specify store patronage as a function of the distance from the store to the shopper's home. Our model includes a measure of distance in the form of travel time, *TRAVTIME*. *TRAVTIME* is operationalized as the time in minutes it takes to travel from the household to the nearest store of a given chain.[10] The underlying assumption is that the shopper travels from home to the closest store of the selected chain, then returns home. In reality, shoppers may reduce their travel time by linking shopping trips together or combining store visits with other required travel. "Trip chaining," as this practice is called (Thill and Thomas, 1987), results in shoppers requiring less than the measured travel time to make a store visit, and possibly shopping more than expected at distant stores. We expect measurement error due to trip chaining to bias the estimated effect of travel time downward.

The models also include household-specific intercepts for each store chain. The intercept reflects intrinsic preference for that particular store chain, including unobserved factors specific to that retailer, which affect shopping behavior. These factors include the retailer's general positioning (e.g., high service, friendly), operational policies and overall excellence in execution. They also include the variety, or breadth, of product categories offered. For example, mass merchandisers sell consumer durables and clothing not available in grocery or drug stores, while grocery stores offer perishable products which cannot be purchased in drug stores or mass merchandisers. Preference for this variety (which does not vary over time) is reflected in the intercept. In addition, the intercept captures preference for *mean levels* of the retailer's marketing policies. For example, mass merchandisers consistently offer lower basket prices compared to grocery and drug stores, independent of short-term variation. Because intercept terms reflect the household's response to these many factors, we do not attempt to interpret their coefficients, per se.

3. *Household Characteristics:* Equations (5) and (6) specify household-level intercept coefficients that have a deterministic component based on known demographic characteristics. Previous research using cross-sectional (Blattberg et.al. 1978, and Hoch et al. 1995) and panel data (Ainslie and Rossi, 1998) suggests that demographics can influence price sensitivity. We include the following demographic variables in our model: (1) income (*INCOME*) measured in thousands of dollars, (2) family size (*FAMSIZE*) which is the number of household members, (3) home ownership (*OWNHOME*) is an indicator (1=*yes*), (4) education (*COLLEGE*) is an indicator (1=*yes*), (5) working adult female (*FEMWORK*) is an indicator (1=*yes*), and (6) the presence of a young child (age 0-6) in the home (*YOUNGKID*) is an indicator (1=*children present*). By including demographic variables in our hierarchical specification, we identify systematic sources of heterogeneity in patronage and spending across households. Descriptive statistics for the demographics of households in our dataset are shown in Table 3.

IV. Empirical Results

We estimate equations (1)-(6) for each chain simultaneously using a Monte Carlo Markov Chain (MCMC) approach. Equations (2) and (4) result in two sets of parameter estimates. The first panel of Table 4 shows coefficients for the probit component of the model, i.e., whether the household will patronize a given store chain (estimates are posterior means, with standard errors given in parentheses below each estimate). The signs of coefficients relate positively to the patronage probability. Alternately, the derivative of the patronage probability with respect to the *j*th variable can be computed as $\phi(\boldsymbol{x}'\boldsymbol{\theta})\,\theta_j$, where $\boldsymbol{x}'\boldsymbol{\theta}$ is the predicted value, and θ_j is the *j*th element of the parameter vector $\boldsymbol{\theta}$. Hence, the derivative is not constant and is influenced by the behavior of $\phi(\boldsymbol{x}'\boldsymbol{\theta})$. The second panel of Table 4 shows coefficients for the continuous component of the model, i.e., how much the household will spend, given that they patronize that retailer. The derivative of the log expenditure component with respect to the *j*th variable is β_j.

A.. Parameter Estimates

1. *Marketing Variables and Travel:* Of the variables that we consider, *PRICE* is the weakest predictor of shopping and spending behavior. This may seem surprising, given that survey research finds price to have a substantial negative effect on store patronage (Arnold, Ma and Tigert, 1978; Arnold and Tigert, 1982; Arnold, Oum and Tigert, 1983). However, the six store chains in our dataset all have very consistent pricing profiles through time, resulting in little variation in retailers' comparative basket prices In fact, the average coefficient of variation for the basket price variable, *PRICE*, across those store chains is only 0.022. The price dispersion commonly observed in brand choice modeling attenuates over the many products that make up the market basket. Appendix A demonstrates that aggregation across products reduces price variation far more than temporal aggregation. As Bell, Ho, and Tang (1998) argue, promotions effectively cancel one another out over the many items in the market basket (p.354, footnote 3). Because variation in *PRICE* within retailers is small, the effects of mean *PRICE* levels are captured through the intercept coefficients, along with other retailer-specific factors.

Prior research also helps us understand why price variation has little impact on store patronage and spending. Hoch et al. (1994) found that consumers are inelastic to price changes for grocery purchases, which is consistent with our findings. Kalyanaram and Little (1994) demonstrate that consumers are not affected by small differences in price, provided that prices are close to their expectations. Moreover, unadvertised promotions, which comprise the majority of discounts, cannot be observed by the shopper until she visits the store. As a result, patronage decisions do not incorporate variation due to unadvertised discounts. Consumers also encounter difficulties in applying price information in basket shopping decisions. Alba, et al. (1994) show that cognitive limitations result in consumers making errorful comparisons of basket prices across retailers, based primarily on frequency cues. In sum, while visit-to-visit price variation strongly influences brand-level purchase decisions, the stability of basket prices, coupled with consumers' difficulty in learning basket prices for use in shopping decisions, explains why *PRICE* variation has little effect on consumer patronage and conditional spending.

PROMO has a positive effect on patronage, with four of six store models positively-signed and significant. In particular, promotions in categories of interest positively affect patronage at mass merchandisers. A priori, we expect that *PROMO* would have a positive effect on store expenditures; i.e., as the depth and number of promotions in categories of interest increase, consumers spend more. The effect of promotions on expenditures is mixed, however, with two significant positive and three significant negative parameter estimates. Note that expenditures respond negatively to promotions in categories of interest at the retailers with highest promotional intensity, the drug store chain and Grocer #1 (see Table 1). One possible explanation is that retailers with high promotional intensity draw a disproportionate number of "cherry pickers" (customers who shop opportunistically across multiple stores during a single period) and so buy less at each store. An alternative explanation is that, while store promotions may succeed in attracting additional shoppers to the store, conditional spending falls because demand is inelastic.

ASSORT also has a positive effect on both patronage and spending. Across the two decisions, seven of the eight significant coefficients are positively signed. We note that assortment has the greatest effect at grocery stores, with positive and highly significant parameter estimates for patronage and spending at both stores. It may appear surprising that assortment has such a large effect on shopping behavior at grocery stores, given the grocery industry's recent focus on reducing retail assortments (Information Resources, Inc. and Willard Bishop Consulting, 1993; *Food and Beverage Marketing*, 1994; Merrefield, 1995) and recent academic research which finds that reduced online assortments leads to sales increases (Boatwright and Nunes, 2001). However, evidence presented in these citations focuses on category sales, and does not address the effect of assortment on patronage or store choice. In fact, Boatwright and Nunes (2001) note "… a significant decrease in the category purchase probability despite the increase in overall sales", (p. 60) which they acknowledge is likely due to customer attrition.

TRAVTIME has a substantial negative effect on store patronage, with five of the six coefficients negative and significant. *TRAVTIME* also has a negative effect on spending, though the effect is limited to drug and grocery stores. At mass merchandisers, differences in travel time across households who patronize the format do not impact their expenditures. This may be caused by higher expenditures per trip at these low-priced stores (Fox, Metters, and Semple, 2002) offsetting the reduction in trips due to longer travel times.

2. *Demographics:* The parameter estimates for equations (5) and (6) are shown in Table 5. Coefficients of these hierarchical equations capture the systematic effects of consumer demographics on the intercept terms, ι_{hi} and α_{hi}, for patronage and spending models, respectively. The first panel of Table 5 shows coefficients of the probit (i.e., patronage) models. The second panel shows the coefficients for the continuous regression (i.e., conditional spending) models. In general, we find relatively weak relationships between intercept coefficients and household demographics. Only 21 of 84 total coefficients (two consumer decisions × six stores × seven variables) are significant. This is not surprising, given limited prior success in relating demographics to category-level consumer decisions (Bucklin and Gupta, 1992; Rossi, et al., 1996; Chintagunta and Gupta, 1994). Family size (*FAMSIZE*) has the largest effect on store preferences, with six of the twelve intercept coefficients significant. A priori, we would expect larger households to spend more, because they have more members. We find that this is true for mass merchandisers, as evidenced by all positive coefficients (most significant) for patronage and spending. This suggests that larger households are more likely to patronize and spend more at mass merchandisers, which offer lower basket prices but fewer promotions.

FEMWORK, *COLLEGE*, *INCOME* and *YOUNGKID* are expected to increase shoppers' opportunity cost of time (Blattberg, et al., 1978; Hoch, et al., 1995). We expect that shoppers with higher opportunity costs of time will shop at fewer chains. The patronage model coefficients offer some support for this expectation for *FEMWORK* and *COLLEGE*. All of the *FEMWORK* patronage coefficients are negative, though none are significant. Most of the *COLLEGE* coefficients in the patronage models are also negative, as are the two significant coefficients. Of the patronage coefficients for *INCOME* and

YOUNGKID, only one is significant and no patterns emerge. Overall, the variables which reflect opportunity cost of time appear to have limited effects on patronage, and no differential influence across formats. Turning to the expenditure models in the second panel, we find that all *FEMWORK* spending coefficients are positive and three are significant. We conclude that households with working women spend more at each retailer they patronize, though they patronize fewer retailers. This suggests that households with working women may be more loyal. Spending coefficients for *COLLEGE*, *INCOME* and *YOUNGKID* offer few insights. The only significant coefficients for these variables are positive, but there are few. Interestingly, Grocer #1 has positive and significant *YOUNGKID* coefficients for both the patronage and expenditure models. We conjecture that this retailer has a unique offering for young children, such as a "Baby Club," or successfully differentiates its stores by effectively merchandising categories such as diapers and baby food.

Home ownership (*OWNHOME*) is commonly interpreted as a proxy for storage space (Blattberg et al., 1978; Hoch et al., 1995). Shoppers with more space are able to "stock-up," taking advantage of promotions, so they can visit more chains in search of deals. Interestingly, we find that the drug store chain is significantly less likely to be visited by homeowners. This is inconsistent with the above rationale, because the drug chain offers the deepest promotional discounts (see Table 1), which home owners could exploit because of their storage space. On the other hand, drug stores are a convenience format, not typically associated with "stocking up," and they carry limited product variety and assortment. It appears that the capability of home owners to stockpile packaged goods reduces their need for the convenience that drug stores offer — they do not stock up at drug stores despite the extensive promotions. Perhaps homeowners use their storage space to exploit the one-stop-shopping benefits of broader-line grocery stores (Messinger and Narasimhan, 1997) and mass merchandisers.

B. Model Specification Testing and Contribution of Predictor Variables

To assess our model specification, we estimate nested models which represent less general variants of our hierarchical multivariate type 2 tobit. Fit statistics for these models are shown in Table 6. We estimate a system of independent type 2 tobit models (model "a" in Table 6) as our baseline model. This baseline specification incorporates neither the individual differences modeled by the hierarchy, nor the estimation efficiencies due to multivariate error structures. We assess the contribution to fit of multivariate error structures by estimating a multivariate type 2 tobit specification(model "b"). This specification offers an improvement in log-likelihood of 892 (u^2=0.054), compared to the baseline. The incremental fit gained from specifying multivariate error structures suggests that there are meaningful unmodeled relationships among retailers in patronage and expenditures.

We then assess the incremental contribution of individual differences by estimating both a multivariate type 2 tobit with random intercepts (model "c") and the full hierarchical multivariate type 2 tobit (model "d"), which allows for both systematic and random differences between households. Allowing random intercepts improves log-likelihood by 1205 over the model with fixed intercept (model "b"), with a u^2 of 0.126. The full hierarchical model offers a log-likelihood improvement of only 163 compared to the random intercepts specification, and a u^2 of 0.136. Clearly, individual differences attributable to household demographics offer only a fraction of the explanation available from unmodeled factors. Taken together, the large improvement in fit of models "c" and "d" over fixed effects models suggest that individual differences offer substantial explanation of shopping behavior.

We also use nested models to assess the relative contributions of marketing variables and travel time. We do this by restricting travel time parameters to zero in model "e", then restricting parameters for marketing variables to be zero in model "f." By comparing the fit of these models with the full model, we find that the marketing variables make a substantially greater contribution to fit than travel time. The full model ("d") is 223 log likelihood points better than model "e," but only 11 log-likelihood points better than model "f".

Minimizing AIC favors selection of the full model, while minimizing BIC, which imposes a more severe penalty for additional parameters, favors a specification without travel time (model "f"). We include travel time because our objective is to make inferences about the effects of such factors on shopping behavior, even at the expense of parsimony.

C. Format-Level Empirical Results

The capability to relate individual-level decisions and parameters to retailer revenues is an important benefit of our model specification. Even though our model is estimated at the chain level, we can use it to predict revenue response at the format level. To do so we make two transformations. First, we focus on expected revenues by (1) combining household patronage and conditional spending decisions into expected expenditures, then (2) summing expected expenditures over households. Next, we sum expected revenues over store chains in each format in order gain a better understanding of how the format as a whole behaves.

The parameters discussed in the previous sub-section can be difficult to interpret individually since they separate the effect on shopper patronage from the effect on conditional spending. To summarize the two effects, we compute revenue elasticities. A revenue elasticity is defined as the average percentage change in the expected revenues of a format (based on expenditures of all households in the sample) in response to a one-percent increase in the *j*th predictor variable (v_j). For example, our price elasticity of revenue for mass merchandisers measures the percent change in revenues that would result from a 1% increase in prices, across all categories at each mass merchandiser. Note that the effect of such an across-the-board price increase would be independent of the household-level consumption weights.

Expected revenues incorporate expectations of both the probability of patronage and conditional expenditures, summed across all households *h*. First, we define the expected revenues at chain *i*:

$$E\left(R_{it}\right) = \sum_{H} E\left(y^{*}_{hit}\right) \Pr\left(z_{hit} = 1\right) \tag{9}$$

where:

$$E\left(y^{*}_{hit}\right) = \alpha_i + \mathbf{x}_{hit}\boldsymbol{\beta}_i + d_{hi}\gamma_i + \mathbf{s}'_t\boldsymbol{\lambda}_i \tag{10}$$

$$\Pr(z_{hit} = 1) = \Phi\left(\ \iota_{hi} + \mathbf{x}'_{hit}\boldsymbol{\theta}_i + d_{hi}\chi_i + \mathbf{s}'_t\boldsymbol{\kappa}_i\right) \tag{11}$$

We now aggregate the chain revenues to the format level:

$$E[\mathrm{R}_{ft}] = \sum_{i \in F} E[\mathrm{R}_{it}] \tag{12}$$

where F defines the set of retailers in format f. Finally, format-level elasticities for variable v are defined as:

$$\eta_{vft} = \frac{\partial E\left(R_{ft}\right)}{\partial v_{ft}} \frac{v_{ft}}{E\left(R_{ft}\right)} \tag{13}$$

Our estimates of format-level revenue elasticities are given in Table 7, with standard errors shown in parentheses below the estimates. The elasticities are estimated directly from the draws of the MCMC sample. Because elasticities are pure numbers, their magnitudes are comparable across formats.

1. Price: Revenue elasticities of price show that mass merchandiser would likely gain revenue by raising prices, while drug and grocery stores would lose revenues. However, none of the elasticities are significantly different than zero — not surprising given the minimal price variation and insignificant parameter estimates (see §III.A.). It is instructive to point out the difference between revenue price-elasticities and the more commonly studied quantity price-elasticities. Revenue price-elasticity is equal to one plus the corresponding quantity price-elasticity.[11] Therefore, the fact that revenue price-elasticities are not significantly different from zero indicates that the corresponding quantity price-elasticities are not significantly different from unity. This is consistent with the findings of Hoch, Dreze, and Purk (1994) who find that grocers tend to face an inelastic aggregate demand curve.

2. Promotion: Average *PROMO* elasticities are highly significant in all formats, though the effect differs by format. The most promotionally oriented format, drug stores, would gain substantial revenues by promoting less (η = -1.323). We infer that the deep promotions do not generate the additional trips, nor the additional spending per trip, needed to offset the revenue lost on promotional discounts. This is consistent with the format's convenience positioning. In contrast, grocery stores (η = 0.633) and mass merchandisers (η = 0.729) would realize additional revenues by increasing promotions. We do not to suggest that these formats would profit by increasing promotions, but consumer spending would increase. Note that revenue elasticities of promotion are inversely related to average promotional intensity. The highly promotional drug store chain (average discount of 23.4%) has a negative elasticity, while the less promotional formats, grocery (average discount of 20.1%) and mass merchandisers (average discount of 16.7%) are positive. We will develop this observation further in the next sub-section.

3. Assortment: Assortment elasticities are highest for grocery stores, 4.972, compared to 0.897 and -0.109 for mass and drug chains. The high sensitivity of grocers' revenues to product assortment levels is consistent with their actual assortment levels, which are far greater than other formats (see Table 1). These elasticities imply that if assortments were uniformly higher in grocery stores, revenues would also be substantially greater. However, given the floor space constraints that grocers face, increasing assortments could prove challenging (and costly). Moreover, much of the grocery industry's recent focus has been on reducing retail assortments to gain cost advantages and operational efficiencies. Our results do not support this approach, suggesting that smaller assortments are associated with substantially lower revenues among grocery stores.

4. Travel Time: Travel time has a consistent negative effect across formats, implying that as travel time increases to stores of each format, expenditures at that format decrease. Average elasticities for all formats are negative (two are significant), and the magnitudes of travel elasticities range from -0.308 and -0.106. Grocers and drug stores have similar mean elasticity estimates, which are both significant. The lower revenue elasticity estimate for mass merchandisers suggests that the format is less sensitive to travel times. Again, this is likely because consumers stockpile goods when making trips to more distant, but lower priced mass merchandisers. This stockpiling offsets the reduced probability of visiting more distant stores.

In summary, we find significant differences in revenue response across formats to marketing and travel variables. Grocery store revenues are highly sensitive to increases in category assortments. Their revenues also increase with increases in promotional intensity and decreases in shoppers' travel times. Mass merchandiser revenues are more sensitive than grocers to increases in promotion, but less sensitive than grocers to increases in assortment. Mass merchandisers suffer less than other formats from longer travel times, which generally result from lower market penetration. Finally, drug store revenues, the most promotional format, would benefit from *decreasing* promotional intensity. Drug stores suffer from increasing consumer travel times almost as much as grocers, but would not benefit at all from increasing category assortments.

D. Patterns of cross-format and intra-format shopping

The hierarchical specification of our multivariate type 2 tobit model generates household-level intercept coefficients, which represent consumers' intrinsic preferences for the store chains and formats being modeled. Understanding how preferences for stores are related within and across formats helps us to understand patterns of retail competition. We compute correlations in preferences among stores using draws from the MCMC sample, and thus develop empirical distributions of store-preference correlations. The 6 × 6 store chain correlation matrices for patronage and spending decisions are reported in Table 8.

The correlations suggest similarities and differences in patterns of competition for the two decisions. We begin with preference correlations for the patronage decision in the upper panel of the table. The highest magnitude correlation is between grocery chains (ρ = -0.633). This large negative correlation suggests that the more consumers prefer one grocer, the less they prefer the other. Thus, preference at one chain is a strong negative predictor of preference at the other. Stated differently, preference is specific to the chain, not shared within the format. This stands in contrast to the three mass merchandisers, for whom preference at one chain is a significant positive predictor of preference at the other two ($0.137 \leq \rho \leq 0.309$). Thus, a preference to patronize mass merchandisers is shared among store chains within the format.

Next, we consider preference correlations for the conditional spending decision in the lower panel of the table. These correlations capture relationships in preference for spending at the six retailers. As with the patronage decision, we find a significant negative relationship in preferences for the two grocery chains (ρ = -0.363). A preference for spending at one grocery chain is therefore a negative predictor of preference for spending at the other. This finding, together with the large negative correlation in patronage preferences, suggests an overall substitution relationship between the two grocery retailers. The remaining conditional spending correlations appear to reflect a household-level preference for promotional levels across stores. We find that spending preferences are positively correlated (ρ = 0.217) at the two most promotional retailers, the drug store chain and Grocer #1 (mean promotional discounts 24.3% and 21.5%, respectively). Spending at the least promotional retailer, Mass Merchandiser #3 (mean promotional discount 14.1%), is largely uncorrelated with spending at other chains, though it is somewhat negatively correlated with Grocer #2 (ρ = -0.127) and Mass Merchandiser #1 (ρ = -0.185). Between these promotional extremes, spending at Grocer #2 and Mass Merchandiser #1 and #2 are all positively correlated and highly significant ($0.246 \leq \rho \leq 0.518$). Thus, spending preferences seem to reflect "promotional tiers", in this case deep, moderate, and shallow discounters.

In summary, patronage preferences are largely correlated within formats, with negative intra-format correlations between grocery stores and positive intra-format correlations among mass merchandisers. In contrast, spending correlations reflect a different retail segmentation, perhaps based on promotional discounting policies. We also note the significant positive correlations between the drug store chain and Mass Merchandiser #1 for both patronage (ρ = 0.210) and spending (ρ = 0.563) preferences. We conjecture that this affinity may be due to the fact that both chains have a large number of stores in urban areas.

Next, we examine preference correlations at the format-level. To do so, household-level intercepts are pooled across chains for each format as follows (patronage models are shown for exposition):

$$M\boldsymbol{\iota}_{it} \sim MVN\left(\mathbf{0}, M\mathrm{P}M'\right) \tag{14}$$

where $\mathbf{0} = [0\ \ 0\ \ \cdots\ \ 0]'$, $\boldsymbol{\iota}_h \sim \mathrm{MVN}(0,\mathrm{P})$,[12] and

$$M = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \end{bmatrix} \tag{15}$$

Pre-multiplying by the matrix, M, sums the intercepts in each of the three formats. Cross-format correlations are computed from the adjusted covariance matrix, $M\mathrm{P}M'$. Because α's (from the conditional spending specifications) represent expectations of the logarithm of spending, we must exponentiate α's before pooling, then take the logarithm of the sum.

Table 9 shows preference correlations between formats. Because our analysis of store-level patronage preferences found correlations primarily within formats, it is not surprising that there are no significant correlations in patronage preferences between formats. Cross-format correlations in spending preferences are all positive, and two are significant. In particular, we find a positive correlation (ρ = 0.363) in spending between grocers and mass merchandisers. While we certainly cannot say that these formats do not compete, we can predict that households that prefer to spend more at grocery stores will also prefer to spend more at mass merchandisers. It is worth noting that all cross-format preference correlations, for both patronage and spending, are positive. This suggests a general household-level preference for shopping that goes across formats.

V. Discussion and Managerial Implications

We began this paper by noting that grocery retailers view mass merchandisers as a competitive threat. Our analysis of unexplained expenditures (see Table 9) does not show a direct substitution relationship, even though the products sold at mass merchandisers overlap with traditional grocers. Households that prefer to spend more at grocery stores also prefer to spend more at mass merchandisers. Moreover, the negative preference correlations for patronage and conditional spending between grocery retailers suggests substitution within the grocery format is much stronger than between grocery and non-grocery formats.

To illustrate the implications of our findings regarding response to the marketing mix, we consider two possible strategic objectives for a grocery retailer: (1) to increase its customer base by attracting more shoppers, and (2) to increase spending per customer in its stores. Achieving either of these objectives will result in higher revenues and, depending upon costs, higher profits for the chain. We conduct a sensitivity analysis to show how these objectives might be achieved by changing marketing policies. Specifically, we use our model to predict how the retailer's customer base and revenues would respond to more aggressive levels of promotion, assortment, and market penetration (i.e., more stores). For example, how would grocery revenues respond if grocers sold 2% more of their items on promotion? What if the retailer offered assortments in every category that were 2% deeper? What if the retailer offered 5% more stores in the market area, and shoppers' travel times were correspondingly shorter? We note, however, that the range of the data for these variables is limited, making predictions beyond a narrow range problematic. Table 10 shows the percentage of households shopping (i.e., customer base), and share of revenues among the stores in our dataset, for Grocers #1 and #2, both with current and hypothetical levels of the marketing variables. Note that Δs in the table are proportional changes in baseline levels of shoppers and market share.

If either grocery chain were to offer deeper assortments or locate more stores in the market area, their customer base and share of revenues would increase. Shoppers are highly sensitive to assortments at both grocery chains. If Grocer #1 were to increase its assortments by 2% across all categories, its customer base would increase to 60.09% of all households (a proportional increase of 3.25%), and its market share would increase by 1.91 share points (a proportional increase of 8.08%). Grocer #2 would also benefit from a similar increase in assortment, though somewhat less so. A 2% assortment increase would raise its customer base to 84.51% of households (a proportional increase of 2.17%), and augment its market share by 2.34 share points (a proportional improvement of 5.19%). Increasing market penetration by 5% for both stores would result in more modest improvements in market share, but differential effects on customer base. If Grocer #1 were to increase its market penetration by 5% (four stores) its customer base would increase dramatically to 61.51% of all households (a proportional increase of 5.68%), while its market share would increase by only 0.58 share points (a proportional increase of 2.45%). Thus, the average customer would spend less if Grocer #1 were to increase its penetration. Grocer #2 would benefit far less by increasing its penetration by 5% (nine stores), perhaps because its current high penetration results in a ceiling effect. Greater market penetration of Grocer #2 would result in a customer base increase to 84.03% (a proportional improvement of only 0.52%) and a market share gain of only 0.35 share points (a proportional increase of only 0.77%).

Increasing promotions would have a differential effect on the two grocery retailers. Were they to unilaterally increase promotions, the smaller, more promotional Grocer #1 would suffer, while the larger, less promotional Grocer #2 would benefit. An increase in promotional intensity at Grocer #1 such that 2% more purchases are made on discounted items, would result in the customer base shrinking slightly to 57.86% of households (a proportional decrease of 0.59%), while losing 0.23 share points (a proportional decrease of 0.95%). A similar increase in promotional intensity at Grocer #2 would result in augmenting the customer base to 83.90% of all households (a proportional gain of 0.36%), and raising market share by 0.63 points (a proportional gain of 1.39%).

Should these grocers focus their efforts on building customer base or increasing customer spending? Grocer #1 has a relatively smaller number of stores (84 in our market area) and a relatively smaller customer base (58.20%). We find that the benefits of increasing penetration and, to a lesser extent increasing assortment, depend on attracting new customers. Thus, expanding its customer base is an appropriate objective for Grocer #1. This is not the case for Grocer #2. This retailer stands to gain few customers from increasing its market penetration (through adding stores to its current total of 171), or by offering more promotions. Grocer #2 could, however, augment its customer base by extending category assortments. Both retailers would realize substantial increases in spending per customer by offering deeper assortments, with market shares increasing at a proportionally higher rate than customer bases. Grocer #2 could also raise spending per customer by increasing promotional intensity. In sum, the more appropriate strategic objective for Grocer #2 is to focus on sales per customer.

How cost effective is it to address these objectives by offering deep assortments? If we assume that each store carries about 25,000 SKUs, then the incremental customers and revenues are available at a cost of inventorying and merchandising equal to carrying only 500 more products (25,000x2%). This is a relatively low cost, particularly when compared to adding stores, with the attendant real estate, inventory, labor, and overhead costs. Note that we have not modeled out-of-stocks, which might increase were assortments extended in each category. Out-of-stocks would certainly have a negative impact on patronage and spending.

VI. Summary and Future Research Directions

This research represents the first study of household-level shopping behavior across retail formats. The hierarchical multivariate type 2 tobit model introduced in this paper provides a flexible framework with which to analyze shopper's decisions about "where to shop" and "how much to spend." We summarize our empirical findings below and highlight hypotheses for future research:

1. Much of the variability in expenditures across formats can be explained by retail format alone. In fact, 31.1% of the variation in household-level monthly expenditures across formats can be explained with a model specifying only retailer intercepts (in a system of independent type 2 tobits with fixed effects).[13] This is likely due to the very different marketing policies that each of these formats follows (see Table 1). An interesting direction for future cross-format research would be to investigate whether consumers' shopping processes have higher-order shopping strategies (i.e., they anticipate long-term needs when making decisions about where to shop).

2. Among marketing variables, store patronage and spending are highly responsive to differences in retailers' promotional intensity, both over time and across shoppers' market baskets. Future research that addresses why we observe differential response to promotions across formats, and how retailers should therefore change promotional strategies, would be useful. Household patronage and spending are also sensitive to differences in retailer assortments across market baskets, particularly at grocery chains. This is somewhat surprising given the grocery industry's focus on finding ways to reduce category-level assortments. Future research on this topic must determine the effect of assortment on patronage or store choice, rather than category sales alone.

3. Consumers' store-level shopping decisions are insensitive to monthly variation in the price of a market basket. We have found that relative basket prices are extremely stable over time (coefficient of variation = 0.022), and consumers are either unable to discern these small changes in basket prices (Alba, et al., 1994) or are not troubled to act on them (Kalyanaram and Little, 1994). Estimated revenue elasticities for all formats are not significantly different from zero, indicating that quantity price elasticities are not significantly different from unity. This suggests the hypothesis that consumer spending is insensitive to observed variation in market basket prices for packaged goods retailers. More general future research, including other markets or non-packaged goods retailers, would offer a useful test of this hypothesis and its limitations.

4. Of the formats considered, mass merchandisers are least sensitive to shoppers' travel time. Future research might address store placement (both where and how many) and how they differ across formats.

5. The two previous findings can be illuminated by relating mean levels of marketing variables and consumer response to cross-sectional (and in some cases temporal) variation in those levels. Revenue elasticities of promotion (η_{drug} = -1.323; $\eta_{grocery}$ = 0.633, η_{mass} = 0.729) are *inversely* related to mean levels of both advertised discount ($discount_{drug}$ = 24.3%; $discount_{grocery}$ = 20.1%; $discount_{mass}$ = 16.7%) and percent of sales on promotion ($\%sales_{drug}$ = 29.3%; $\%sales_{grocery}$ = 18.2%; $\%sales_{mass}$ = 13.9%). Thus, less promotional formats could realize greater revenues by increasing promotional intensity, while more promotional formats would benefit by reducing promotions. By contrast, revenue elasticities of assortment (η_{drug} = -0.109; $\eta_{grocery}$ = 4.972, η_{mass} = 0.897) are *positively* related to mean assortment indices ($assortidx_{drug}$ = 0.408; $assortidx_{grocery}$ = 1.868; $assortidx_{mass}$ = 0.587). This indicates that formats with greater assortments could benefit by increasing their offerings, while the lowest assortment format could not. In other words, while retailers across formats are responding to consumers' sensitivity to assortment, grocers in particular would benefit from offering even deeper assortments. We also find that revenue elasticities of travel (η_{drug} = -0.243; $\eta_{grocery}$ = -0.308, η_{mass} = -0.106) are somewhat related to mean levels of travel time ($traveltime_{drug}$ = 9.6; $traveltime_{grocery}$ = 11.0; $traveltime_{mass}$ = 15.6), which result from retailers' market penetration strategies. We find that the lower penetration of mass merchandisers is consistent with shopper's insensitivity to travel for this format. We believe that these travel time elasticities are biased downward because of measurement error due to trip chaining. Future research concerning how retailers could more effectively respond to differential sensitivity to the market mix across formats would be important.

6. Households that have higher intrinsic preferences for spending at grocery stores also prefer to spend more at other formats, particularly mass merchandisers. Within grocery stores, spending preferences are negatively related. It also appears that spending preferences exist within promotional "tiers", i.e., spending preferences at the most promotional stores (drug chain and Grocer #1) are positively related, while preferences at moderately promotional stores (Grocer #2, Mass Merchandiser #1 and #2) are also positively

related. No strong relationships exist for patronage preferences across formats, though relationships within formats are apparent. Between the two grocery stores we study, an intrinsic preference for patronizing one chain is a strong negative predictor of preference for the other. Among mass merchandisers, a preference to patronize one chain is a positive predictor of preference for the others. Taken together, these findings indicate that competition between formats is fundamentally different than competition within formats, and suggest that, across formats, stores are not close substitutes. Studies that include multiple geographic areas and larger panels are needed to verify our initial findings about competition across retailer formats. While recent work has considered why consumers choose different stores on different trips, little has been done to determine the substitutability or complementarity of stores of different formats. In addition, we offer the hypothesis for future study that, across formats, consumers prefer to shop at stores with similar promotional policies.

In conclusion, we hope that our results will foster more research in the area of cross-format shopping. We must point out the limitations of our study, however. Our data comes from only one metropolitan market over a two-year span. Other markets may exhibit different characteristics, and the time span of our data may not be long enough to capture long-term trends. In addition, we have focused on the household's aggregate purchases across all categories on a monthly basis. We believe that separating products into those categories which are carried in common across the stores (e.g., dry packaged groceries) and those that are not (e.g., produce, meat, and bakery items) would be an important advance over our current research. Unfortunately, this increases the dimension of the problem substantially. Further, it is likely that some households are using higher-order shopping strategies, i.e., visiting multiple stores on a single shopping visit, or dynamically determining "stock-up" and "fill-in" trips. Taking a more holistic approach to consumption, purchases, time allocation, and the household production function would also greatly advance our understanding of cross-format shopping. It is our hope that the results from this study will aid future research on these topics.

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TABLE 1 Descriptive Statistics for Marketing Policies Across Store Chains and Retail Formats

	Price Index	Shelf Price Index	Promotional Discount	% Sales on Promotion	Assortment Index	Travel Time (Minutes)
Grocery 1	1.012	1.019	21.5%	21.7%	1.824	11.9
Grocery 2	1.023	1.016	18.6%	14.7%	1.913	10.1
Grocery Avg.	*1.017*	*1.017*	*20.1%*	*18.2%*	*1.868*	*11.0*
Mass Merch. 1	0.950	0.916	18.1%	13.2%	0.647	14.1
Mass Merch. 2	0.921	0.916	18.0%	17.9%	0.602	15.2
Mass Merch. 3	0.918	0.902	14.1%	10.5%	0.513	17.6
Mass Merch. Avg.	*0.930*	*0.912*	*16.7%*	*13.9%*	*0.587*	*15.6*
Drug Store	*0.995*	*1.022*	*24.3%*	*29.3%*	*0.408*	*9.6*

TABLE 2 Descriptive Statistics for Shopping Behaviors Across Store Chains and Retail Formats

	Interval Between Trips (Days)	Total Spending / Trip	Patronage - % of Housholds Shopping / Month
Grocery 1	10.1	$85.70	58.2%
Grocery 2	7.1	$88.65	83.6%
Grocery Avg.	*8.6*	*$87.18*	*70.9%*
Mass Merch. 1	29.1	$78.71	28.4%
Mass Merch. 2	13.6	$80.52	36.9%
Mass Merch. 3	18.3	$84.09	33.2%
Mass Merch. Avg.	*15.9*	*$81.11*	*32.9%*
Drug Store	*19.7*	*$36.36*	*46.0%*

TABLE 3 Descriptive Statistics for Household Demographics

	Mean	StdDev
Family Size (#)	2.98	1.39
Income (x $1000)	52.1	25.7
Working Woman (%)	65.6%	47.5%
College Educated (%)	15.6%	36.3%
Homeowner (%)	86.5%	34.2%
Children Under 6 (%)	16.7%	37.3%

TABLE 4 **Marketing Mix and Travel Time Parameter Estimates**

PATRONAGE - *WHERE TO SHOP*	Drug	Grocery 1	Grocery 2	Mass 1	Mass 2	Mass 3
INTERCEPT	-0.201 *	0.826 ***	3.284 ***	-1.159 ***	-1.011 ***	-0.555 ***
	(0.104)	(0.169)	(0.467)	(0.122)	(0.114)	(0.130)
PRICE	0.012	-0.048	0.153	0.210 ***	-0.087 **	0.070
	(0.036)	(0.120)	(0.105)	(0.063)	(0.036)	(0.061)
PROMO	-0.025	-0.144	0.510 *	0.167 **	0.239 ***	0.424 ***
	(0.039)	(0.183)	(0.203)	(0.057)	(0.056)	(0.076)
ASSORT	0.055	0.526 ***	0.550 ***	-0.017	0.535 ***	-0.001
	(0.039)	(0.113)	(0.138)	(0.051)	(0.062)	(0.079)
TRAVTIME	-0.111 **	-1.085 ***	-0.375 *	-0.201 ***	0.011	-0.400 ***
	(0.044)	(0.160)	(0.173)	(0.068)	(0.052)	(0.086)

EXPENDITURE - *HOW MUCH TO SPEND*	Drug	Grocery 1	Grocery 2	Mass 1	Mass 2	Mass 3
INTERCEPT	3.596 ***	4.646 ***	5.189 ***	4.628 ***	4.404 ***	4.512 ***
	(0.101)	(0.076)	(0.059)	(0.188)	(0.133)	(0.131)
PRICE	-0.018	0.008	-0.019	-0.066	0.044	0.056
	(0.036)	(0.042)	(0.021)	(0.074)	(0.047)	(0.070)
PROMO	-0.191 ***	-0.102 *	0.217 ***	0.082	0.283 ***	-0.165 *
	(0.039)	(0.057)	(0.028)	(0.077)	(0.072)	(0.085)
ASSORT	-0.045	0.280 ***	0.191 ***	-0.117 *	0.316 ***	0.286 **
	(0.041)	(0.066)	(0.023)	(0.060)	(0.043)	(0.089)
TRAVTIME	-0.065 *	-0.304 ***	-0.044 **	-0.037	-0.011	0.021
	(0.041)	(0.089)	(0.017)	(0.096)	(0.045)	(0.089)

Note: * Statistically Significant a=0.05
** Statistically Significant a=0.01
*** Statistically Significant a=0.001

TABLE 5 **Demographic Parameter Estimates from Hierarchy**

	Drug	Grocery 1	Grocery 2	Mass 1	Mass 2	Mass 3
PATRONAGE - *WHERE TO SHOP*						
INTERCEPT	1.395 *	-0.365	4.217	-0.979 *	0.355	-2.035
	(0.746)	(1.353)	(3.707)	(0.684)	(2.095)	(1.435)
FAMSIZE	-0.082	-1.576 ***	1.084	0.524 **	2.243 **	0.485
	(0.227)	(0.488)	(1.163)	(0.234)	(0.801)	(0.473)
INCOME	-0.138	0.104	0.208	-0.219	0.277	-0.183
	(0.214)	(0.452)	(1.145)	(0.187)	(0.655)	(0.433)
OWNHOME	-1.355 *	0.930	2.871	1.109 *	-0.022	1.712
	(0.706)	(1.250)	(3.109)	(0.620)	(1.916)	(1.238)
FEMWORK	-0.348	-0.649	-1.296	-0.255	-1.827	-0.608
	(0.449)	(0.910)	(2.323)	(0.385)	(1.383)	(0.868)
COLLEGE	-1.061 *	-1.380	1.600	-0.758	-3.487 *	0.296
	(0.591)	(1.112)	(3.287)	(0.594)	(1.943)	(1.172)
YOUNGKID	0.430	3.092 **	-0.749	-0.477	-1.980	1.038
	(0.593)	(1.148)	(3.073)	(0.527)	(1.860)	(1.166)

	Drug	Grocery 1	Grocery 2	Mass 1	Mass 2	Mass 3
EXPENDITURE - *HOW MUCH TO SPEND*						
INTERCEPT	0.024	-0.685 *	0.013	-0.453 *	0.173	-0.466
	(0.263)	(0.370)	(0.354)	(0.227)	(0.273)	(0.330)
FAMSIZE	-0.005	-0.180	0.359 ***	0.136 *	0.330 ***	0.053
	(0.083)	(0.123)	(0.113)	(0.070)	(0.088)	(0.106)
INCOME	-0.030	-0.040	0.063	-0.015	0.209 *	-0.147
	(0.086)	(0.105)	(0.111)	(0.070)	(0.091)	(0.112)
OWNHOME	-0.311	0.431	-0.124	0.256	-0.166	0.156
	(0.234)	(0.339)	(0.319)	(0.222)	(0.256)	(0.298)
FEMWORK	0.365 *	0.365	0.245	0.259 *	0.086	0.374 *
	(0.167)	(0.238)	(0.230)	(0.125)	(0.179)	(0.198)
COLLEGE	-0.102	-0.109	-0.124	0.542 **	-0.392	0.298
	(0.226)	(0.291)	(0.296)	(0.180)	(0.248)	(0.259)
YOUNGKID	0.125	0.563 *	-0.262	-0.099	-0.167	0.216
	(0.228)	(0.323)	(0.315)	(0.171)	(0.221)	(0.256)

Note: * Statistically Significant a=0.05
** Statistically Significant a=0.01
*** Statistically Significant a=0.001

TABLE 6 **Nested Model Tests**

Model	Predictors	Individual Differences	Error Structure	Params	Log-Like	u^2	BIC	AIC
a	Marketing,Travel,Season	None	Independent	96	-16601	0.000	33599	33394
b	Marketing,Travel,Season	None	Multivariate	96	-15709	0.054	31815	31609
c	Marketing,Travel,Season	Random Intercepts	Multivariate	102	-14504	0.126	29430	29212
d	Marketing,Travel,Season	Hierarchy w/ Demographics	Multivariate	138	-14341	0.136	29254	28959
e	Travel,Season	Hierarchy w/ Demographics	Multivariate	120	-14564	0.123	29625	29368
f	Marketing,Season	Hierarchy w/ Demographics	Multivariate	132	-14352	0.135	29250	28967

TABLE 7 **Format-Level Elasticity Estimates**

	Drug		Grocery		Mass	
PRICE	-0.372		-1.050		1.299	
	(0.945)		(1.531)		(1.274)	
PROMO	-1.323	***	0.633	***	0.729	***
	(0.282)		(0.153)		(0.273)	
ASSORT	-0.109		4.972	***	0.897	*
	(0.212)		(0.554)		(0.413)	
TRAVTIME	-0.243	*	-0.308	***	-0.106	
	(0.163)		(0.089)		(0.156)	

Note: * Statistically Significant a=0.05
** Statistically Significant a=0.01
*** Statistically Significant a=0.001

TABLE 8 **Preference Correlations across Chains**

PATRONAGE - *WHERE TO SHOP*	Drug	HiLo Gro 1	HiLo Gro 2	Mass 1	Mass 2	Mass 3
Drug	1	0.273 **	-0.063	0.210 ***	0.003	0.064
		(0.051)	(0.066)	(0.050)	(0.049)	(0.048)
Grocery 1		1	-0.633 ***	-0.058	-0.082	0.076
			(0.054)	(0.073)	(0.052)	(0.059)
Grocery 2			1	-0.036	0.141 *	-0.012
				(0.071)	(0.069)	(0.084)
Mass 1				1	0.309 ***	0.137 **
					(0.047)	(0.049)
Mass 2					1	0.238 ***
						(0.052)
Mass 3						1

EXPENDITURE - *HOW MUCH TO SPEND*	Drug	HiLo Gro 1	HiLo Gro 2	Mass 1	Mass 2	Mass 3
Drug	1	0.217 **	-0.019	0.563 ***	-0.093	-0.032
		(0.074)	(0.061)	(0.077)	(0.098)	(0.130)
Grocery 1		1	-0.363 ***	0.180	-0.011	0.045
			(0.047)	(0.118)	(0.068)	(0.102)
Grocery 2			1	0.246 ***	0.518 ***	-0.127 *
				(0.104)	(0.055)	(0.073)
Mass 1				1	0.339 *	-0.185
					(0.122)	(0.121)
Mass 2					1	0.013
						(0.101)
Mass 3						1

Note:
* Statistically Significant a=0.05
** Statistically Significant a=0.01
*** Statistically Significant a=0.001

TABLE 9 **Preference Correlations Across Formats**

PATRONAGE - *WHERE TO SHOP*			
	Drug	Grocery	Mass
Drug	1	0.072	0.073
		(0.077)	(0.044)
Grocery		1	0.090
			(0.078)
Mass			1

EXPENDITURE - *HOW MUCH TO SPEND*			
	Drug	Grocery	Mass
Drug	1	0.161 **	0.123
		(0.065)	(0.094)
Grocery		1	0.363 ***
			(0.064)
Mass			1

Note: * Statistically Significant a=0.05
** Statistically Significant a=0.01
*** Statistically Significant a=0.001

TABLE 10 **Sensitivity Analysis - Marketing Variables**

	Actual Baseline	Δ Expected if Promotion Increased by 2%	Δ Expected if Assortment Increased by 2%	Δ Expected if Penetration Increased by 5%
GROCERY STORE #1				
% of Households Shopping	58.20%	-0.59%	3.25%	5.68%
Share of Revenues	23.64%	-0.95%	8.08%	2.45%
GROCERY STORE #2				
% of Households Shopping	83.59%	0.36%	2.17%	0.52%
Share of Revenues	45.11%	1.39%	5.19%	0.77%

Appendix A

Aggregation Effects on Price Variation

In order to assess the impact of aggregation on price variation, we evaluate prices at different levels of aggregation. We define aggregation along two dimensions — products and time. Aggregation over products is intended to reflect shopping decisions at different levels. For brand choice and quantity decisions, UPC or item-level prices are germane, so this provides our baseline. For category incidence, prices are typically evaluated at the category level (e.g., Dillon and Gupta, 1996, in another study in which item prices are weighted components of category attractiveness). For store-level shopping decisions, the relevant price is for a basket of products, including many categories (e.g., Bell, Ho and Tang, 1998; Bell, Bucklin, and Sismiero, 2000). Temporal aggregation levels are weekly and monthly. Retailer prices change weekly, so this is the usual baseline level (although in fact a very small percentage of prices are changed each week). Our *PRICE* variable, used to predict store-level patronage and quantity, is aggregated at the monthly level.

To examine price variation at different levels of aggregation, we compute "true" prices from merchandise files for all items which are sold at the two grocery and one drug store chain in our dataset, across nine categories (2262 total UPCs).[14] The coefficient of variation (standard deviation / mean) is computed to measure price variation. For UPC and category cross-sectional levels, the coefficients of variation are computed at that level, then averaged over the 2,262 products or nine categories, respectively. Note that our small market basket captures prices in only a few of the 261 packaged goods categories, and so does not reflect the true breadth of the average market basket. As such, it represents a conservative test of the effect of product aggregation at the basket level. The three store chains provide repeated measures of price variation. Results are reported in the following table:

		Cross-Sectional Aggregation								
		UPC			Category			Small Market Basket*		
		Drug	Grocery 1	Grocery 2	Drug	Grocery 1	Grocery 2	Drug	Grocery 1	Grocery 2
Temporal	Weekly	0.0642	0.0718	0.0597	0.0747	0.0713	0.0747	0.0308	0.0267	0.0342
Aggregation	Monthly	0.0487	0.0532	0.0502	0.0706	0.0659	0.0706	0.0297	0.0248	0.0331

* Small basket is comprised of products in nine categories: beer & ale, chocolate candy, salty snacks, internal analgesics, sanitary napkins, cigarettes, diapers, dog food, and household cleaners.

We observe that, in general, there is less variation in prices computed on a monthly basis than a weekly one. However, as cross-sectional aggregation increases, the effect of temporal aggregation is attenuated. In fact, more than 95% of price variation for the small market basket is preserved when aggregating prices from weekly to monthly (across the three retailers). In contrast, price variation decreases quite rapidly when aggregating from the "category" to the "small market basket" level (less than 42% of price variation is retained). An ANOVA of the data in the table shows very clearly that cross-sectional, or product, aggregation has an order-of-magnitude larger effect on the coefficient of variation (mean square = 0.0027) compared to temporal aggregation (mean square = 0.0002). These two factors together explain the coefficient of variation quite well, with $R^2 = 0.947$.

An important benefit of computing basket prices and promotional intensity across a great many categories is that we need make no assumptions about the representativeness of a small number of categories for the shopper's entire basket. Thus, our individually-weighted measure incorporating all packaged goods categories should more accurately reflect the true basket prices and promotions faced by the shopper. However, we do implicitly assume that the relative price, promotion and assortment levels of packaged goods reflect non-packaged goods as well (e.g., perishables such as produce and meat, clothing and durable items). Prices of such items are not available in syndicated panel data.

Appendix B

Using Residual Correlations for Prediction

The residual covariances have predictive value. Note that the conditional distribution for patronage of chain i is:

$$\Pr(z_{hit} = 1 | z^*_{hkt}) = \Phi\left(\phi_i + \mathbf{x}'_{hit}\boldsymbol{\vartheta}_i + d_{hi}\lambda_i + \mathbf{w}'_h\theta_i + \frac{\lambda_{ik}}{\lambda_{kk}}(z^*_{hk} - E[z^*_{hk}])\right), \tag{15}$$

where $i \neq k$ and $\lambda_{ik}=[\Lambda]_{ik}$. Suppose we know that, if a household frequents Mass Merchandiser #3 more than expected, the probability of frequenting Grocer #2 is also higher than expected. More precisely, suppose that the unconditional probability that a household visits Grocer #2 is 50%. If we know that this household has a higher probability of visiting Mass Merchandiser #3 than expected (e.g., let $(z^*_{hk} - E[z^*_{hk}])/\sqrt{\lambda_{kk}} = 2$), then the conditional probability of this household visiting Grocer #2 is 65%.

Alternatively, if the probability of shopping at all other stores is known except the one of interest, we can compute the reduction in standard deviation of z^*_{hi} to assess how this additional information can improve the prediction of whether a household will come to the chain of interest. For example, if we are interested in predicting patronage at Mass Merchandiser #3, and we know patronage at all other stores, the standard deviation of z^*_{hi} will be reduced by 31%. The range of reductions goes between 17% and 31% for the six chains in this study. Clearly, deviations from expected patronage at other stores can be very valuable to a retailer in predicting whether an individual will shop at their store.

Technical Report

Markov Chain Monte Carlo Estimation of a Hierarchical Multivariate Type-2 Tobit Model

We begin by modifying our notation. We rewrite the parameters for equation (2), the expenditure equation, $\boldsymbol{\omega}_{hi} = [\ \alpha_{hi}\ \ \boldsymbol{\beta}'_i\ \ \gamma_i\ \ \boldsymbol{\lambda}'_i\ ]'$. Similarly, we rewrite the parameters for equation (4), the patronage equation, $\boldsymbol{\zeta}_{hi} = [\ \iota_{hi}\ \ \boldsymbol{\theta}'_i\ \ \chi_i\ \ \boldsymbol{\kappa}'_i\ ]'$. We also rewrite the predictor variables common to the two equations, $\mathbf{m}_{hit} = [\ 1\ \ \mathbf{x}'_{hit}\ \ t_{hi}\ \ \mathbf{s}'_t\ ]'$. We then stack (1) the dependent variables of both equations for all households h and time periods t so that $\mathbf{y}^*_i = [\ y^*_{1i1}\ \ y^*_{1i2}\ \dots\ y^*_{HiT}\ ]'$ and $\mathbf{z}^*_i = [\ z^*_{1i1}\ \ z^*_{1i2}\ \dots\ z^*_{HiT}\ ]'$, (2) the error terms of both equations for all households h and time periods t so that $\boldsymbol{\varepsilon}_i = [\ \varepsilon_{1i1}\ \ \varepsilon_{1i2}\ \dots\ \varepsilon_{HiT}\ ]'$ and $\mathbf{u}_i = [\ u_{1i1}\ \ u_{1i2}\ \dots\ u_{HiT}\ ]'$, and finally (3) the predictor variables shared by the two equations, $M_i = [\ \mathbf{m}_{1i1}\ \ \mathbf{m}_{1i2}\ \dots\ \mathbf{m}_{HiT}\ ]'$. We allow for contemporaneous correlation of the error terms in equations (2) and (4) by adopting the SUR forms shown below.

$$\begin{bmatrix} \mathbf{y}_1^* \\ \mathbf{y}_2^* \\ \vdots \\ \mathbf{y}_S^* \end{bmatrix} = \begin{bmatrix} M_1 & & & \\ & M_2 & & \\ & & \ddots & \\ & & & M_S \end{bmatrix} \begin{bmatrix} \boldsymbol{\omega}_1 \\ \boldsymbol{\omega}_2 \\ \vdots \\ \boldsymbol{\omega}_S \end{bmatrix} + \begin{bmatrix} \boldsymbol{\varepsilon}_1 \\ \boldsymbol{\varepsilon}_2 \\ \vdots \\ \boldsymbol{\varepsilon}_S \end{bmatrix} \quad , \quad \begin{bmatrix} \mathbf{z}_1^* \\ \mathbf{z}_2^* \\ \vdots \\ \mathbf{z}_S^* \end{bmatrix} = \begin{bmatrix} M_1 & & & \\ & M_2 & & \\ & & \ddots & \\ & & & M_S \end{bmatrix} \begin{bmatrix} \boldsymbol{\zeta}_1 \\ \boldsymbol{\zeta}_2 \\ \vdots \\ \boldsymbol{\zeta}_S \end{bmatrix} + \begin{bmatrix} \mathbf{u}_1 \\ \mathbf{u}_2 \\ \vdots \\ \mathbf{u}_S \end{bmatrix}$$

where, for $\{i = 1, \dots, S\}$:

$\boldsymbol{\varepsilon}_i$ is an HT vector of disturbances such that $E(\boldsymbol{\varepsilon}_i) = 0$ and $E(\boldsymbol{\varepsilon}_i\boldsymbol{\varepsilon}_j') = \sigma_{ij}I_{HT}$, and

$\mathbf{u}_i$ is an HT vector of disturbances such that $E(\mathbf{u}_i) = 0$ and $E(\mathbf{u}_i\mathbf{u}_j') = \theta_{ij}I_{HT}$,

$$\text{with } \Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1S} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2S} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{S1} & \sigma_{S2} & \cdots & \sigma_{SS} \end{bmatrix} \quad , \quad \Lambda = \begin{bmatrix} \theta_{11} & \lambda_{12} & \cdots & \lambda_{1S} \\ \lambda_{21} & \lambda_{22} & \cdots & \lambda_{2S} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{S1} & \lambda_{S2} & \cdots & \lambda_{SS} \end{bmatrix}$$

Finally, for clarity we rewrite the SUR equations above as: $\mathbf{y}^* = M\boldsymbol{\omega} + \boldsymbol{\varepsilon}$ and $\mathbf{z}^* = M\boldsymbol{\zeta} + \mathbf{u}$.

Now, we write the hierarchies associated with the two shopping decisions. We stack (1) the intercept coefficients for all households h so that $\boldsymbol{\alpha}_i = [\ \alpha_{1i}\ \ \alpha_{2i}\ \dots\ \alpha_{Hi}\ ]'$ and $\boldsymbol{\iota}_i = [\ \iota_{1i}\ \ \iota_{2i}\ \dots\ \iota_{Hi}\ ]'$, (2) the common predictor variables for the two equations, $W = [\ \mathbf{w}_1\ \ \mathbf{w}_2\ \dots\ \mathbf{w}_H\ ]'$, and (3) the error terms of the hierarchical equations for all households h, $\boldsymbol{\xi}_i = [\ \xi_{1i}\ \ \xi_{2i}\ \dots\ \xi_{Hi}\ ]'$ and $\boldsymbol{\tau}_i = [\ \tau_{1i}\ \ \tau_{2i}\ \dots\ \tau_{Hi}\ ]'$. We allow for contemporaneous correlation of unexplained preferences across store chains in equations (5) and (6) by using the SUR forms below.

$$\begin{bmatrix} \boldsymbol{\alpha}_1 \\ \boldsymbol{\alpha}_2 \\ \vdots \\ \boldsymbol{\alpha}_S \end{bmatrix} = \begin{bmatrix} W & & & \\ & W & & \\ & & \ddots & \\ & & & W \end{bmatrix} \begin{bmatrix} \boldsymbol{\delta}_1 \\ \boldsymbol{\delta}_2 \\ \vdots \\ \boldsymbol{\delta}_S \end{bmatrix} + \begin{bmatrix} \boldsymbol{\xi}_1 \\ \boldsymbol{\xi}_2 \\ \vdots \\ \boldsymbol{\xi}_S \end{bmatrix} \quad , \quad \begin{bmatrix} \boldsymbol{\iota}_1 \\ \boldsymbol{\iota}_2 \\ \vdots \\ \boldsymbol{\iota}_S \end{bmatrix} = \begin{bmatrix} W & & & \\ & W & & \\ & & \ddots & \\ & & & W \end{bmatrix} \begin{bmatrix} \boldsymbol{\psi}_1 \\ \boldsymbol{\psi}_2 \\ \vdots \\ \boldsymbol{\psi}_S \end{bmatrix} + \begin{bmatrix} \boldsymbol{\tau}_1 \\ \boldsymbol{\tau}_2 \\ \vdots \\ \boldsymbol{\tau}_S \end{bmatrix}$$

where, for $\{i = 1, ..., S\}$ $\boldsymbol{\xi}_i$ is an H vector of disturbances such that $E(\boldsymbol{\xi}_i) = 0$ and $E(\boldsymbol{\xi}_i\boldsymbol{\xi}_j') = v^{\alpha}_{ij}I_H$, and $\boldsymbol{\tau}_i$ is an H vector of disturbances such that $E(\boldsymbol{\tau}_i) = 0$ and $E(\boldsymbol{\tau}_i\boldsymbol{\tau}_j') = v^{\iota}_{ij}I_H$,

with $V_\alpha = \begin{bmatrix} v^{\alpha}_{11} & v^{\alpha}_{12} & \cdots & v^{\alpha}_{1S} \\ v^{\alpha}_{21} & v^{\alpha}_{22} & \cdots & v^{\alpha}_{2S} \\ \vdots & \vdots & \ddots & \vdots \\ v^{\alpha}_{S1} & v^{\alpha}_{S2} & \cdots & v^{\alpha}_{SS} \end{bmatrix} \quad , \quad V_\iota = \begin{bmatrix} v^{\iota}_{11} & v^{\iota}_{12} & \cdots & v^{\iota}_{1S} \\ v^{\iota}_{21} & v^{\iota}_{22} & \cdots & v^{\iota}_{2S} \\ \vdots & \vdots & \ddots & \vdots \\ v^{\iota}_{S1} & v^{\iota}_{S2} & \cdots & v^{\iota}_{SS} \end{bmatrix}$

We summarize the SUR equations above as: $\boldsymbol{\alpha} = \mathrm{W}\boldsymbol{\delta} + \boldsymbol{\xi}$ and $\boldsymbol{\iota} = W\boldsymbol{\psi} + \boldsymbol{\tau}$.

Both the SUR structures of the models above and the hierarchical specification preclude analytical solutions of the S-model system of equations under consideration. Moreover, the high dimension of the integral makes the use of numerical integration techniques infeasible for our systems of equations. Due to the limitations of analytical and numerical estimation techniques for the hierarchical multivariate Tobit specification, we use an MCMC approach to estimate the marginal distributions of the latent dependent variables, parameters and covariances. The MCMC algorithm involves sampling sequentially from the relevant conditional distributions over a large number of iterations. These draws can be shown to converge to the marginal posterior distributions.

Our implementation of the MCMC algorithm has three steps that are described below.

A. Conditional distributions

The first implementation step requires that we specify conditional distributions of the relevant variables. The solutions of these distributions follow from the normality assumption of the disturbance terms. We employ natural conjugate priors. Specifications of the conditional distributions are as follows:

1. y^*_{hit} is y_{hit} if y_{hit}>0, otherwise y^*_{hit} is drawn from a normal distribution, truncated above at 0.

$$y^*_{hit}|\mathbf{y}^*_{h,j\neq i,t},\boldsymbol{\omega}_i,\alpha_{hi},\Sigma \sim \begin{cases} y_{hit}|y_{hit}>0 \\ N_T\left(\mathbf{m}_{hit}\boldsymbol{\omega}_i+\alpha_{hi}-\boldsymbol{\sigma}_{ij}\Sigma^{-1}_{jj}\mathbf{y}_{h,j\neq i,t},\sigma_{ii}-\boldsymbol{\sigma}_{ij}\Sigma^{-1}_{jj}\boldsymbol{\sigma}_{ji}\right) \textit{ otherwise} \end{cases}$$

$$\text{where: } \mathbf{y}^*_{ht}=\begin{bmatrix} y^*_{hit} \\ -- \\ \mathbf{y}^*_{h,j\neq i,t}\end{bmatrix} \text{ and } \Sigma=\begin{bmatrix} \sigma_{ii} & | & \boldsymbol{\sigma}_{ij} \\ -- & + & -- \\ \boldsymbol{\sigma}_{ji} & | & \Sigma_{jj}\end{bmatrix}$$

As the notation suggests, the $\mathbf{y}^*_{ht}$ vector and Σ matrix are partitioned between the store chain of interest, *i*, and all other store chains, $j \neq i$. Without loss of generality, we have shown the store chain of interest to be the first. Each chain is then drawn in succession for household *h*, conditioning on $\mathbf{y}^*_{h,i\neq j,t}$, a vector of latent dependent variables for all $j \neq i$, and Σ.

The truncated normal variates are drawn using the inverse cdf method. Given the truncation value of zero, the conditional expected value of the dependent variable,

$$E\left(y^{*(t)}_{hit}\right)|\mathbf{y}^{*(t-1)}_{h,j\neq i,t},\boldsymbol{\omega}^{(t-1)}_i,\alpha^{(t-1)}_{hi},\Sigma^{(t-1)}=\mathbf{m}_{hit}\boldsymbol{\omega}^{(t-1)}_i+\alpha^{(t-1)}_{hi}-\sigma^{(t-1)}_{ij}\Sigma^{-1(t-1)}_{jj}\left(\mathbf{y}^{*(t-1)}_{h,j\neq i,t}-E\left(\mathbf{y}^{*(t-1)}_{h,j\neq i,t}\right)\right),$$

and the conditional standard deviation of the dependent variable,

$\sigma^{(t-1)}_{y^*}|\Sigma^{(t-1)}=\sigma^{(t-1)}_{ii}-\boldsymbol{\sigma}^{(t-1)}_{ij}\Sigma^{-1(t-1)}_{jj}\boldsymbol{\sigma}^{(t-1)}_{ji}$, we draw the truncated normal values using the following procedure. (Note that conditioning arguments are dropped for clarity):

- Compute the upper limit for uniform interval: $L=\Phi\left[\left(0-E\left(y^{*(t)}_{hit}\right)\right)/\sigma^{(t-1)}_{y^*}\right]$, where Φ[·] represents the Normal cdf.
- Draw a uniform variate: $U \sim$ *Uniform*(0,L).
- Compute the realized value of the uniform draw: $y^{*(t)}_{hit}=\Phi^{-1}(U)\sigma^{(t-1)}_{y^*}+E\left(y^{*(t)}_{hit}\right)$.

Note that, when using this procedure, values of U approaching 0 tend toward - ∞ while values of U approaching L tend toward zero, the truncation point.

2. In a similar fashion, we draw the latent dependent variable values for the probit component of the model. If the indicator variable $z_{hit} = 1$, then z^*_{hit} is drawn from a normal distribution, truncated below at 0. Otherwise, z^*_{hit} is drawn from a normal distribution, truncated above at 0.

$$z^*_{hit} | \mathbf{z}^*_{h,j\neq i,t}, \boldsymbol{\zeta}_i, \iota_{hi}, \Lambda \sim N_T\left(\mathbf{m}_{hit}\boldsymbol{\zeta}_i + \iota_{hi} - \boldsymbol{\lambda}_{ij}\Lambda^{-1}_{jj}\mathbf{z}^*_{h,j\neq i,t}, \lambda_{ii} - \boldsymbol{\lambda}_{ij}\Lambda^{-1}_{jj}\boldsymbol{\lambda}_{ji}\right)$$

where: $\mathbf{z}^*_{ht} = \begin{bmatrix} z^*_{hit} \\ -- \\ \mathbf{z}^*_{h,j\neq i,t} \end{bmatrix}$ and $\Lambda = \begin{bmatrix} \lambda_{ii} & | & \boldsymbol{\lambda}_{ij} \\ -- & + & -- \\ \boldsymbol{\lambda}_{ji} & | & \Lambda_{jj} \end{bmatrix}$

As in the conditional spending model, the latent probit dependent variables are drawn using the inverse cdf method with mean and variance as follows:

$$E\left(z^{*(t)}_{hit}\right) | \mathbf{z}^{*(t-1)}_{h,j\neq i,t}, \boldsymbol{\zeta}^{(t-1)}_i, \iota^{(t-1)}_{hi}, \Lambda^{(t-1)} = \mathbf{m}_{hit}\boldsymbol{\zeta}^{(t-1)}_i + \iota^{(t-1)}_{hi} - \lambda^{(t-1)}_{ij}\Lambda^{-1(t-1)}_{jj}\left(\mathbf{z}^{*(t-1)}_{h,j\neq i,t} - E\left(\mathbf{z}^{*(t-1)}_{h,j\neq i,t}\right)\right)$$

$$\lambda^{(t-1)}_{y^*} | \Lambda^{(t-1)} = \lambda^{(t-1)}_{ii} - \boldsymbol{\lambda}^{(t-1)}_{ij}\Lambda^{-1(t-1)}_{jj}\boldsymbol{\lambda}^{(t-1)}_{ji}$$

3. The store-level parameters in $\boldsymbol{\omega}_{hi}$ (which include a mean intercept term, $\overline{\alpha}_i$) are drawn from a SUR model with variance/covariance matrix of disturbances $\boldsymbol{\Sigma}$. Individual intercepts are drawn in step 5.

$$\boldsymbol{\omega}^{(t)} | \mathbf{y}^{*(t)}, \Sigma^{(t-1)} \sim N\left(\left(M_i'\left(\Sigma^{-1(t-1)} \otimes I_{HT}\right)\mathbf{y}^{*(t)}_i\right)O, O\right)$$

where $O = \left(M_i'\left(\Sigma^{-1(t-1)} \otimes I_{HT}\right)M_i\right)^{-1}$

4. The store-level parameters in $\boldsymbol{\zeta}_{hi}$ (which include a mean intercept term, $\bar{\iota}_i$) are drawn from a SUR model with variance/covariance matrix of disturbances Λ. Individual intercepts are drawn in step 6.

$$\boldsymbol{\zeta}^{(t)}|\mathbf{z}^{*(t)},\Lambda^{(t-1)} \sim N\left(\left(M_i'\left(\Lambda^{-1(t-1)} \otimes I_{HT}\right)\mathbf{z}_i^{*(t)}\right)P, P\right)$$

where $P = \left(M_i'\left(\Lambda^{-1(t-1)} \otimes I_{HT}\right)M_i\right)^{-1}$

5. The vector of household intercepts $\boldsymbol{\alpha}_h$ is drawn from a SUR model with variance/covariance matrix of disturbances Σ.

$$\boldsymbol{\alpha}_h^{(t)}|\mathbf{y}^{*(t)},\boldsymbol{\omega}^{(\mathbf{t})},\Sigma^{(t-1)},V_\alpha^{(t-1)},\boldsymbol{\delta}^{(t-1)},\overline{\boldsymbol{\alpha}}_h \sim N\left(\left(U_h'\left(\Sigma^{-1(t-1)} \otimes I_T\right)\mathbf{r}_h^\alpha + V_\alpha^{(t-1)}W_h\boldsymbol{\delta}^{(t-1)}\right)Q,Q\right)$$

where $Q = \left(U_h'\left(\Sigma^{-1(t-1)} \otimes I_T\right)U_h + V_\alpha^{(t-1)-1}\right)^{-1}$,

$$U = \begin{bmatrix} \mathbf{1}_T & & & \\ & \mathbf{1}_T & & \\ & & \ddots & \\ & & & \mathbf{1}_T \end{bmatrix},\ W_h = \begin{bmatrix} \mathbf{w}_h' & & & \\ & \mathbf{w}_h' & & \\ & & \ddots & \\ & & & \mathbf{w}_h' \end{bmatrix}, \text{ and}$$

$$\mathbf{r}_h^\alpha = \begin{bmatrix} \mathbf{y}_{h1}^{*(t)} \\ \mathbf{y}_{h2}^{*(t)} \\ \vdots \\ \mathbf{y}_{hS}^{*(t)} \end{bmatrix} - \begin{bmatrix} M_{h1} & & & \\ & M_{h2} & & \\ & & \ddots & \\ & & & M_{hS} \end{bmatrix}\boldsymbol{\omega}^{(t)}.$$

6. The vector of household intercepts $\boldsymbol{\iota}_h$ is also drawn from a SUR model with variance/covariance matrix of disturbances Λ.

$$\boldsymbol{\iota}_h^{(t)}|\mathbf{z}^{*(t)},\boldsymbol{\varsigma}^{(\mathbf{t})},\Lambda^{(t-1)},V_i^{(t-1)},\boldsymbol{\psi}^{(t-1)},\bar{\boldsymbol{\iota}}_h \sim N\left(\left(U_h'\left(\Lambda^{-1(t-1)} \otimes I_T\right)\mathbf{r}_h^\iota + V_\iota^{(t-1)}W_h\boldsymbol{\psi}^{(t-1)}\right)R,R\right)$$

where $R = \left(U_h'\left(\Lambda^{-1(t-1)} \otimes I_T\right)U_h + V_\iota^{(t-1)-1}\right)^{-1}$, and

$$\mathbf{r}_h^t = \begin{bmatrix} \mathbf{z}_{h1}^{*(t)} \\ \mathbf{z}_{h2}^{*(t)} \\ \vdots \\ \mathbf{z}_{hS}^{*(t)} \end{bmatrix} - \begin{bmatrix} M_{h1} & & & \\ & M_{h2} & & \\ & & \ddots & \\ & & & M_{hS} \end{bmatrix} \boldsymbol{\varsigma}^{(t)}.$$

7. The vector of hyper-parameters, $\boldsymbol{\delta}$, is drawn from a SUR model with variance/covariance matrix of disturbances, V_α.

$$\boldsymbol{\delta}^{(t)} | \boldsymbol{\alpha}^{(t)}, V_\alpha^{(t-1)}, V_\delta, \bar{\boldsymbol{\delta}} \sim N\left(\left(Q'\left(V_\alpha^{-1(t-1)} \otimes I_H\right)\boldsymbol{\alpha} + V_\delta \bar{\boldsymbol{\delta}}\right)S, S\right)$$

where $S = \left(Q'\left(V_\alpha^{-1(t-1)} \otimes I_H\right)Q + V_\delta^{-1}\right)^{-1}$, and $Q = \begin{bmatrix} D & & & \\ & D & & \\ & & \ddots & \\ & & & D \end{bmatrix}$

8. The vector of hyper-parameters, $\boldsymbol{\psi}$, is drawn from a SUR model with variance/covariance matrix of disturbances, V_ι.

$$\boldsymbol{\psi}^{(t)} | \boldsymbol{\iota}^{(t)}, V_\iota^{(t-1)}, V_\psi, \overline{\boldsymbol{\psi}} \sim N\left(\left(Q'\left(V_\iota^{-1(t-1)} \otimes I_H\right)\boldsymbol{\iota} + V_\psi \overline{\boldsymbol{\psi}}\right)T, T\right)$$

where $T = \left(Q'\left(V_\iota^{-1(t-1)} \otimes I_H\right)Q + V_\psi^{-1}\right)^{-1}$

9. Σ is drawn from an inverted Wishart distribution with $HT+\nu_\Sigma$ degrees of freedom.

$$\Sigma^{-1(t)} | \boldsymbol{\omega}^{(t)}, \mathbf{y}^{*(t)}, \boldsymbol{\delta}^{(t)}, \Sigma^{(t)}, V_\alpha^{(t)}, V_\Sigma, \nu_\Sigma \sim W\left(HT + \nu_\Sigma, \left(V_\Sigma + \boldsymbol{\varepsilon\varepsilon}'\right)^{-1}\right)$$

10. Λ is also drawn from an inverted Wishart distribution with $HT+\nu_\Lambda$ degrees of freedom.

$$\Lambda^{-1(t)} | \boldsymbol{\zeta}^{(t)}, \mathbf{z}^{*(t)}, \boldsymbol{\psi}^{(t)}, \Lambda^{(t)}, V_\iota^{(t)}, V_\Lambda, \nu_\Lambda \sim W\left(HT + \nu_\Lambda, \left(V_\Lambda + \mathbf{uu}'\right)^{-1}\right)$$

11. V_α is drawn from an inverted Wishart distribution with $H+\nu_\alpha$ degrees of freedom.

$$V_\alpha^{-1(t)} | \boldsymbol{\omega}^{(t)}, \mathbf{y}^{*(t)}, \boldsymbol{\delta}^{(t)}, V_\alpha^{(t)}, \overline{V}_\alpha, \nu_\alpha \sim W\left(H + \nu_\alpha, \left(\overline{V}_\alpha + \boldsymbol{\xi\xi}'\right)^{-1}\right)$$

12. V_ι is drawn from an inverted Wishart distribution with $H+\nu_\iota$ degrees of freedom.

$$V_\iota^{-1(t)} | \boldsymbol{\varsigma}^{(t)}, \mathbf{z}^{*(t)}, \boldsymbol{\psi}^{(t)}, V_\iota^{(t)}, \bar{V}_\iota, \nu_\iota \sim W\left(H + \nu_\iota, \left(\bar{V}_\iota + \boldsymbol{\tau\tau}'\right)^{-1}\right)$$

B. Prior distributions

The second implementation step is to specify prior distributions for the parameters of interest. Note that the priors are set to be non-informative so that inferences are driven by the data.

1. The prior distribution of $\boldsymbol{\delta}$ is MVN($\bar{\boldsymbol{\delta}}, V_\delta$), where $\bar{\boldsymbol{\delta}} = \mathbf{0}$ and V_δ = diag(10^3).
2. The prior distribution of $\boldsymbol{\psi}$ is MVN($\bar{\boldsymbol{\psi}}, V_\psi$), where $\bar{\boldsymbol{\psi}} = \mathbf{0}$ and V_ψ = diag(10^3).
3. The prior distribution of Σ^{-1} is Wishart: W(ν_Σ, V_Σ), where $\nu_\Sigma = 10$ and V_Σ = diag(10^{-3}).
4. The prior distribution of Λ^{-1} is Wishart: W(ν_Λ, V_Λ), where $\nu_\Lambda = 10$ and V_Λ = diag(10^{-3}).
5. The prior distribution of V_α^{-1} is Wishart: W(ν_α, V_α), where $\nu_\alpha = 1$ and V_α = diag(10^{-3}).
6. The prior distribution of V_ι^{-1} is Wishart: W(ν_ι, V_ι), where $\nu_\iota = 1$ and V_ι = diag(10^{-3}).

C. Initial values

The third implementation step is to set initial values for the parameters of the marginal distributions. The starting values for $\boldsymbol{\omega}_i$ from equation (2) are computed by OLS, using ln(y_{bit}) as the dependent variable of the regression. The individual-level intercepts, α_{bi}, are computed using the residuals from the regression model above as the dependent variable, and regressing the design vector U on those residuals using OLS. The covariance matrix, Σ, is initiated by taking the residuals of the second-stage regression, ε_{hot}, (conditioned on the initial parameter values) and using them to compute sample covariances. In a similar fashion, the starting values for the patronage equation parameters, $\boldsymbol{\varsigma}_i$, are computed by OLS, using z_{bit} as the dependent variable. Again, the individual-level intercepts, ι_{bi}, are computed using the residuals from the first-stage regression model as the dependent variable, and regressing the design vector U on those residuals. Again, the residuals from this second-stage regression, u_{bit}, are used to compute the sample covariances, which serve as the initial value for Λ. Note that other initial values were used to ensure that estimates were not dependent on a particular starting point.

The final step is to generate $N_1 + N_2$ random draws from the conditional distributions. The number of initialization iterations, N_1, is determined empirically. We use a "burn in" period of 3500 iterations. To reduce autocorrelation in the MCMC draws, we "thin the line," using every fifth draw in the sequence that comprises N_2 for our estimation. In this way, the last N_2 iterations are used to estimate marginal posterior distributions of the parameters of interest. Note that the means and variances of these distributions are computed directly using the means and variances of the final N_2 draws of each parameter.

Footnotes

1. Mass merchandisers (discount stores, warehouse clubs, and other mass merchants) reported 1998 sales of $302.7 billion dollars (computed from Discount Store News, 1999) for both grocery and non-grocery items. Walmart, the most prominent mass merchandiser, alone had sales in 1999 of $137.6 billion. In comparison supermarkets reported 1998 sales of $346.1 billion (Progressive Grocer Report of the Grocery Industry, 1999).

2. We eliminated households with suspect or incomplete information from our analysis. A household was omitted if either the majority of its purchases were made outside the chains included in this study or if the household did not record a purchase during any given month over the two-year period of our analysis. This screen can potentially eliminate households who might have been on vacation for extended periods, but we believe that most of the households screened were not faithfully recording their purchases. The demographics of the remaining households were checked against the demographics of the zip codes in which they lived and found to be representative of these areas.

3. The entire dataset, including those omitted as described in endnote 2, is used to compute this table.

4. All ANOVAs reported in this section are one-way analyses that use format to predict chain-level averages over the period of our data.

5. Disaggregate data for price, promotion, and assortment variables is particularly sparse for drug stores and mass merchandisers. For example, of the 2,000 products that they purchase most frequently, our panelists purchase only 52 and 22 products weekly at the average mass merchant and drug store chain, respectively. Creating price and promotional measures that reflect the many products therefore requires pooling observations over multiple weeks.

6. To understand why price variability is stable over temporal aggregation consider that the majority of items remain at regular shelf price throughout the month, and unadvertised promotions persist for multiple weeks to nearly a month (four weeks) in this market. The prices which do change weekly, feature advertised items, are fixed in number by space limitations in the advertising circular. Thus, the assortment of feature-advertised items change weekly, but their number is relatively constant. Weekly advertised discount

depth is also fairly constant over time (mean = 23.5%, stdev = 3.8%). As a result, price variation due to advertised promotions is not affected by temporal aggregation.

7. Jain, Vilcassim and Chintagunta (1994) find that most household-level heterogeneity in brand choice is due to differences in intrinsic brand preferences. By allowing for household-specific preferences for store chains, we control for unmodeled individual differences, including average basket size (Bell and Lattin, 1998). We thank an anonymous reviewer for raising this point.

8. This argument is advanced and then tested by Ainslie and Rossi (1998), who use household-level shopping behavior variables to predict brand choice. They note, "These variables are computed as long-run averages of shopping behavior in which bursts of promotional activity will be averaged out." (p. 97) They report results with and without shopping behavior variables, and find no evidence of endogeneity.

9. Following Levy and Weitz (1999), we consider assortment as the depth of the product offering in a category (e.g., the number of products offered per category), as opposed to variety, which is the breadth of the product offering (i.e., the number and diversity of categories offered). Variety is captured, along with other unobserved chain-specific variables, in the chain intercept term.

10. In our dataset, distance is measured from the centroid of the zip+4 in which the household is located to the street address of the closest store in the chain using a closest road algorithm. This measurement of distance is superior to that used in previous research because the panelist locations are considerably more precise and because the road distance more effectively captures the shopper's expected travel. The *TRAVTIME* variable is based on road distance and is adjusted for expected driving speed and traffic.

11. Let p, q, r represent price, quantity, and revenue respectively, and the relationship between these variables is $r=p\,q$. Differentiating both sides with respect to price, and re-expressing in percentage change terms, we find that $\frac{\partial r}{\partial p}\frac{p}{r} = 1 + \frac{\partial q}{\partial p}\frac{p}{q}$. In other words, for the price elasticity of revenue equals one plus the price

elasticity of quantity. Obviously this holds true only for a single product, although we can think of our product in this case as a composite of all consumer packaged goods.

12. α_{hi}'s and ι_{hi}'s estimated in the hierarchy have a zero-mean because $\overline{\alpha}_i$ and $\overline{\iota}_i$ are estimated during the first

stage.

13. This figure reported is a pseudo R^2 computed from the residuals of the specified system of tobit models.

14. Among the stores captured in the analysis, merchandise files are available for only these three retailers.