A Parsimonious Model of Stock-Keeping Unit Choice

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Managerial Summary

This article develops a model to describe and predict consumer stock-keeping unit (SKU) choice in frequently bought product categories. The model posits that a product category consists of several salient attributes and that each attribute has different levels and represents a SKU as an attribute-level combination. Our latent-class 2-segment model has a fixed number of 59 parameters for a category with 3 salient attributes, and in general has *11 + 12 (K+1)* parameters for a *K*-attribute product category. We achieve this model parsimony by neither discarding data nor aggregating the level of analysis beyond the SKU level. Since the number of parameters *does not* depend on either the number of SKUs in the category or number of levels in each salient attribute, it is particularly useful for demand forecasting and inventory planning in large product categories that have hundreds of SKUs.

Our model relies on three behavioral premises on how consumers choose products over time. First, the consumers accumulate not only a product-level experience but also attribute-level experiences. Second, these experiences have both consumption and shopping components. While consumption occurs only for the chosen attribute levels and product, shopping applies to all familiar and available attribute levels and products. Third, the consumption and shopping experiences increase with attribute-level and product familiarities.

Using an extensive panel-level data set of sixteen categories involving more than one hundred and thirty thousands purchase records, we show that our model can describe and predict SKU choice well. In addition, we benchmark our model against the classical Guadagni and Little's model and its extension Fader and Hardie's model in a subset of seven small categories (where the number of the parameters for the latter models are less than 200). On average, our model fits 7% better in-sample and predicts 8% better out-of-sample in hit probability. In terms of adjusted pseudo R-square, the model is 8% and 11% higher in-sample and out-of-sample, respectively. This superior performance requires only one-half the number of parameters.

Below are several ways how brand managers can use our model in practice:

- *Base volume forecasting*: Our model can be used to forecast regular sales volume (i.e., base volume) of any SKU in a product category. Our model reveals the relative contribution of each attribute level to the base volume while controlling for the marketing mix effects.
- *Relative importance of each attribute*: Using the model, one can easily analyze the relative importance of each salient attribute. This analysis can be done at the individual consumer level and across time.
- *Forecasting sales for line extensions*: An attractive feature of our model is its ability to forecast sales for line extensions, whether or not these extensions introduce new attribute levels to a category.

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Abstract

The authors develop a model to describe and predict consumer stock-keeping unit (SKU) choice in frequently bought product categories. The model posits that a product category consists of several salient attributes with numerous attribute levels. It represents a SKU as an attribute-level combination. The model uses $11 + 12 \cdot (K + 1)$ parameters to describe a K-attribute product category with 2 latent segments. This parsimony is achieved without discarding data or aggregating level of analysis beyond SKU. With the number of parameters not depending on either the number of SKUs in the category or number of levels in each salient attribute, the model is particularly useful for large product categories.

The model utilizes three behavioral premises on how consumers choose products over time. First, consumers accumulate not only a product-level experience but also attribute-level experiences. Second, these experiences have both consumption and shopping components. While consumption occurs only for the chosen attribute levels and product, shopping applies to all familiar and available attribute levels and products. Third, the consumption and shopping experiences increase with attribute-level and product familiarities.

The authors demonstrate the descriptive and predictive power of their model using a panel-level data set of sixteen categories involving 133,492 purchase incidences. In benchmarking against the models of Guadagni & Little (1983) and Fader & Hardie (1996) using a subset of seven small categories (with less than 200 parameters for both models), the authors show that their model fits 7% better in-sample and predicts 8% better out-of-sample in hit probability. In

terms of adjusted pseudo R-square, the model is 8% and 11% higher in-sample and out-of-sample, respectively. This superior performance requires only one-half the number of parameters.

INTRODUCTION

Most consumer product categories have hundreds of SKUs and they continue to grow (Quelch and Kenny 1994). It is a challenge to estimate most prevailing consumer choice models (e.g., Allenby and Rossi 1991, Erdem and Keane 1996, Guadagni and Little 1983) because these models consist of product-specific parameters that are at least as large as the number of items in the categories.

Three approaches have been adopted to overcome this challenge. The first approach reduces the number of product-specific parameters by focusing on a subset of the SKUs. In this approach, either all purchase incidences of the least frequently bought SKUs are discarded (e.g., Fader, Lattin and Little 1992, Siddarth, Bucklin and Morrison 1995) or all purchase incidences of consumers who bought these products are discarded (e.g. Chintagunta 1993). Both ways of discarding data amount to choice-based sampling (see Ben-Akiva and Lerman 1985), which can lead to potential bias in the product-specific parameters (Manski and Lerman 1977).

The second approach aggregates the level of analysis to a higher level (e.g., from SKU to brand-size combination as in Bucklin and Gupta 1992, Guadagni and Little 1983) or aggregates a subset of products into a composite product (e.g., aggregate several least frequently bought products into a composite ‘other’ product as in Chiang 1991, Erdem and Keane 1996, Papatla and Krishnamurti 1992). Choice aggregation may lead to biased product-specific parameters (Ben-Akiva and Lerman 1985), if the composition of the member products changes over time due to varying product availability.[1] Product availability can vary widely because of stock-out and periodic product line extensions and deletions. For example, over a 2-year period, our data set sees a minimum of 8 extensions and 8 deletions in the egg category and as many as 141 extensions and 127 deletions in the detergent category.

Besides producing potentially biased estimates, the above two approaches do not estimate demand for all SKUs, which is essential for effective inventory planning and shelf-space allocation. For this latter reason, operations management researchers have found it difficult to incorporate scanner-based choice models into their inventory planning tools (Ho and Tang 1998). Our model aims to address this deficiency. As shown in Chong, Ho and Tang (2001), such a micro-level model can be very useful for selecting optimal product assortment.

The third approach overcomes these limitations by assuming that a product category consists of a small number of salient attributes and that each salient attribute has different levels. A SKU derives its intrinsic value from the attribute levels it assumes (Fader and Hardie 1996). The product-specific parameters become sums of attribute-level values. This approach will work if the total number of attribute levels for each salient attribute is small. However, this is often not the case. Nine out of sixteen product categories in our data set have more than 90 attribute levels (see Table 1).

In this paper, we develop a model that will work well for large categories with many attribute levels. Building on the work of Guadagni and Little (1983, GL henceforth) and Fader and Hardie (1996, FH henceforth), we modify the standard utility function commonly used in the scanner data literature by capturing several behavioral regularities reported in the consumer research.

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[1] If one can assume the existence of a nested logic structure in the consumer choice process, aggregating level of analysis may not lead to biased estimates. We thank an anonymous reviewer for bringing this to our attention.

Thus, our approach is behavioral in nature, and our goal is to develop a more predictive utility function. Our approach leads to a parsimonious model because we specify a dynamic structure to capture the ways a consumer experiences a product and attribute levels over time. In addition, we allow for autoregressive error structures at both the attribute and product levels.

Our model suggests that a consumer’s utility for an attribute level changes over time because the consumer accumulates a consumption experience for the chosen attribute level and a shopping experience for all familiar and available attribute levels, both of which depend on the associated attribute-level familiarity. The notion of shopping experience is new and, as we shall show below, is crucial in describing product choice behavior. It also allows us to predict how variety-seeking occurs. If shopping experience increases with attribute-level familiarity, familiar attribute levels are more likely to be chosen in the future than unfamiliar attribute levels. Because of stronger shopping experience, a familiar and unchosen attribute level can receive a higher overall experience than a chosen but unfamiliar attribute level. Other things being equal, our model predicts that the consumer is more likely to switch back to products with more familiar attribute levels.

Besides the attribute-level experience, the consumer develops an idiosyncratic product-specific experience. Like attribute-level experience, this product-level experience consists of shopping and consumption, and it increases with familiarity. Since the familiarity with a product evolves over time, the consumer not only responds differently to different products on the same purchase occasion, she also responds to the same product differently over time.

Our model makes three contributions.

First, It uses all purchase data, does not aggregate SKUs, and has a number of parameter that does not increase with the number of SKUs or attribute levels. For example, if a product has three salient attributes (e.g., brand, size, and flavor), our model has only 59 parameters. In general, our two-segment model has $11+12\cdot(K+1)$ parameters for a K-attribute product category. Consequently, it can be used to model product choice in any frequently bought product categories, including those with hundreds of SKUs. More importantly, it fits and predicts SKU choice better than the FH model. Second, using panel-level data from seven small product categories, we benchmarked our model against the FH and GL models. On average our model fits 7% better than FH model in-sample and predicts 8% better out-of-sample in hit probability. In terms of adjusted R-square, it is 8% and 11% higher in-sample and out-of-sample respectively. The improvement in fit over the GL model is even better. For example, the improvement in adjusted R-square is 15% in-sample and 19% out-of-sample. In addition, this superior performance is achieved with only one-half the number of parameters. Third, the model incorporates several behavioral regularities that have been documented in consumer research. We use scanner data to test memory-based grocery shopping (e.g., Alba, Hutchinson, and Lynch 1991, Lynch, Marmorstein, and Weigold 1988) in the field and find strong support for the phenomenon.

The rest of the paper is organized as follows. In the next section, we present our model. Section 3 tests the behavioral premises underlying our model, provides empirical evidence to substantiate the superior performance (in fit and prediction) of our model, and discusses several empirical regularities. In section 4, we discuss managerial implication and application, and suggest future research directions.

THE SKU CHOICE MODEL

Consider consumer *i* who visits a store to buy a SKU in a particular product category. The product category has many SKUs indexed by *j*. The consumer evaluates the product category by a set of *K* salient attributes indexed by *k*. Each salient attribute *k* has L_k attribute levels indexed by l. Each SKU *j* offers an attribute-level combination. For example, the ice cream product category may be evaluated by such salient attributes as brand, size and flavor. The possible attribute levels for ice cream flavor are vanilla, chocolate, strawberry, and etc. A SKU offers an attribute level combination such as [*Ben & Jerry's, 16 oz, Vanilla*]. The consumer makes product purchase on multiple occasions. On each purchase occasion, she decides which SKU *j* to buy and consume, given all SKUs' marketing mix activities.[2] The goal of the model is to predict which SKU *j* the consumer *i* will choose on a purchase occasion given her purchase history.

Each purchase occasion defines a time epoch. Each time epoch *t* begins with store visit, followed by shopping and purchase, and ends with attribute-level and product-level consumption. During shopping, the consumer gathers information on the marketing mix activities of products on the choice menu. Consumer *i*'s utility for SKU *j* at the end of shopping (but before purchase) in time epoch *t* (denoted by $U_{ij}(t)$) is a sum of two components, namely consumer *i*'s intrinsic value for SKU *j* (denoted by $V_{ij}(t)$) and the value associated with SKU *j*'s marketing mix activities (denoted by $M_j(t)$). We have

(1) $$U_{ij}(t) = V_{ij}(t) + M_j(t) + \varepsilon_{ij}(t),$$

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[2] It is possible that the consumer may purchase multiple SKUs on a particular shopping occasion. In model calibration, one can either treat the purchases as simultaneous or sequential observations in model updating (such as equations (3) and (4)). We adopt the simultaneous approach because it does not use purchase information of a product to predict the purchase of another product on the same store visit. We also estimated the model using the sequential approach and found both approaches generated similar parameter estimates but (obviously) better fit.

where $\varepsilon_{ij}(t)$ is an aggregate error term that consists of multiple error components, each of which may exhibit a serial correlation across time. We shall discuss the exact composition of the error term in greater detail below.[3] The additive form has been used by most prior models and is adopted here for simplicity.

Intrinsic Value of a SKU

The intrinsic value of SKU j is the additive sum of the cumulative attractions of the attribute levels SKU j assumes ($A_{ikl}(t)$) and the product as a whole ($A_{ij}(t)$). Formally,

(2) $$V_{ij}(t) = \sum_{k=1}^{K} \sum_{l=1}^{L_k} A_{ikl}(t) \cdot I_{jkl} + A_{ij}(t),$$

where the indicator variable I_{ikl} is 1 if SKU j has attribute level l in salient attribute k and 0 otherwise. For example, consumer i's intrinsic value for SKU j with attribute-level combination [*Ben & Jerry's, 16 oz, Vanilla*] is a sum of her cumulative attractions for [*Ben & Jerry's*], [*16 oz*] and [*Vanilla*], as well as the product j as a whole. The cumulative attractions for an attribute level and a product are updated over time as follows:

(3) $$A_{ikl}(t) = \phi_k \cdot A_{ikl}(t-1) + R_{ikl}(t),$$

(4) $$A_{ij}(t) = \phi_p \cdot A_{ij}(t-1) + R_{ij}(t),$$

where ϕ_k and ϕ_p are decay factors. The consumer- and attribute-level-specific variable $R_{ikl}(t)$ is an incremental reinforcement consumer i derives from level l in attribute k in time epoch t. Similarly, $R_{ij}(t)$ is the incremental reinforcement consumer i derives from product j as a whole.

[3] We have also estimated the model with i.i.d. double exponential errors. The results are reported in a previous version of this paper, Ho and Chong (1999).

The difference between the two incremental reinforcements is that the attribute-level reinforcement affects the intrinsic value of all products that share similar attribute levels while the product-level reinforcement does not. This distinction captures a product's unique and shared characteristics with other products.

Attribute-Level Reinforcement

The incremental reinforcement for an attribute level l in time epoch t depends on whether it was chosen in time epoch t -1. If attribute level l were chosen, it would have both consumption and shopping experiences. Otherwise, the incremental reinforcement would only have the shopping experience. The consumption experience occurred in time epoch t -1 (i.e., before the current store visit), $C_{ikl}(t-1)$, while the shopping experience happened in time epoch t (i.e., during the current store visit), $S_{ikl}(t)$. Also, shopping experience applies only to the available attribute levels. That is,

$$(5) \qquad R_{ikl}(t) = \begin{cases} C_{ikl}(t-1) + S_{ikl}(t) & \text{if level } l \text{ in attribute } k \text{ was chosen in } t\text{-1} \\ S_{ikl}(t) & \text{otherwise,} \end{cases}$$

where both consumption and shopping experiences depend on the familiarity with attribute level l. This attribute-level familiarity is a function of the number of previous consumptions. We denote consumer i's familiarity with attribute level l after consumption in time epoch t by $F_{ikl}(t)$. The consumption experience for the attribute level chosen in time epoch t-1 is given by:

$$(6) \qquad C_{ikl}(t-1) = C_{k0} + C_{k1} \cdot F_{ikl}(t-2).$$

Note that the consumption experience lags behind the shopping experience by one time period because we define the beginning of the time epoch by the initiation of a store visit. The above specification has two implications. First, the incremental reinforcements derived from trial and repeat consumption are different. Note that $F_{ikl}(t\text{-}2) = 0$ if i consumes attribute level l for the first time in time epoch t - 1. Thus, one can interpret C_{k0} as the reinforcement received from trial consumption. Second, if $C_{k1} < 0$, each subsequent consumption counts less and less as consumer i becomes more familiar with the attribute level l. This captures satiation and implies diminishing marginal utility at the attribute level. On the other hand, if $C_{k1} > 0$, we have an increasing marginal utility. That is, the consumer likes the attribute level more after each consumption.

Similarly, the shopping experience for an attribute level during time epoch t is given by:

(7) $$S_{ikl}(t) = S_{k0} + S_{k1} \cdot F_{ikl}(t-1).$$

The shopping experience allows us to make better use of information contained in the available but unchosen attribute levels. Since the set of unchosen attribute levels is large, a modeler could potentially do better by distinguishing them according to the level of familiarity the consumer has with each (earlier models ignore this information and assume that all unchosen attribute levels have zero shopping experience). Behaviorally, shopping experience captures the intuition that the consumer looks only at a small set of attribute levels when she purchases a product and we hypothesize that the small set of attribute levels consists of those with which the consumer is familiar. Thus, it captures how the consumer activates her ‘memory’ of attribute levels during the act of choosing (Alba, Hutchinson and Lynch 1991, Lichtenstein and Srull 1987).

A basic premise of our model is that attribute-level familiarity leads to ease of memory recall. The number of prior consumptions seems a good proxy for measuring familiarity in the absence of other more direct memory-based measures. We measure familiarity with an attribute level and a product by the number of times they are consumed. For instance, if $T_{ikl}(t)$ is the number of times consumer i consumes attribute level l of salient attribute k prior to and including time epoch t, one can posit different functional forms to relate the familiarity function ($F_{ikl}(t)$) with the number of consumptions ($T_{ikl}(t)$).[4] We capture a diminishing effect of additional consumption by using a log functional form as follows:

$$F_{ikl}(t) = \ln(1 + \theta_a \cdot T_{ikl}(t)), \quad (8)$$

where θ_a is a parameter that controls the rate of diminishing for each additional consumption.

Product-Level Reinforcement

Unlike attribute-level reinforcement, product-level reinforcement captures the consumer's idiosyncratic liking for a product beyond the shared attribute levels. Consequently, product-level reinforcement for a product affects only its own cumulative attraction and will not influence the attractions of other products. The product-level incremental reinforcement depends on whether the product j was chosen in time epoch t - 1. If j were chosen, it would have consumption and shopping experiences. Otherwise, it would have only the shopping experience. Again, shopping experience only applies to available products. That is,

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[4] In an earlier version, we experimented three different functional forms (step, linear, and log) in order to capture different rates of memory development: 'instantaneous,' 'constant return to scale,' and 'diminishing return to scale,' respectively. We used Horowitz (1983)'s test to determine whether these functional forms have different adjusted pseudo R-squares and found that log function fit the data the best. The log attribute-level familiarity predicts an interesting asymmetric spillover effect on a major brand by priming a minor brand. Nedungadi (1990) found that priming a minor brand in an unfamiliar attribute level benefited a major brand more than priming it in a familiar attribute level. This is consistent with a log familiarity function because the marginal increase in familiarity is smaller in a familiar attribute level due to priming.

(9) $$R_{ij}(t) = \begin{cases} C_{ij}(t-1) + S_{ij}(t) & \text{if product } j \text{ was chosen in } t\text{-1} \\ S_{ij}(t) & \text{otherwise,} \end{cases}$$

where $F_{ij}(t)$ is consumer i's familiarity with product j after consumption in time epoch t. The consumption experience for the product chosen in time epoch t - 1 is given by:

(10) $$C_{ij}(t-1) = C_{p0} + C_{p1} \cdot F_{ij}(t-2).$$

Analogous to attribute-level consumption, the above specification allows us to differentiate between trial and repeat consumption at the product level. If the consumer is new to a product before consumption in time epoch t - 1, we will have $C_{ij}(t\text{-}1) = C_{p0}$. If $C_{p1} < 0$, each additional consumption receives a smaller reinforcement because the consumer becomes satiated with the product; if $C_{p1} > 0$, each consumption increases the marginal utility for next consumption.

Similarly, the shopping experience for product j in time epoch t is given by:

(11) $$S_{ij}(t) = S_{p0} + S_{p1} \cdot F_{ij}(t-1),$$

In a category with many SKUs, the shopping experience 'singles out' a small set of products with which the consumer is familiar. This recognizes the fact that the consumer considers a small set of products before purchase and the evaluation process consists of memory activation and recall.

Like before, we model product-level familiarity by a log functional form as follows:

(12) $$F_{ij}(t) = \ln(1 + \theta_p \cdot T_{ij}(t)),$$

where $T_{ij}(t)$ is the number of times consumer i consumes SKU j up to and including time epoch t[5] and θ_p is the product-level diminishing rate to be estimated.

Our model is related to the GL and FH model in the following ways. The GL model has a product-specific intercept term whereas the FH model replaces this intercept term with attribute-levels the product assumes. Since the total number of attribute levels in all salient attributes is less than the number of SKUs, the FH model uses less parameter. Formally, we have GL and FH models specified as follows:

$$V_{ij}(t) = v_j + A_{ij}(t), \qquad \text{(GL Model)} \tag{13}$$

$$V_{ij}(t) = \sum_{k=1}^{K}\sum_{l=1}^{L_k}[v_{kl} + A_{ikl}(t)] \cdot I_{jkl} \qquad \text{(FH Model)} \tag{14}$$

where v_j and v_{kl} are intercept terms associated with product j and level l in salient attribute k respectively. In addition, their model restricts C_{k1}, C_{p1}, S_{k0}, S_{k1}, S_{p0} and S_{p1} to be zero. There are no attribute-level and product shopping experiences.

Like the FH model, our model decomposes the intrinsic value of a SKU into its attribute level components. Thus, our approach yields each consumer's part-worths for all attribute levels at

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[5] It is reasonable to measure $T_{ikl}(t)$ and $T_{ij}(t)$ over a rolling time horizon in order to discard distant past consumption experiences and to avoid them growing indefinitely. We use a 1-year time horizon in this paper. Krishnamurthi and Raj (1991) define product familiarity $F_{ij}(t)$ as 1 if consumer i chooses j in at least 50% of all previous purchases and 0 otherwise. Thus, the consumer can be familiar with only one product at a time.

any point in time and can be used to predict the demand for any new product, even when a new attribute level is introduced.[6]

Error Structure

We assume the error structure for utility $U_{ij}(t)$ to consist of 2 components; attribute-specific errors and product-specific error. Attribute-specific errors capture serial correlations in attribute-level utilities ($A_{ikl}(t)$) and product-level error captures serial correlation in product-specific utilities ($A_{ij}(t)$) across time. In particular, we have

$$\varepsilon_{ij}(t) = \sum_{k=1}^{K}\sum_{l=1}^{L_k} \xi_{ikl}(t) \cdot I_{jkl} + \xi_{ij}(t), \tag{15}$$

where both $\xi_{ikl}(t)$ and $\xi_{ij}(t)$ are assumed to follow an AR(1) autoregressive process of order 1 as follows:

$$\xi_{ikl}(t) = \rho_k \cdot \xi_{ikl}(t-1) + v_{ikl}(t), \tag{16}$$

$$\xi_{ij}(t) = \rho_p \cdot \xi_{ij}(t-1) + v_{ij}(t), \tag{17}$$

where ρ_k and ρ_p capture the autocorrelations. We assume $v_{ikl}(t) \sim N(0, \sigma_k^2)$ for all k and l. Similarly, $v_{ij}(t) \sim N(0, \sigma_p^2)$ for all j. Hence, $\varepsilon(t)$ is a multivariate normal distribution with means zero and covariance $\Pi(t) = \sum_{k=1}^{K} \frac{\sigma_k}{1-\rho_k^2} \cdot I_k^{'} I_k \cdot \Gamma_k + \frac{\sigma_p}{1-\rho_p^2} \cdot \Gamma_p$ where the (s,t) elements of Γ_k and Γ_p are $\rho_k^{|s-t|}$ and $\rho_p^{|s-t|}$ respectively, and I_k is a matrix of indicator variables for attribute levels of all

[6] One can set a consumer's familiarity with a new attribute level to zero when the consumer is not aware of the level and a positive value if she is aware of it (perhaps due to advertising or word-of-mouth).

SKUs. We allow for the same serial correlated error structure for the FH and GL models for ease of comparison.

The Log-likelihood Function

We control for the effects of the marketing mix variables with $M_j(t)$ as follows:

(18) $$M_j(t) = \beta^P \cdot P_j(t) + \beta^D \cdot D_j(t) + \beta^{AD} \cdot AD_j(t).$$

The variables $P_j(t)$, $D_j(t)$, $AD_j(t)$ are unit price, store display, and advertising feature of SKU j as observed by consumer i during shopping on time epoch t. We use this functional form so that we can benchmark our model against the FH model (which uses the same functional form).

The probability of consumer i choosing SKU j in time epoch t is given by:

(19) $$\Pr_{ij}(t) = \Pr ob(U_{ij}(t) > U_{ij^{'}}(t), \forall j^{'} \neq j, j^{'} \in J(t))$$

$$= \int_{-\infty}^{W_{ij1}(t)} \cdots \int_{-\infty}^{W_{ijJ}(t)} MVN(\eta_{ijj^{'}}, \forall j^{'}) \partial \eta_{ij1} \cdots \partial \eta_{ijJ}$$

$$= \Phi(W_{ij.}(t))$$

where $J(t)$ corresponds to the set of SKUs available to consumer i on time epoch t. $W_{ijj^{'}} = V_{ij} + M_{ij} - V_{ij^{'}} - M_{ij^{'}}$ corresponds to the difference in deterministic components and $MVN(\eta_{jj^{'}}, \forall j^{'})$ is a multi-variate normal distribution with $\eta_{ijj^{'}} = \varepsilon_{ij^{'}} - \varepsilon_{ij}$.

Finally, we build in heterogeneity by estimating a 2-segment latent-class model (Kamakura and Russell, 1989). The log-likelihood function is given as follows:

(20) $$LL = \sum_i \ln\left[\sum_{s=1}^{2} \pi^s \cdot \prod_j \prod_t \Phi(W_{ij.}^s(t))^{I_{ij}(t)}\right]$$

where the indicator variable $I_{ij}(t)$ is 1 if consumer i bought SKU j in time epoch t and 0 otherwise. π^s is the size of segment s.

Note that there is neither product-specific nor attribute-specific intercept term in our model, which helps to reduce the number of parameters. There are altogether 5 parameters associated with the update of the cumulative attraction of attribute levels in each of the three salient attributes (i.e., ϕ_k, $C_{k0}, C_{k1}, S_{k0}, S_{k1}$) and product (i.e., ϕ_p, $C_{p0}, C_{p1}, S_{p0}, S_{p1}$), 3 marketing mix response sensitivity parameters, and 2 parameters (i.e., θ_a and θ_p) for modeling familiarity for the log model. To identify the model, we set S_{k0} and S_{p0} equal to 1. There are two parameters associated with each of the four error components (ρ_k, ρ_p and σ_k, σ_p). Thus, our model has a total of 5+6·(K+1) for a product category that has K salient attributes. For K = 3, there is a total of 29 parameters for a single-segment model. For a 2-segment model, the number of parameters becomes 2·29 + 1 = 59.

Behavioral Premises and Rationale

Our model is based on three behavioral premises: (1) the consumer accumulates attribute level and product-level experiences, 2) the experiences consist of consumption and shopping components, and 3) both consumption and shopping experiences depend on familiarity. These behavioral premises rest on existing research found in consumer behavior and experimental economics.

The first premise is based on a theoretical framework proposed by Lynch, Marmorstein, and Weigold (1988). They suggest that the consumer uses recalled prior attribute-level and product-level experiences as inputs in choosing products. They show that the relative importance of the two kinds of memory recalls depends on their relative accessibility and diagnosticity. We see our model as a first step towards operationalizing this framework in scanner data research. Our parameters S_{k1} and S_{p1} measure the relative importance of attribute-level and product-level familiarity. We can interpret them as their relative diagnosticity for product choice because they translate familiarity into reinforcement and choice probability. Our log functional form parameters θ_a and θ_p transform the number of consumptions into familiarity, and hence, can be interpreted as their relative accessibility. The higher the θ s, the higher the relative accessibility is.

The second premise suggests that the consumer acquires a shopping experience for an attribute level and a product without consuming it via mental simulation of whether it would have been better. Camerer and Ho (1999) and Camerer, Ho, and Chong (2002) show that people care about the foregone payoffs of available actions that they did not choose but could have chosen. This foregone payoff, which they call simulated reinforcement, is found to be substantial and very useful for predicting subjects' switching behavior in strategic games. The shopping experience seems particularly relevant when the consumer is faced with a large number of attribute levels and is likely to have a very different shopping experience for each of them. For instance, if the consumer pays only attention to familiar attribute levels, then her shopping experience for them is likely to be much more intense than for unfamiliar attribute levels. Ignoring shopping experience implies that the consumer treats all unchosen attribute levels identically, which seems unreasonable when the number of attribute levels is large.

The third behavioral premise posits that familiarity is the main determinant of the level of consumption and shopping experiences. Erdem (1998) shows a consumer's attraction for a product changes as the consumer learns more about its attributes through additional usages. Similarly, Alba, Hutchinson, and Lynch (1991) provide three reasons why attribute-level and product-level familiarity might play a central role in grocery shopping. First, since the grocery-shopping environment is highly complex, consumers often rely on recall to recognize products on the shelf and to evaluate them. Second, when consumers look at the grocery store display without preconceptions, attribute level and product familiarity are likely to influence how easily specific products catch their eye and enter into their consideration set. Third, consumers often have very low motivation to spend time when they shop for groceries. For example, Dickson and Sawyer (1986) reported that consumers shopping for toothpaste, margarine, coffee, and cold cereal spent an average of 12 seconds from the time the shelf was approached to the time the selected item was placed in their carts. Product- and attribute-level familiarities play a central role in the identification and evaluation of products in this highly efficient shopping process.

Familiarity-based shopping and consumption experiences provide a natural way to account for variety-seeking behavior. This inter-temporal switching behavior is well documented (e.g., Bawa 1990, Feinberg 1997, Feinberg, Kahn and McAlister 1994, Givon 1984, Lattin and McAlister 1985, Trivedi, Bass and Rao 1994). For a comprehensive review on variety-seeking behavior, see Kahn (1998). A consumer seeks variety if the conditional probability of choosing a product on a given occasion (given that the same product was chosen in the last occasion) is smaller than the unconditional probability of choosing the product (Kahn, Kalwani and Morrison 1986). Several researchers have attempted to capture variety seeking by having a negative incremental reinforcement for the chosen attribute levels and product (see for example Lattin 1987, Papatla and Krishnamurthi 1992). In our framework, they model variety-seeking behavior by having $R_{ikl}(t) < 0$ for the chosen attribute level (and $R_{ij}(t) < 0$ for the chosen product). This implies that the consumer is less likely to choose the chosen attribute level (product) on the next purchase occasion.[7]

In our model, variety-seeking occurs because the consumer gets satiated with the chosen attribute level and/or receives a simulated reinforcement from unchosen attribute levels which make her want to switch to them. We can demonstrate this using equations (5), (6) and (7). Consider two attribute levels *l* (chosen) and *l'* (unchosen). Assume that the latter is twice as familiar as the former (e.g., $F_{ikl'}(t-1) = 2 > F_{ikl}(t-1) = 1)$ and $F_{ikl}(t-2) = 0.5$. Consequently, the incremental reinforcement for the unchosen attribute level *l* ($R_{ikl'}$) is greater than that for the chosen attribute level (R_{ikl}) if $S_{k1} > C_{k0} + 0.5 \cdot C_{k1}$.[8] This results in *l'* more likely to be chosen than l.

Our model predicts that the consumer would switch to those attribute levels that receive a higher simulated reinforcement from shopping whereas existing approaches do not make such a prediction. Switching to an unfamiliar attribute level can occur if the products with that attribute

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[7] Our model does not distinguish between individual-level variety-seeking behavior and intra-household taste variation. That is, the model cannot separate purchase behavior of a multiple-member household whose members have different tastes from that of a single-member household who seeks variety due to satiation. This is a limitation imposed on our model by data availability. If intra-household consumption histories are known, we can potentially have a separate consumption experience for each household member. We can however study such distinction by adding an interaction term that captures the size of the household to the consumption and shopping experience.

[8] Different consumers with the same set of parameters will have different variety-seeking propensity if they have different familiarities with the attribute levels. For instance, if the familiarity for the unchosen level is 1 instead of 2, then the incremental reinforcement for the chosen level is higher than the unchosen level. These consumers will have a smaller variety-seeking propensity.

level are on promotion (i.e., higher $M_j(t)$ value). Switching back to the familiar attribute levels, which occurs frequently in our dataset, is captured by this familiarity-based shopping experience.

EMPIRICAL ANALYSIS

We estimate our model using the method of simulated maximum likelihood. We use the Geweke-Hajivassiliou-Keane (GHK) recursive probability simulator to evaluate the SKU choice probability in equation (2.19) (see Geweke, Keane and Runkle (1997) for details). The estimation is implemented in a GAUSS program. Dual stopping criteria are used. The optimization routine is terminated if the changes in parameter estimates are less than 10^{-3} and the improvement in average log-likelihood per observation is less than 10^{-5}.

Data Description

We estimate our model on two IRI scanner panel data sets drawn from two different cities in United States capturing 133,492 purchase incidences and spanning 16 product categories. The first dataset contains shopping information of 548 households over a 2- year period (June 1991 - June 1993). It contains purchase information of 15 product categories at five stores located in the same area. These 15 products consist of 10 food categories (bacon, cola, egg, frozen pizza, hot dog, ice cream, potato chip, regular cereal, spaghetti sauce and yogurt) and 5 non-food categories (bathroom tissue, detergent, paper towel, soap and toothpaste). The data set also contains information regarding product availability at each store, as well as marketing mix information, such as prices, advertising features, and in-store displays, on a weekly basis.[9] The second dataset

[9] Since we cannot detect temporary intra-week stock-outs, we assume the products experiencing intra-week stock-outs are available throughout the week when we update the shopping experiences.

captures fabric softener purchases of 594 households over a two-and-a-half year period (January 1990 to June 1992) in Philadelphia. Like the first dataset, it contains product availability and marketing mix information. This dataset allows us to check the robustness of our model because the fabric softener has four (instead of three) salient attributes and has a different set of panelists living in a different city and shopping over a different time horizon. Table 1 provides detailed information for each product category. The categories are sorted in the total number of attribute levels in all salient attributes.

The input variables for our auto-regressive probit model are defined as follows. First, the price of each SKU is computed according to the price per basic unit (e.g., price per oz.). In addition, the variables $AD_j(t)$ (the advertising feature) and $D_j(t)$ (the in-store display) are treated as zero-one variables.

Unlike the fabric softener dataset, the first dataset uses three data fields to describe a product. They are brand name, package size, and flavor. Consequently, we use these three salient attributes to represent the SKUs. We use the product descriptions provided by the manufacturers to delineate attribute levels. To be comprehensive, we treat each different description as a new attribute level. Table 1 gives some examples of brands, package sizes and flavors for each category. In our data set, 2 SKUs rarely share the same attribute level combination. Note that even if 2 SKUs have the same attribute levels, the consumer could develop different attractions for them because she has a different product-specific experience for each of them.

There are an average of 202 SKUs per category. Out of the 16 product categories in our data sets, only 3 (the bacon, egg and fabric softener categories) have less than 100 SKUs. There are an average of 28 brands, 32 package sizes, and 35 flavors in a category. The soap category has the highest number of brands of 47 while the eggs category has the least number of 12. The frozen pizza category has as many as 145 package sizes and the eggs category has only 3. In terms of flavor, the ice cream category has the most with 145 flavors while the eggs category has 5 different egg sizes.

Estimation Results

Our 2-segment model has a fixed 59 parameters for all categories. A 2-segment GL or FH model can have hundreds of parameters. For instance, a 2-segment GL and FH model has 853 and 401 parameters respectively for the ice-cream category. We benchmark our model against the GL and FH models for product categories where these models have less than 200 parameters. These "small product categories" (see Table 1) are egg, fabric softener, bathroom tissue, cola, bacon, paper towel, and hotdog. We did this for 2 reasons. First, it is difficult to obtain reliable parameter estimates when a model has hundreds of parameters. Second, we wanted to give our model a stringent test because some of our model constructs (e.g., shopping experience) were developed specifically for "large product categories" that have many SKUs and attribute levels. Since the competing models ignore these model constructs, they are more likely to work well in small product categories.

To estimate our model parameters and to validate our model out-of-sample, we divide the 104 weeks of data for all 16 categories except FH's fabric softener as follows: the first 13 weeks of data are used for initialization, the next 65 weeks for calibration, and the last 26 weeks for model validation. Fader and Hardie (1996) used 52 weeks of data for initialization in their fabric softener data set to which we adhere for ease of comparison. We have also estimated our model using 7 weeks of initialization period. The two sets of results were not different and we report the 13-week results because prior studies often used at least 3-month of initialization period.[10] A detailed breakdown of the sample size in calibration and validation for all 16 categories is given in Table 1.

Top half of table 2 shows the calibration results for small product categories. We use log-likelihood, average hit probability, and adjusted pseudo R-square to evaluate the models.[11] Overall, our model performs better than the FH model, which in turn does better than the GL model, in all three measures. Below we compare our model with the FH model in greater details.

The average ρ^2 for the FH model is 0.55 and the average ρ^2s for our model is 0.60 respectively. Out of the seven categories, the smallest improvement category (fabric softener) has an adjusted ρ^2 improvement of 4% whereas the best performing (bacon) shows a 13%

[10] Across categories, the average differences in total log-likelihood over the same time horizon are 0.5% (22 LL points) and 1.4% (19 LL points) in-sample and out-of-sample respectively. The differences between the two sets of parameter estimates (C_{k1}, C_{p1}, S_{k1}, S_{p1}, ρ_k, σ_k, ρ_p, σ_p) were not statistically significant. Details available upon request from the authors.

[11] The adjusted pseudo R-square (ρ^2) measures the proportion of the log-likelihood of the empirical frequency model explained by the model of interest. The adjusted ρ^2 for a model M is given by:

$$\rho^2(M) = \frac{LL(0) - LL(M) - NP(M)}{LL(0)} \tag{3.1}$$

where $NP(M)$ is the number of parameters for model M, LL(0) is the log-likelihood value of the empirical frequency model, and LL(M) is the maximized log-likelihood value of model M. The empirical frequency model assigns to each product a choice probability based on its aggregate market share in the first 78 weeks of the data set which cover the initialization and calibration periods. The adjusted ρ^2 is a good measure because it captures the fit while adjusting for the number of parameters.

improvement. Bottom half of Table 2 shows our model is consistently better in all categories in the validation phase.[12] It predicts an average of 11% better than the FH model in adjusted ρ^2. Our worst performing category (fabric softener) has an improvement of 6%, while our best performing category (eggs) shows a 20% improvement.

An intuitive way of judging the models is to determine their average hit probability. Table 2 shows the empirical frequency model and the FH model have an average hit probability of 0.10 and 0.52 respectively in calibration. Our model shows an average hit probability of 0.56. This represents an average improvement of 10%. A similar pattern shows up in the validation phase. Our model has an average hit probability of 0.55 while the FH model has an average hit probability of 0.51.

Table 3 shows the calibration and validation results for our model in nine large categories. The superiority of our model over the empirical frequency model is even more pronounced here than in small product categories. In terms of adjusted ρ^2, our model for large (small) categories averages 0.76 (0.60) and 0.82 (0.60) in-sample and out-of-sample respectively. Note that the improvement over the empirical frequency model is higher out-of-sample than in-sample, suggesting that our model does not over-fit the data in large product categories. We believe (as evidenced by results given in Table 4) that this can be accounted partly by more pronounced shopping experience in large product categories.

[12] The GL and FH models can not forecast purchases made to new products or new products that introduce new attribute levels to the category. To give these models their best shot, these purchases were excluded in the validation phase.

Tests of Key Behavioral Premises

Our first behavioral premise posits that the consumer accumulates both attribute-level and product-level reinforcements. We can easily test whether this is true by estimating two special cases of the general model: 1) a model without attribute-level reinforcement (i.e., $C_{k0} = C_{k1} = S_{k1} = 0$) and 2) a model without product-level reinforcement (i.e., $C_{p0} = C_{p1} = S_{p1} = 0$). The top panel (labeled as 'Behavioral Premise 1') of the estimation results (in Table 4) clearly show that both kinds of reinforcement are necessary for developing a predictive model of SKU choice. In all product categories, both special cases are strongly rejected in favor of the more general model. These results provide a nice, albeit indirect, support of Lynch, Marmorstein, and Weigold's (1988) theoretical framework in the field.

Our second behavioral premise suggests that the consumer accumulates both consumption and shopping experiences. We can test this premise by determining the model fits of two special cases of the model: 1) a model without consumption experience (i.e., $C_{k0} = C_{k1} = C_{p0} = C_{p1} = 0$) and 2) a model without shopping experience (i.e., $S_{k1} = S_{p1} = 0$). The middle panel of the results (labeled as 'Behavioral Premise 2') strongly suggests that both kinds of experiences are crucial in fitting and predicting SKU choice. Note that the likelihood ratios were much higher in large product categories. This is indicative of the greater importance of shopping experience in these categories.

Our third premise is that both shopping and consumption experiences depend on familiarity. Thus the consumer can have a different incremental reinforcement for the same attribute level or product over time. We test this premise by estimating a special case of our model where $C_{k1} = S_{k1} = C_{p1} = S_{p1} = 0$. The bottom panel of estimation results (labeled as 'Behavioral Premise 3') strongly suggests that both consumption and shopping experiences are familiarity-based. These results suggest that consumers use memory cues to narrow down products during shopping and derive marginally higher utility in repeated consumptions.

Shopping and Consumption Experiences

Our extensive data set allows us to develop several empirical regularities on shopping and consumption experiences across categories. This effort is exploratory in nature and focuses on the unique features of our model (i.e., S_{k1}, C_{k1}, S_{p1} and C_{p1}).

As discussed below, positive S_{k1} and S_{p1} would suggest a memory activation effect that results in switching to familiar attribute levels or products. A negative C_{k1} and C_{p1} means decreasing marginal utility; on the other hand, a positive C_{k1} and C_{p1} imply increasing marginal utility at the attribute level and product level. Table 5 shows the parameter estimates. We note the following:

There is a 'memory activation' effect for familiar attribute levels. Sixty out of the seventy statistically significant S_{k1}s are positive. Thus, shopping experience in general increases with attribute-level familiarity. This occurs in at least one segment of all 14 significant categories for *brand*, 14 out of 15 significant categories for *size*, and 12 out of 14 significant categories for *flavor*. This finding suggests that when consumers switch away from the chosen attribute levels, they are more likely to switch to familiar attribute levels. This propensity to choose familiar attribute levels (e.g., brand) is consistent with the finding of Erdem and Keane (1996) where risk-averse consumers were found to avoid less familiar brands because they were uncertain about their benefit.

Product-level shopping experience also increases with familiarity. The 30 S_{p1} parameters are significant and positive in all categories. Hence, consumers tend to switch back to products with which they are familiar. This implies that consumers are reluctant to spend time evaluating unfamiliar products during shopping.

Surprisingly, we observe an increasing marginal utility at the attribute-level in a majority of the categories. Forty out of the fifty statistically significant C_{k1} are positive. This phenomenon occurs in at least one segment in 10 out of 11 categories with significant C_{k1} for *brand*, 8 out of 10 categories for *size*, and 12 out 14 categories for *flavor*. The same phenomenon however occurs less frequently at the product level. Only 17 out of the 30 C_{p1} are statistically different from zero. Twelve of them are positive, suggesting increasing marginal utility at the product-level.

The memory for attribute consumption is less ‘accessible’ and less ‘diagnostic’ than the memory for product consumption. We find that $\theta_p > \theta_a$ in at least one segment of 11 out of 16 product categories and $S_{p1} > S_{k1}$ in at least one segment of all 16 categories. Since the parameters θ_a and θ_p convert the number of consumptions into familiarity, a higher θ implies a better accessibility to the memory of past consumptions. The relative diagnosticity of these familiarities in consumer choice depends, however, on the values of the parameters S_{k1} and S_{p1} because they translate these familiarities into reinforcements and attractions. In short, these results suggest that past product consumption is easier to recall than past attribute consumption and remembered product consumption influences consumer choice more heavily than remembered attribute consumption.

Autoregressive Error Structures

The parameters ρ_k and ρ_p allow us to study whether there is any serial correlation in random utilities over time. Table 6 shows the parameter estimates for ρ_k and ρ_p. A majority of the attribute-level correlation parameters (61 out of 98) are not significantly different from zero. Of those that are significantly different from zero, only eight have an absolute value higher than 0.5. Half of these higher serial correlations occur in brand. A majority of the product-level serial correlation parameters (22 out of 32) are not significantly different from zero. Of those that are significantly different from zero, only four have an absolute value higher than 0.5. They occur in bacon, cola, and bathroom tissue. Overall, our results suggest that serial correlation in random utilities over time is very modest.

The variances of the attribute-level error terms (σ_k) provide clue as to the degree of correlation among products that share similar attribute levels. Most of the estimated σ_k are small (when compared to the product-level variance term σ_p) (see Table 6) except for bathroom tissue, bacon, hotdogs, toothpaste, and soap. These results suggest that correlations among utilities of SKUs are small within a product category at a particular purchase incidence.

DISCUSSION AND CONCLUSION

In this research, we have shown that it is possible to develop a SKU choice model with parameters independent of the number of SKUs and the number of attribute levels the product category has. With three salient attributes, our model has only 59 parameters (compared to an average of 199 and 118 for GL and FH models for seven small product categories). Our model uses all data to describe as well as predict choices made to all SKUs. We have shown that this highly parsimonious model performs substantially better in log-likelihood, average hit probability, and adjusted pseudo R-square. This superior performance occurs in all product categories. In addition, we have demonstrated that our model describes and predicts choices well in nine large product categories.

Our model was developed by modifying the standard utility specification and by incorporating familiarity-based consumption and shopping experience at both the attribute and product levels. Our results suggest that both the attribute-level and the product-level familiarities are important for predicting SKU choice in small and large product categories. If familiarities for attribute levels and products are induced by a consumer's memory for them, our result supports the notion of memory-based decision-making (Alba, Hutchinson, and Lynch 1991). In some way, this work has shown that incorporating research findings from consumer research can be powerful for improving the descriptive and predictive power of a choice model in the scanner data literature.

We model attribute-level and product-level familiarities as a function of the number of consumptions in the respective attribute levels and products. We should be quick to point out that attribute-level and product-level familiarities can also be a function of other factors, such as TV commercials, word-of-mouth communication, and consumer reports. For example, Erdem and Keane (1996) use advertising exposure, besides the number of consumptions, to model brand familiarity.[13] It would be worthwhile to explore how these other factors affect attribute-level and product familiarities in the future.

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[13] They use the commercial viewing file of a household to determine the advertising exposure of a brand. Unfortunately, we do not have similar information at the SKU level to enhance the way we model attribute- and product-level familiarities.

We have found strong evidence that shopping experience exists at both the attribute and product levels and increases with familiarity. To the best of our knowledge, this is the first demonstration of the effect of shopping experience on product choice in the scanner data research. This result suggests that the consumer may use attribute-level and product-level familiarities to narrow down product alternatives during shopping. This allows us to capture the frequent phenomenon that the consumer may occasionally experiment with a new product but often returns to buying the existing set of familiar products. The 'memory activation' effect provides a theoretical rationale for the occurrence of variety-seeking behavior frequently observed in our product categories.

There are immediate and future effects of price and nonprice promotion. Our notion of shopping experience provides a behavioral mechanism by which the future benefit of promotion can be realized. If promotion leads to higher familiarity, and higher familiarity leads to increased shopping experience, then promotion can increase future product purchases. Since product-level shopping experience tends to be stronger and easier to recall than attribute-level (e.g., brand) shopping experience, managers might find it more effective to engage in product-level promotion than in attribute-level promotion.

An alternative way to interpret shopping experience is to examine the way we exploit information contained in unchosen attribute levels and products. Unlike other models, our models do not treat all unchosen attribute levels and products equally. We assume the consumer pays special attention to those attribute levels and products that she consumed on previous occasions. The way we extract information from the unchosen attribute levels and products is, however, somewhat simplified. More sophisticated approaches, particularly behavioral-based, can be formulated to differentiate attribute levels and products in order to obtain a better fit and prediction. For instance, consumers may be allowed to have imperfect memory and may gradually forget what they have bought previously. This will lead to a different familiarity function that may improve fit and prediction power. We suggest this subject for future research.

Finally, we would like to suggest a few ways the proposed model can be by brand managers and is indeed currently used in practice.

Base volume forecasting: Our model can be used to forecast regular sales volume (i.e., base volume) of any SKU in a product category. Our model reveals the relative contribution of each attribute level to the base volume while controlling for the marketing mix effects.

Relative importance of each attribute: Using the model, one can easily analyze the relative importance of each salient attribute. This analysis can be done at the individual consumer level and across time.

Forecasting sales for line extensions: As indicated above, an attractive feature of our model is its ability to forecast sales for line extensions, whether or not they introduce new attribute levels to a category.

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Table 1: Data Description of Product Categories

	Small Product Categories							Large Product Categories								
	Egg	Fabric Softener	Bathroom Tissue	Cola	Bacon	Paper Towel	Hotdog	Potato Chip	Yogurt	Spaghetti Sauce	Soap	Toothpaste	Detergent	Regular Cereal	Ice Cream	Frozen Pizza
Category Summary																
Total Sample Size	9903	9781	14590	14705	3698	12218	4111	7022	12594	4226	5214	2993	7171	12978	6977	5311
Number of Households	482	594	528	429	314	495	334	382	356	320	384	306	471	480	420	337
Number of SKUs	38	59	106	141	62	108	128	285	288	194	243	259	321	242	421	337
Total Number of Levels in All Salient Attributes [1]	20	22	40	41	45	53	64	95	96	102	107	119	124	153	191	256
Number of Parameters																
Our Model	59	73	59	59	59	59	59	59	59	59	59	59	59	59	59	59
Fader and Hardie	75	79	115	117	125	141	163	225	227	239	249	273	283	341	417	547
Guadagni and Little	91	133	227	297	139	231	271	585	591	403	501	533	657	499	857	689
Salient Attribute Description																
Brand																
Total Number	12	10	21	17	26	27	38	29	15	41	47	24	41	35	37	40
Example	Crystal Fm.	Downy	Scottissue	Coca Cola	Oscar Mayer	Bounty	Oscar Mayer	Jays	Dannon	Ragu	Dial	Crest	Tide	Kellogg	Value Pak	Tombstone
	Prv. Label	Snuggle	Northern	Pepsi	W.CornKing	Scottowels	Hygrade	Lays	Yoplait	Prego	Dove	Colgate	Wisk	Gnrl Mills	Haagen Dazs	Bravissimo
	W.R.Valley	Bounce	Charmin	Ryl Crown	Lazy Maple	Versatile	W.CornKing	Ruffles	Kemps	Hunts	Ivory	Arm&Hammer	All	Post	Dreyers	Jacks
Package Size																
Total Number	3	4	11	16	7	9	11	34	7	30	42	44	62	73	9	145
Example	12 ct.	Small	4 rl.	67.6 oz.	16 oz.	1 rl.	16 oz.	6.5 oz.	6 oz.	30 oz.	15 oz.	6.4 oz.	64 oz.	12 oz.	64 oz.	22 oz.
	18 ct.	Medium	1 rl.	288 oz.	12 oz.	3 rl.	12 oz.	7 oz.	8 oz.	26 oz.	14 oz.	4.6 oz.	128 oz.	18 oz.	16 oz.	20 oz.
	6 ct.	Large	12 rl.	144 oz.	24 oz.	2 rl.	40 oz.	6 oz.	32 oz.	14 oz.	9.5 oz.	6 oz.	42 oz.	15 oz.	32 oz.	17 oz.
Flavor/Ingredient																
Total Number	5	4	8	8	12	17	15	32	74	31	18	51	21	45	145	71
Example	Large	Regular	Unscented	Regular	Regular	White Paper	Beef	Regular	Plain	Plain	Regular	Tartar Ctrl	Reg. Liquid	Corn	Vanilla	Sausage
	Extra Large	Staingard	Regular	Diet	Smoked	Print	Chckn&Pork	BBQ	Strawberry	Itln. Garden	Original	Bk. Soda	Con. Pwd	Wheat Bran	Neapolitan	Cheese
	Jumbo	Light	Soft Scented	Caffn. Free	Hkry Smoked	As.Colors	Pork&Turkey	SC & Onion	Raspberry	Tmt. & Herb	Unscented	Regular	Reg. Pwd	Rice	Chocolate	Deluxe
Formula		4														
Total Number		Regular														
Example		Staingard														
		Light														

Note 1: The product categories are arranged in increasing order of the total number of levels in all salient attributes

Table 2: Calibration and Validation Results for the Small Product Categories

	Egg	Fabric Softener	Bathroom Tissue	Cola	Bacon	Paper Towel	Hotdog
Calibration							
Sample Size	6252	4417	9303	9241	2383	7768	2577
Log-likelihood							
Our Model	-5414	-2600	-11287	-10592	-3272	-8845	-3635
Fader and Hardie	-5699	-3074	-13196	-11911	-3523	-9407	-3927
Guadagni and Little	-5978	-3039	-	-	-3892	-	-
Empirical Frequency	-8691	-15504	-30384	-34861	-6000	-25104	-8502
Average Hit Probability							
Our Model	0.55	0.83	0.51	0.60	0.37	0.56	0.47
Fader and Hardie	0.53	0.82	0.45	0.55	0.32	0.52	0.44
Guadagni and Little	0.53	0.81	-	-	0.27	-	-
Empirical Frequency	0.33	0.03	0.06	0.03	0.12	0.05	0.06
Adjusted ρ^2							
Our Model	0.37	0.83	0.63	0.69	0.44	0.65	0.57
Fader and Hardie	0.34	0.80	0.56	0.65	0.39	0.62	0.52
Guadagni and Little	0.30	0.80	-	-	0.33	-	-
Validation							
Sample Size	2494	2137	3510	3495	842	2889	927
Log-likelihood							
Our Model	-2262	-1484	-4357	-3910	-1201	-3194	-1445
Fader and Hardie	-2486	-1814	-5346	-4527	-1283	-3467	-1556
Guadagni and Little	-2518	-1650	-	-	-1521	-	-
Empirical Frequency	-3781	-7867	-12108	-12463	-2461	-11781	-3089
Average Hit Probability							
Our Model	0.56	0.81	0.50	0.58	0.39	0.57	0.46
Fader and Hardie	0.53	0.80	0.42	0.53	0.33	0.54	0.42
Guadagni and Little	0.55	0.79	-	-	0.26	-	-
Empirical Frequency	0.30	0.03	0.05	0.03	0.11	0.04	0.06
Adjusted ρ^2							
Our Model	0.39	0.80	0.64	0.68	0.49	0.72	0.51
Fader and Hardie	0.32	0.76	0.55	0.63	0.43	0.69	0.44
Guadagni and Little	0.31	0.77	-	-	0.33	-	-

Table 3: Calibration and Validation Results for the Large Product Categories

	Potato Chip	Yogurt	Spaghetti Sauce	Soap	Toothpaste	Detergent	Regular Cereal	Ice Cream	Frozen Pizza
Calibration									
Sample Size	4395	7949	2701	3197	1892	4596	8262	4351	3396
<u>Log-likelihood</u>									
Our Model	-5485	-6930	-3076	-3605	-1762	-4287	-8998	-2854	-2496
Empirical Frequency	-17868	-36341	-10601	-13007	-7636	-20008	-36301	-19318	-14915
<u>Average Hit Probability</u>									
Our Model	0.57	0.74	0.60	0.65	0.70	0.71	0.68	0.77	0.76
Empirical Frequency	0.03	0.01	0.03	0.02	0.02	0.02	0.02	0.02	0.01
<u>Adjusted ρ^2</u>									
Our Model	0.69	0.81	0.70	0.72	0.76	0.78	0.75	0.85	0.83
Validation									
Sample Size	1698	3189	1085	1268	792	1677	3040	1623	1412
<u>Log-likelihood</u>									
Our Model	-1309	-2755	-1147	-1269	-693	-1036	-2686	-880	-894
Empirical Frequency	-7210	-15202	-4304	-5598	-4067	-10015	-13265	-7960	-7017
<u>Average Hit Probability</u>									
Our Model	0.65	0.73	0.60	0.67	0.72	0.79	0.71	0.80	0.77
Empirical Frequency	0.04	0.01	0.03	0.02	0.02	0.02	0.02	0.02	0.01
<u>Adjusted ρ^2</u>									
Our Model	0.81	0.81	0.72	0.76	0.82	0.89	0.79	0.88	0.86

Table 4: Tests of Behavioral Premises: Log-likelihood Ratios of Nested Models

	Small Product Categories							Large Product Categories									
	Egg	Fabric Softener	Bathroom Tissue	Cola	Bacon	Paper Towel	Hotdog	Potato Chip	Yogurt	Spaghetti Sauce	Soap	Toothpaste	Detergent	Regular Cereal	Ice Cream	Frozen Pizza
The Full Model (Log-likelihood)	-5414	-2600	-11287	-10592	-3272	-8845	-3635	-5485	-6930	-3076	-3605	-1762	-4287	-8998	-2854	-2496
Behavioral Premise 1																
No Attribute-level Reinforcement	246*	722*	2370*	936*	568*	1281*	405*	3014*	414*	2110*	1479*	1932*	695*	581*	728*	2598*
No Product-level Reinforcement	1080*	176*	3868*	3385*	568*	3699*	1013*	4523*	694*	3400*	846*	2196*	618*	2215*	293*	2748*
Behavioral Premise 2																
No Consumption Experience	306*	70*	737*	326*	237*	1487*	370*	3226*	1299*	1646*	234*	2202*	309*	230*	44*	533*
No Shopping Experience	775*	1027*	2566*	1725*	556*	1751*	449*	5134*	724*	3288*	1801*	2168*	2093*	8038*	1680*	1621*
Behavioral Premise 3																
No Familiarity	765*	549*	3636*	1498*	1623*	3075*	719*	1763*	696*	2259*	3469*	2074*	955*	4813*	293*	645*

Note 1: * indicates significance at 1%.

Table 5: Maximum Likelihood Parameter Estimates of Shopping and Consumption Experiences

	Small Product Categories							Large Product Categories								
	Egg	Fabric Softener	Bathroom Tissue	Cola	Bacon	Paper Towel	Hotdog	Potato Chip	Yogurt	Spaghetti Sauce	Soap	Toothpaste	Detergent	Regular Cereal	Ice Cream	Frozen Pizza
Segment 1 Parameters																
Shopping Experience, S_{k1}																
Brand	0.22*	-0.02	0.29*	0.26*	0.01	0.35*	0.40*	0.02	-0.01	0.15*	0.49*	0.16*	0.12*	0.17*	0.03	0.29*
Size	0.08*	0.33*	0.16*	0.35*	0.23*	0.05*	0.05*	0.01	0.10*	-0.04	0.03	0.21*	0.27*	-0.15*	-0.07*	0.16*
Flavor	-0.02	0.02	0.06*	0.54*	0.40*	0.11*	0.32*	0.04*	0.21*	-0.14*	0.46*	0.29*	0.06	-0.02	0.64*	0.14*
Formula		0.14*														
SKU, S_{p1}	0.60*	0.32*	0.27*	0.40*	0.48*	0.34*	0.95*	0.53*	0.83*	0.79*	0.86*	0.54*	0.47*	0.96*	0.34*	-0.38*
Consumption Experience, C_{k1}																
Brand	0.12*	0.00	0.11*	0.07*	-0.01	0.19*	-0.02	0.02	-0.02	0.21*	-0.14*	-0.19*	0.04	-0.01	0.65*	0.18*
Size	0.01	0.00	0.08*	0.05*	0.05*	0.06*	0.17*	-0.01	0.09*	0.04	0.03	-0.27*	0.04	0.03*	0.00	0.06*
Flavor	0.09*	0.00	0.09*	0.04*	0.11*	0.02	-0.01	-0.11*	0.00	0.10*	-0.03	0.25*	0.07*	0.12*	-0.16*	-0.34*
Formula		0.03*														
SKU, C_{p1}	-0.02	0.01	0.27*	0.05*	0.06*	0.08*	0.10*	-0.07*	-0.02	-0.01	0.14*	-0.08*	0.44*	0.08*	0.00	0.00
θ_a	5.11*	15.06*	4.27*	2.80*	3.87*	4.61*	5.49*	4.89*	4.79*	4.94*	6.34*	5.09*	5.17*	1.58*	4.72*	4.64*
θ_p	5.15*	0.74*	4.27*	4.73*	6.59*	4.57*	1.54*	1.09*	0.85*	4.97*	5.17*	4.70*	5.10*	5.37*	4.78*	4.77*
Segment 2 Parameters																
Shopping Experience, S_{k1}																
Brand	0.10*	0.30*	-0.25*	0.22*	1.10*	0.21*	0.14*	-0.02	0.00	0.00	-0.56*	-0.01	0.12*	0.21*	0.43*	0.12
Size	-0.04	0.13*	0.20*	0.12*	0.24*	0.14*	0.15*	0.07*	0.00	0.42*	0.43*	-0.19*	-0.09*	-0.32*	0.27*	0.21*
Flavor	-0.05*	0.00	0.11*	0.15*	0.27*	-0.05	0.24*	0.10	0.00	-0.12*	0.67*	0.11	-0.02	0.05*	0.02	0.33*
Formula		0.16*														
SKU, S_{p1}	0.46*	0.51*	1.04*	0.48*	0.50*	0.57*	0.45*	0.31*	1.03*	0.39*	0.77*	0.93*	0.31*	0.70*	0.77*	0.59*
Consumption Experience, C_{k1}																
Brand	0.04*	0.03	0.00	0.05*	-0.03	0.15*	0.16*	-0.14*	0.00	-0.04	0.28*	0.41*	0.18*	0.02	0.19	0.22*
Size	0.04	0.04*	0.04*	0.08*	0.16*	-0.02	-0.26*	-0.07*	0.00	0.03	-0.09*	-0.39*	0.17*	0.03*	0.11	-0.06
Flavor	0.07*	0.07*	0.04*	0.00	0.14*	-0.09*	0.13*	0.17*	0.00	0.11*	0.07*	-0.17*	0.09*	0.06*	-0.02	-0.02
Formula		0.01														
SKU, C_{p1}	-0.04*	0.01	-0.02	0.02	0.38*	0.14*	0.13*	-0.15*	-0.14*	-0.02	0.01	0.25*	0.03	0.06*	0.14	0.06
θ_a	4.77*	15.06*	5.05*	2.41*	4.96*	4.72*	4.96*	5.24*	5.08*	4.38*	4.29*	4.32*	4.75*	1.14*	4.99*	4.96*
θ_p	4.82*	1.01*	4.20*	5.36*	5.14*	4.95*	0.43*	2.41*	2.64*	4.81*	5.51*	4.85*	4.86*	4.90*	5.09*	5.01*

Note 1: * indicates significance at 1%.

Table 6: Maximum Likelihood Parameter Estimates of Autoregressive Error Structures

	Small Product Categories							Large Product Categories								
	Egg	Fabric Softener	Bathroom Tissue	Cola	Bacon	Paper Towel	Hotdog	Potato Chip	Yogurt	Spaghetti Sauce	Soap	Toothpaste	Detergent	Regular Cereal	Ice Cream	Frozen Pizza
Segment 1 Parameters																
Serial Correlation, ρ_k																
Brand	0.00	0.00	0.52*	0.19*	-0.10*	-0.32*	-0.01	0.00	0.00	0.00	0.68*	-0.36*	0.00	0.00	0.00	0.00
Size	0.00	0.00	-0.35*	-0.07*	0.31*	-0.06*	0.75*	0.00	0.00	0.00	0.07*	0.05	0.00	0.00	0.00	0.00
Flavor	0.00	0.00	0.59*	-0.32*	-0.06*	-0.17*	-0.18*	0.00	0.00	0.00	0.00	-0.19*	0.00	0.00	0.00	0.00
Formula		0.00														
SKU, ρ_p	0.00	0.00	0.61*	0.75*	-0.18*	0.21*	0.22*	0.00	0.00	0.00	0.00	-0.22*	0.00	0.00	0.00	0.00
Variance, σ_k																
Brand	0.49*	0.05*	0.60*	0.15*	1.73*	0.80*	0.67*	0.41*	0.02	0.06	0.17*	0.47*	0.01	0.08*	0.03	0.28*
Size	0.14*	0.01	0.25*	0.53*	1.13*	0.06*	0.54*	0.27*	0.00	0.04	0.42*	0.24*	0.34*	0.05*	0.04*	0.25*
Flavor	0.17*	0.04*	0.49*	0.16*	4.59*	0.23*	0.49*	0.28*	0.01	0.07*	0.15*	0.44*	0.26*	0.04*	0.14*	0.41*
Formula		0.04*														
SKU, σ_p	1.79*	1.65*	2.02*	1.42*	2.91*	1.97*	2.11*	1.92*	1.64*	1.78*	1.62*	1.72*	1.68*	1.70*	1.80*	1.89*
Segment 2 Parameters																
Serial Correlation, ρ_k																
Brand	0.00	0.00	0.64*	0.00	-0.31*	0.69*	0.11*	0.00	0.00	-0.23*	-0.29*	0.46*	0.00	0.00	0.00	0.00
Size	0.00	0.00	-0.15*	0.00	0.17*	0.15*	0.30*	0.00	0.00	0.10*	0.36*	0.22*	0.00	0.00	0.00	0.00
Flavor	0.00	0.00	-0.18*	0.00	0.20*	0.29*	-0.66*	0.00	0.00	-0.23*	0.52*	0.09	0.00	0.00	0.00	0.00
Formula		0.00														
SKU, ρ_p	0.00	0.00	-0.62*	0.00	0.54*	0.14*	0.02	0.00	0.00	0.00	-0.09*	0.04	0.00	0.00	0.00	0.00
Variance, σ_k																
Brand	0.00	0.11*	0.61*	0.10*	1.09*	0.12*	0.95*	0.23*	0.02	0.11*	4.14*	0.18*	0.10*	0.04*	0.01	0.09*
Size	0.10*	0.07*	3.14*	0.12*	2.39*	0.22*	2.33*	0.17*	0.01	1.19*	0.40*	0.34*	0.32*	0.03*	0.01	0.10*
Flavor	0.85*	0.01	0.69*	0.17*	3.31*	0.33*	1.01*	0.01	0.05*	0.02	2.20*	4.92*	0.18*	0.06*	0.03	0.10
Formula		0.02														
SKU, σ_p	1.72*	1.64*	2.24*	1.75*	2.51*	1.76*	1.79*	1.76*	1.69*	1.68*	2.16*	1.77*	1.72*	1.68*	1.64*	1.66*

Note 1: * indicates significance at 1%.