PRODUCT LINE MANAGEMENT AS DYNAMIC,

ATTRIBUTE-LEVEL COMPETITION

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14 November, 2003

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ABSTRACT

Product lines are composed of SKUs from the same manufacturer which compete directly with one another. Understanding how consumers choose among numerous alternatives of brand, size and format is complicated by the multitude of possibilities among which they can switch over time. We approach this problem in terms of *dynamic attribute satiation*: that households seek out specific attributes over time, and that their switching patterns will explicitly reflect this tendency. We formulate a dynamic model of sequential choice which relies on the following insight: although households may entirely disagree on the relative merits of two products, they are far more likely to agree on how similar they are. That is, while product *preferences* may differ markedly across households, product *positionings* will not.

The resulting model offers a number of unique benefits over and above parsimoniousness. Operationalizing product similarity in terms of *observed* attributes – information typically available in existing scanner panel data – describes the data better than sidestepping such attribute information in lieu of unobserved attributes. Estimated "part worths" enable one to characterize how substitutable or complementary two products are from the consumption perspective of households: for example, in one category, we find brand name to be a crucial determinant of how similarly two products are perceived, though in another apparently similar category, size is the critical attribute. While on the one hand this suggests that manufacturers may be able to capitalize upon a strong brand name by umbrella branding, it also suggests that products may cannibalize one another's sales if other attributes in the product category are perceived to be unimportant.

Switching probabilities depend on household-level inertia as well as on inter-product similarities, allowing an understanding of both these effects as well as their interplay. This stands in contrast with state dependence models that ignore inter-product similarities, which force different products to be always complements for a variety-seeking household, and always substitutes for an inertial household. The model accounts for patterns of *asymmetric substitutability*, and suggests that complementarity and substitutability should not be construed solely at the category level.

Key-words: State Dependence, Inertia, Variety-seeking, Dynamic Choice, Market Structure, Similarity Structure

INTRODUCTION

Firms like Procter and Gamble manage several product lines – laundry detergent, hand soap, shampoo, dishwashing liquid, toothpaste, coffee, toilet tissue, deodorant, disposable diapers – and within each further manage a host of products. For example, in the laundry detergents category, P&G offers not only a variety of brands (Tide, Cheer, Bold etc.), but also variants of each brand along attributes such as product type (Liquid Tide versus Powder Tide) and product size (Liquid Tide 32 oz. versus Liquid Tide 64 oz.). Effective product line management by P&G in the laundry detergents category involves an intimate understanding of how different products in the category compete with one another. If competition were based, at least in part, on the relative locations of products in some multiattribute space, then it would be important to understand the interplay of two key factors: differences across households in the relative importances of underlying attributes (*consumer heterogeneity*), and inter-product differences in the levels of the underlying attributes (*product positions*). Such an understanding of the market would assist P&G in pruning redundant products within its product lines (e.g., those which cannibalize sales of other P&G products) or adding new products to its product lines (i.e., products that fill positions within a line where none currently exists).

There is a long and rich literature in marketing that characterizes these two components of market structure, consumer heterogeneity and product positioning, using empirical data. Why is it important to understand these two components? First, consider *product positions*. To the extent that two products are perceived as being very similarly positioned, they attract similar types of consumers, namely, those who value the attributes that the two products share. For example, *Tide* and *Wisk* (manufactured by P&G and Unilever, respectively) are both perceived as "all-purpose family detergents" that can be used for a variety of fabrics and uses, and therefore compete "heavily" against each other, in the sense of attracting consumers who value the specific attributes they have in common. From a product line perspective, P&G must consider whether it is prudent to offer two brands which are touted as being "all-purpose", as this may substantially increase the likelihood of their cannibalizing one another's sales[1].

Second, consider *consumer heterogeneity*. To the extent that different consumers place varying degrees of emphasis on the various benefits that can be obtained from laundry detergents (effectiveness, economy, fresh smell, etc.), they may have differing preferences for the same product. For example, consumers with sensitive skin may prefer a "dermatologist tested" brand such as *Cheer*, while consumers who seek value may prefer a low-priced brand such as *Dash*. All else being equal, consumers seeking similar benefits from the product category are likely to switch heavily among the group of products offering them those benefits, and less so among those which fail to offer them. Understanding which attributes are important to households, as well as heterogeneity across households in such tastes, allows product managers to make more effective decisions regarding their product lines.

Researchers who have empirically estimated choice models on individual-level data have found that household choices are a function of observable attributes in the product category, in line with the economic choice theory of Lancaster (1971). For example, Fader and Hardie (1996) operationalize a product/SKU in terms of its constituent attributes, and recover "part-worth" estimates of attribute importances to explain observed choices of households. From a market structure perspective, the methodology proposed by Fader and Hardie (1996) enables one to understand inter-product competition explicitly along observable attribute dimensions.

Since the pioneering work Guadagni and Little (1983), there is a vaunted tradition of research in Marketing suggesting that previous choices made by households influence their current choices. This tendency, referred to as *state dependence*, persists over and above measurable effects of product attributes and consumer heterogeneity. Such state dependence effects can arise, for example, for the following simple reason: households may prefer to 'balance' their consumption of various product attributes, which, over time, leads to *variety-seeking* in their choices (McAlister 1982, Lattin 1987, Kahn et al. 1997, Ratner et al. 1999). Such 'variety-seeking' households may switch heavily among products that are very dissimilar in terms of their constituent attributes. A market structure model which ignores such variety-seeking effects may spuriously imply that products are 'close' to each other along some (unobservable) attribute dimensions when, in fact, they are not.

An early study that explicitly addressed the issue of variety-seeking in terms of shared product attributes was that of Lattin and McAlister (1985). The authors demonstrated that inferences about market structure are systematically distorted if one does not account for the effects of variety-seeking. Since that study however, the marketing literature has progressed along both data availability as well as modeling

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[1] Unless there are other benefits to having both brands in the marketplace, such as garnering more shelf-space and collectively "edging Wisk out."

dimensions. Specifically, researchers have found that, when studying market structure in a model that accounts for variety-seeking, it is also important to account for a number of additional factors, four prominent amongst them:

1. *The effects of marketing variables on household choice behavior*. It has been found that the estimated effect of state dependence on market structure will be overstated if the effects of marketing variables are not accounted for (Seetharaman et al. 1999).

2. *The effects of inertia in household choices*. Some households repeatedly buy the same product, or very similar ones over time, if these products offer high levels of the household's preferred attributes. Ignoring the effects of inertia may lead to spurious inferences; for example: Suppose household A is 'inertial' and frequently switches between two products because they are perceived to be very similar to one another. The model may incorrectly suggest that the two products are in fact highly dissimilar, and that the household switches between them in order to seek variety. Using packaged goods scanner panel data, recent empirical studies have begun to accommodate the effects of both inertia and variety-seeking (see Erdem 1996) in a dynamic framework.

3. *The effects of unobserved heterogeneity in household response parameters.* In order to make use of household scanner panel data to estimate the parameters of a reasonable dynamic model, one must explicitly accommodate the effects of unobserved heterogeneity, to avoid the well-known pooling bias in estimated parameters (e.g., Kamakura and Russell 1989).

4. *The effects of observable attributes on product positions*. Using observable attribute information allows managers to understand households' patterns of product choices in the "space of product characteristics" (in the sense of Fader and Hardie 1996). Further, it enables us to empirically distinguish between equally valid, yet contrasting, explanations about state dependence for the same empirical phenomenon (see point 2 above). For example, if two products have nearly-identical levels of all observable attributes and a household is observed to switch frequently between them, one can reasonably conclude that the products' positions are similar and, moreover, that the household is relatively inertial in nature (as opposed to the products' positions being very different, and the household seeking variety over time). We view this distinction as critical, yet models which fail to appropriately account for the nature of household-level state-dependence effects run the risk of making incorrect inferences about not only the structure of the category, but the very reasons why households engage in the patterns of inter-brand switching that they do.

In this study, we investigate the effects of state dependence on market structure using scanner panel data, specifically addressing the four issues raised above. In other words, we seek to understand market structure – conceptualized in terms of pairwise product-level competition – using a household-level choice model accommodating four effects of known importance: (1) marketing mix variables, (2) inertia and/or variety-seeking, (3) unobserved heterogeneity, and (4) product attributes. Given these objectives, we start from the parsimonious stochastic choice model of Lattin and McAlister (1985), modifying it to accommodate marketing variables and inertia. We then allow for unobserved heterogeneity across households and, lastly, operationalize inter-product similarity to be a function of observed product attributes. Two key findings emerging from a formal analysis of two packaged goods categories are summarized below.

- Accommodating the effects of inertia, marketing variables and unobserved heterogeneity is critical to obtaining correct inferences about market structure, particularly so when available scanner panel data offer no evidence of variety-seeking behavior. For example, a model which allows for variety-seeking, but which ignores the other three effects, may incorrectly conclude that variety-seeking drives market structure even when it does not.

- When product positions are characterized in terms of inter-product similarity measures, operationalizing these measures in terms of *observed* product attributes (information that is generally available in existing scanner panel data) not only gives excellent "face validity" to the model, but also fits the data better than a model which ignores such attribute information *in lieu* of unobserved attributes.

A previous study that has investigated market structure after allowing for variety-seeking and the four additional effects accounted for here (inertia, marketing variables, unobserved heterogeneity and product attributes) is that of Erdem (1996). Our study differs, however, in the following key respect: Erdem (1996) operationalizes inter-product similarities (that drive state dependence) along *unobservable*, rather than *observable*, product attributes[2]. To the extent that practitioners wish to understand market structure in terms of attributes that they incorporate into, and use as the basis of both differentiating and advertising, their products, a legitimate managerial question concerns whether important effects due to observable attributes indeed exist. A natural question that would then arise is whether one can compare the results from the proposed specification with that of Erdem (1996). Given the different model structures (as we show in the next section),

[2] This is in much the same spirit as Multidimensional Scaling (MDS), wherein estimated attribute dimensions are given 'physical' meaning *post hoc* in terms of observable attributes.

a direct comparison is not meaningful. However, we do provide a comparison of the observed versus unobserved attributes operationalizations *within* the context of our model structure. Specifically, because our model is constructed by overlaying successive structures on the basic Lattin and McAlister (1985) formulation, a natural benchmark is a specification incorporating unobservable product attributes in a manner analogous to Lattin and McAlister (1985) and Erdem (1996).

The remainder of the paper is organized as follows. In the next section, we review salient aspects of the dynamic choice model of Lattin and McAlister (1985). In section 3, we develop the proposed model and discuss the associated estimation procedure. Section 4 presents the empirical results for the two categories studied, as well as the substantive managerial insights arising from this empirical analysis. In section 5, we conclude with a brief summary and directions for future research.

DYNAMIC CHOICE MODEL OF LATTIN AND MCALISTER (1985)

The Lattin and McAlister (1985; henceforth LM) model is a first-order Markov model of choice which rests on the following premise: households switching among products in response to their variety-seeking needs are, on a given purchase occasion, more likely to buy a product that is dissimilar to the one purchased on the most recent purchase occasion. The LM model presumes that, in the absence of variety-seeking, an individual household goes about its purchases in multinomial fashion; each product *i* has an *unconditional* probability, π_i, of being purchased on a particular occasion. However, for a household seeking variety, products similar to that just purchased are less attractive. This is modeled as follows.

$$P_{j \to i} = \frac{\pi_i - VS_{ji}}{1 - V\sum_{k=1}^{K} S_{jk}}, \tag{1}$$

where $P_{j \to i}$ stands for the household's probability of switching from product *j* to product *i* (i.e., the household's *conditional* probability of buying product *i* given that product *j* was purchased at the previous purchase occasion), $V \in [0,1]$ denotes the household's propensity to seek variety, and S_{ji} measures the degree of similarity between products *j* and *i*. The interested reader is directed to Lattin and McAlister (1985) and Feinberg, Kahn and McAlister (1992) for the models' derivation, logical consistency constraints and steady-state implications. We note for completeness that (for all appropriate indices) $S_{ij} = S_{ji}$, $S_{ji} \in [0, \min\{\pi_i, \pi_j\}]$, and that by definition $S_{ii} = \pi_i$.

For the present study, we make use of the interproduct similarity parameters, S_{ji}, which can be conveniently rescaled in a manner ensuring conformity to the model's logical boundedness constraints, as follows:

$$S_{ji} = c_{ji}\, min(\pi_j, \pi_i) \tag{2}$$

where $c_{ji} \in [0,1]$, $c_{ij} = c_{ji}$, and $c_{ii} = 1$.

As per equation (1), the greater the value of V, the greater the degree to which a household seeks variety. $V = 0$ indicates a complete lack of variety-seeking (and implies that $P_{j \to i} = \pi_i$, corresponding to a zero-order stochastic choice model in the tradition of Bass et al. 1976), whereas $V = 1$ corresponds to maximal variety-seeking (achieved, for example, by switching back and forth between a pair of dissimilar products). The parameter c_{ji} is a measure of inter-product similarity between products j and i, so that $c_{ji} = 0$ indicates a lack of similarity (that is, no shared features), and $c_{ji} = 1$ corresponds to complete similarity (only shared features, in that the smaller-share brand of the pair offers no unique features beyond its larger-share competitor).

We stress the following point, which argues for both the structure and specific parameterization of the model: while households are likely to differ from one another in terms of their intrinsic *preferences* for products, they are far less likely to differ in terms of how similar they evaluate two products to be *in terms of the features they share*. That is, two households may disagree entirely about which of a pair of products they would choose for themselves, but – due to the ubiquitous influence of branding and advertising claims – would be quite likely to agree as to whether those products are similar or dissimilar to one another, relative to the category as a whole.

Thus, while the parameters of the original LM model can each differ substantially between households, the $\{c_{ji}\}$ re-parameterization used in the present paper allows for stability *across* the market as a whole, as it parsimoniously captures this degree of agreement on attribute-based inter-brand similarity. This observation will allow a parsimonious characterization of market structure on a product-pair basis, while allowing for dramatically different purchase patterns across households.

The appealing feature of the LM model is that it not only models the effects of variety-seeking on household choice behavior (through the parameter V), but also allows such effects to depend on inter-product similarities in a parsimonious manner (through the parameters c_{ji}). Further, because the traditional zero-order ("static") model is nested within the "dynamic" model as a special case (for $V=0$), statistical tests can be performed to compare them. The model is computationally straightforward to implement, and its adoption of pair-wise similarity measures is in accordance with Batsell and Polking's (1985) findings that parsimonious (i.e., lower-order, or pair-wise) specifications are typically adequate for the purpose of characterizing interdependencies in choice data. With n products, the model requires the estimation of a total of $n\,(n+1)/2$ parameters[3] (Feinberg et al. 1994).

PROPOSED DYNAMIC MODEL OF MARKET STRUCTURE

Despite its ability to simultaneously estimate the joint effects of households' variety-seeking and inter-product similarities on product choices, the LM model does not account for the effects of marketing variables, inertia, unobserved heterogeneity and product attributes. As noted previously, our motivation to extend the LM model is, therefore, fourfold: firstly, we account for marketing variables by replacing the household's unconditional Multinomial Choice probabilities (π_i) by their Multinomial Logit (MNL) counterparts (P_i); secondly, we allow for the possibility that households can be either inertial or variety-seeking in their sequential product choices; thirdly, we allow for unobserved heterogeneity by allowing the inertia / variety parameter and the marketing mix parameters to vary across households; lastly, we operationalize inter-product similarities in terms of observable product attributes in order to understand the underlying attributes that drive dynamic choice behavior.

The proposed model can be interpreted in the economic framework of Lancaster (1976) in the sense that it allows household choices to intrinsically depend on underlying product attributes. While we do not explicitly derive the proposed model using the economic primitives of household utility maximization, the following analogies may be useful: static utility maximization would correspond to $V = 0$, and dynamic utility maximization would correspond to a first-order Markov process (with $V \neq 0$). We explain our proposed refinements of the LM model below.

Effects of Marketing Mix Variables. In order to account for marketing variables, we replace the unconditional Multinomial Choice probabilities (π_i) with their MNL counterparts, given as usual

[3] There are $(n-1)$ independent π_i parameters, $n(n-1)/2$ similarity parameters and a single V parameter.

by $P_{it} = \exp(X_{it}\beta) / \sum_{k=1}^{k=K} \exp(X_{kt}\beta)$, where $\mathbf{X_{it}}$ is the vector of marketing variables characterizing product *i* at time *t*, and β is the corresponding vector of response parameters (assumed to be common across products). The MNL choice probability P_{it} represents the household's probability of choosing product *i* at time *t* if their choice decision were governed only by the effects of their intrinsic product preferences and marketing variables. This specifically allows the household's choice probabilities for different products to depend on the marketing mix.

State Dependence. In order to account for the effects of inertia, we allow the parameter *V* to take values less than zero so that instead of restricting $V \in [0, 1]$ as in Lattin and McAlister, the range of allowable values for *V* is extended to $[-\infty, 1]$. In this scenario, $V > 0$ corresponds to variety-seeking (as in Lattin and McAlister), while $V < 0$ corresponds to inertia. Three points of this range are particularly noteworthy in terms of the type of behavior with which they correspond: $V = 0$ indicates that choice behavior is essentially zero-order, or that shared attributes fail to play a privileged role in driving sequential choices; $V = 1$, by contrast, suggests a complete discounting of features previously consumed, so that all that matters are the *unique* features offered by the next potential product choice; finally, $V \rightarrow -\infty$ suggests that only *shared* features are important, that products are desirable to the extent that they 'overlap' with that most previously consumed. It is useful to note that both the probabilistic interpretation of $P_{j \rightarrow i}$, as well as the characterization of inertia on the basis of inter-product product similarities, are preserved in this formulation.

Household-level Heterogeneity. In order to account for the effects of unobserved heterogeneity across households, we allow the model parameters to follow a multivariate discrete distribution across households (Kamakura and Russell 1989). This entails the formulation of each household's likelihood function as a weighted average of separate likelihoods based on the supports of the discrete heterogeneity distribution. The number of optimal supports for the heterogeneity distribution is determined using the Schwarz Bayesian Criterion (see Kamakura and Russell 1989 for details)[4].

[4] We recognize that recent Bayesian methods (e.g., Allenby and Rossi 1999) better capture unobserved heterogeneity by estimating parameters at the household level. However, since product line decisions are

Parametric Inter-Product Similarity Structure. The representation of the inter-product similarity parameters in terms of the underlying product attributes (such as product size, product flavor, etc.) in the category is operationalized through a linear specification, $c_{ji} = c_o + \Sigma_q (I_{jiq}\, c_q)$, where $c_q \in [0,1]$ reflects the importance of attribute q in characterizing inter-product similarity, $c_o \in [0,1]$ is a baseline level of similarity between all pairs of products (with $c_o + \Sigma q\ c_q = 1$), and I_{jiq} is an indicator variable taking the value 1 if products j and i share attribute q, and 0 otherwise. Estimating the parameters $\{c_q\}$ affords an understanding of how pair-wise similarities of products (c_{ji}) can be "decomposed" in terms of the underlying observable attributes in the product category. This approach is in the spirit of Fader and Hardie (1996), who estimated attribute-level "part worths" in an MNL model of SKU choice using scanner panel data. In our case, we estimate attribute-level "part worths" to characterize the pair-wise similarity parameters, $\{S_{ji}\}$ (which, of course, can be reconstructed from $\{c_{ji}\}$ and $\{\pi_i\}$). For example, in the peanut butter category, the products "Jif Creamy 18 oz." and "Jif Chunky 18 oz" are similar along two attributes (brand name, size) while the two products "Peter Pan Creamy 18 oz." and "Control Brand Chunky 18 oz." are similar along one attribute only (size). In determining inter-product similarities, if the size attribute is very important, and the brand name far less so, then both pairs of products may have nearly identical levels of shared attributes. However, if both brand name and size are equally important in determining inter-product similarities, the first pair of products (i.e., Jif Creamy 18 oz. and Jif Chunky 18 oz.) has higher inter-product similarity than the second. Our formulation allows for such flexible characterizations of inter-product similarities in terms of product attributes.

If the proposed formulation is supported by the data, then it presents a highly parsimonious alternative to estimating the full similarity matrix $\{c_{ij}\}$, the approach taken, at the individual-level, by Lattin and McAlister (1985). The LM study made use of long purchase histories at the individual level, which enabled reliable estimation of the similarity matrix. However, scanner panel data are typically not characterized by

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typically motivated from the perspective of satisfying distinct market segments, without necessarily targeting households at the individual-level, we believe that the latent class methodology is suitable for the present purposes, and is far more easily deployed in a managerial context. The choice of *discrete* heterogeneity is made on this basis, and in accordance with recent evidence (Kamakura and Wedel, 2001) that discrete heterogeneity typically performs at least as well as continuous in random utility models.

such lengthy purchase histories at the household-level. One advantage, therefore, of the proposed approach is that it is more relevant in the context of typical scanner panel data sets, which consist largely of shorter purchase strings. Explicitly comparing our parameterization of the similarity matrix to LM's "non-parametric" approach allows us to investigate whether the parsimonious parametric approach is superior from an explanatory vantage point.

In a product category with a large number of SKUs, our approach can be integrated with that proposed by Fader and Hardie (1996) to obtain a dynamic variant of their SKU choice model. Such a model characterizes state dependence and inter-product similarities in addition to the attribute-level part worths. This may be of significant practical value to practitioners given the importance of brand loyalty and the increased competition along product attributes.

This completes the step-by-step discussion of how the proposed model is constructed. The model itself is given formally as below:

$$P_{h,\, j \to i,t} \quad = \quad \sum_{r=1}^{R} \pi_r \frac{P_{rit} - V_r S_{ji}}{1 - V_r \sum_{k=1}^{K} S_{jk}}, \tag{3}$$

where $P_{h,\, j \to i,t}$ stands for household h's probability of switching from product j to product i at time t, P_{rit} stands for household h's MNL probability of buying product i given that it belongs to support r of the discrete heterogeneity distribution, $V_r \in [-\infty, 1]$ is the household's state dependence parameter given that it belongs to support r (with $V_r < 0$ capturing inertia, and $V_r > 0$ capturing variety-seeking), π_r stands for the mass associated with support r of the heterogeneity distribution, and S_{ji} stands for the inter-product similarity characterizing products j and i. Further, the inter-product similarity parameter S_{ji} is operationalized as:

$$S_{ji} \;=\; c_{ji}\, min(P_j, P_i) \tag{4}$$

where $c_{ji} = c_o + \Sigma_q\, (I_{jiq}\, c_q),\ c_q \in [0,1],\ c_o + \Sigma_q\, c_q = 1$, and I_{jiq} is an indicator variable that takes the value 1 if products j and i share attribute q and 0 otherwise. Inter-product similarity parameters (c_{ji}) are, as discussed previously, taken to be common across households[5]. In this formulation, the intercept c_o must be interpreted as

[5] It is not possible to separately identify heterogeneity across households simultaneously in parameters V and c_{ij}. Product positions are typically assumed to be common across households, while household preferences for attributes are heterogeneously estimated (see Erdem 1996).

a baseline similarity level that is presumed to exist between all pairs of products. In other words, instead of restricting this intercept to zero, we empirically estimate it. If products are perceived to be very similar in some categories but not in others, this intercept captures such differences.

The household's MNL choice probability P_{rit} captures the influence of the household's intrinsic product preferences and marketing variables on its product choices. The parameter V_r is a measure of the household's degree of seeking inertia or variety (depending on whether $V_r < 0$ or $V_r > 0$ respectively). $V_r = 0$ corresponds to no state dependence (and implies a zero-order heterogeneous choice model in the tradition of Kamakura and Russell 1989). The parameter c_{ji} is a measure of inter-product similarity, and is decomposed in terms of the underlying attributes in the product category. c_q is a measure of the importance of attribute q in characterizing inter-product similarities, and the summation restriction $c_o + \Sigma q\ c_q = 1$ is imposed to ensure that a product has a similarity of 1 with itself,[6] i.e., $c_{ii} = 1$. The greater the value of c_{ji}, the greater the similarity between products j and i: $c_{ji} = 0$ corresponds to no similarity, and $c_{ji} = 1$ corresponds to a maximal degree of similarity. In the proposed model, the higher the value of c_{ij}, the more likely an inertial household is to switch between products i and j; conversely, the lower the value of c_{ij}, the more likely a variety-seeking household is to switch between products i and j.

This completes the proposed model formulation, which reduces to the LM model if the effects of inertia, marketing variables and unobserved heterogeneity are ignored and if c_{ij} is non-parametrically estimated for all pairs of products, rather than being parameterized using underlying product attributes (as explained earlier). In order to explicitly investigate the advantages of the proposed parsimonious characterization of the product similarity parameter, we benchmark our model against one that non-parametrically estimates c_{ij} for all i, j. The proposed model also nests two other familiar models as special cases: $V = 0$ yields the heterogeneous MNL model (Kamakura and Russell 1989, Chintagunta et al. 1991, Gonul and Srinivasan 1993), while $V = 0$ and the absence of marketing variables (or, equivalently, $\beta = \mathbf{0}$) yields the heterogeneous stochastic choice model (Massy et al. 1970, Bass et al. 1976, Jeuland et al. 1980)

The proposed model is estimated by maximizing the sample likelihood function given below.

[6] Since a product shares all attributes with itself, $c_{ii} = c_o + \Sigma q\ c_q$

$$L \;=\; \prod_{h=1}^{H} \left[\sum_{r=1}^{R} \pi_r \prod_{t=1}^{T_h} \prod_{i=1}^{I} \left(\frac{P_{rit} - V_r S_{j_{h(t-1)}i}}{1 - V_r \sum_{k=1}^{K} S_{j_{h(t-1)}k}} \right)^{\delta_{hit}} \right] \;,$$

where δ_{hit} is an indicator variable that takes the value *1* if product *i* is purchased by household *h* at time *t*, $j_{h(t-1)}$ is the product purchased by household *h* on the previous purchase occasion, *H* is the number of households, T_h is the number of purchases made by household *h*, and all other variables are as defined previously (see equation 3). We address the *initial conditions* problem by assigning the MNL choice probability P_{ri0} for each household's first purchase (at time $t = 0$).

Consumption Substitutability and Complementarity

In order to investigate the consequences of state dependence on the estimated degree of inter-product competition for a given pair of products *i* and *j*, we can compute the difference between the household's conditional and unconditional probabilities of purchasing *i* given that *j* was purchased at the previous purchase occasion. We adopt the competitive measure used in the LM model, $C_{i|j} = P_{i|j} - P_i$, an estimate of the competitive impact of product *j* on product *i* due to state dependence effects at the household level. A negative value of $C_{i|j}$ indicates that buying product *j* decreases the household's likelihood of purchasing product *i* at the next purchase occasion, and so suggests that products *j* and *i substitute* for each other in meeting the household's needs over time[7]; conversely, a positive value suggests a *complementary* relationship between the products in question. Note that, because $P_{i|j}$ depends on the state dependence parameter *V* as well as on the inter-product similarity parameter c_{ij}, two products *j* and *i* can be consumption complements for two seemingly diametric reasons: they may be very similar to each other (c_{ij} is close to *1*) and households are predominantly inertial (*V* is negative), or they are very *dis*similar to each other (c_{ij} is close to *0*) and households predominantly seek variety (*V* is positive). Analogously, two products *k* and *l* can be substitutes for two distinct reasons: either they are very dissimilar to each other (c_{kl} is close to *0*) and households are predominantly inertial (*V* is negative), or they are very similar to each other (c_{kl} is close to *1*) and households are predominantly variety-seeking in nature (*V* is positive).

[7] We define the notion of consumption substitutability and complementarity at the household-level as a consequence of its state dependence. This must not be confused with the economic definitions of substitutes and complements, which are based on how a product's demand varies with competing products' price changes.

A market characterized by negligible state dependence will lead to $C_{i|j} \approx 0$, suggesting that there is little competitive impact of product *j* on product *i* due solely to state dependence effects. Further, a market of relatively distinct products (i.e., characterized by low inter-product similarity, $c_{ij} \approx 0 \; \forall \; i, j$) will also yield $C_{i|j} \approx 0$, so that even if households are characterized by state dependence, such tendencies do not manifest themselves in their substituting or complementing one product for another to meet their consumption needs over time.

Asymmetric Complementarity

A final, and most interesting, feature of the competitive measure $C_{i|j}$ is that it can be asymmetric across products. For example, suppose choice of product *i* (at the current purchase occasion) greatly increases a household's probability of purchasing product *j* at the next purchase occasion, thus indicating a *complementary* relationship for the pair of products in the direction $i \rightarrow j$. Conversely, it may be the case that choice of product *j* decreases the household's probability of purchasing product *i*, thus indicating a *substitute* relationship for the same pair of products in the opposite direction $i \leftarrow j$. To our knowledge, existing attribute-based dynamic models of market structure do not allow for such asymmetries in product competition. If Procter and Gamble's detergents are believed to be acceptable complements for competitors' detergents in terms of facilitating households' product switching over time, while at the same time not inducing the same households to switch away to competitors' detergents in a search for complementarity, this constitutes important positive information for P&G from the perspective of assessing its 'competitive clout' in the market.

EMPIRICAL RESULTS

Data Description

We employ A.C. Nielsen scanner panel data from the Sioux Falls, SD market on household purchases during 1986-1988 in two categories of packaged goods: peanut butter and ketchup. The peanut butter category involves products that vary along three attributes: 1. Brand name (Peter Pan, Control Brand, Jif), 2. Type (Creamy, Chunky), and 3. Size (18 oz., 28 oz.). For peanut butter, we include those households that purchased only from among the top 8 products in the category (accounting for 70% of aggregate category sales) and which made no fewer than five purchases over the study period (488 households, 4715 purchases); descriptive statistics pertaining to this dataset are provided in Table 1a. Salient aspects of the category include that the creamy 18 oz. versions of Peter Pan and Control Brand are the largest products in the category (accounting together for 56.9% market share), that Control brand is, on average, cheaper than other brand names (Peter Pan and Jif, the least displayed and featured name brand), and that the 18 oz. product size is the most popular in the product category, accounting for 92 % on a unit volume basis.

The ketchup category involves products that vary along two attributes: Brand name (Heinz, Control Brand, Hunts, Del Monte) and Size (14 oz., 28 oz., 32 oz., 44 oz., 64 oz.). For ketchup, we include those households that purchased only from among the top 8 products in the category (accounting for 87% of aggregate category sales) and which made no fewer than seven purchases over the study period (529 households, 5954 purchases); descriptive statistics pertaining to this dataset are provided in Table 1b. Heinz 32 oz. is the most popular product in this category by a wide margin (accounting for 37.8% market share); Heinz controls five of the top eight products in the ketchup category (collectively accounting for 61.5 % market share). Overall, the 32 oz. size is dominant in the category (accounting for 76.3% market share), Hunts 32 oz. enjoys the most display activity, while Del Monte 32 oz. is the most featured product.

Effects and Models

Recall that the proposed model incorporates four distinct effects on household product choices: (1) marketing variables, (2) variety-seeking / inertia, (3) unobserved heterogeneity, and (4) inter-product similarity. Further, inter-product similarity (effect 4) can be operationalized in one of two ways: either by using a non-parametric approach that estimates c_{ij} for all pairs of products i and j, or by using a parametric approach (as explained in the previous section) that decomposes the similarity parameter in terms of the underlying product attributes (equation 4). We estimate the proposed models using both operationalizations, calling the two specifications *Proposed Model (Non-parametric)* and *Proposed model (Parametric)*, respectively. In addition to these two versions of the proposed model, we also estimate the standard heterogeneous MNL model, due to its ubiquity both in marketing literature and practice. Thus, the three estimated models types are:

1. Proposed model (Parametric)
2. Proposed model (Nonparametric)
3. Heterogeneous Multinomial Logit

Model 2 (Proposed model, nonparametric) can be understood as being the LM model plus marketing variables plus inertia plus unobserved heterogeneity plus inter-product similarities. Model 1 (Proposed model, parametric) is identical to Model 2, except that it characterizes inter-product similarities using observable attributes, instead of nonparametrically estimating them, resulting in a dramatically more parsimonious model. Model 3 (MNL) can be understood as the proposed model (either 1 or 2) without accounting for variety-seeking, inertia or inter-product similarities. Estimating the MNL model enables us to illustrate the consequences of ignoring dynamic effects and inter-product similarities while estimating a relatively flexible class of choice models. We also estimate homogeneous versions of Models 1, 2 and 3 in order to understand the consequences of ignoring unobserved heterogeneity in model parameters.

Model Fit and Comparative Implications

In Table 2, we report measures of model fit for the three models and their homogeneous counterparts. In terms of the Schwarz Bayesian Criterion (SBC)[8], widely used to compare non-nested models in terms of their ability to fit observed choices, the parametric version of the proposed model is markedly superior to the non-parametric version for both product categories. The parametric model, therefore, not only allows for additional structure by modeling the similarity parameters in terms of product attributes, but also explains household purchases better than the non-parametric model. This is reminiscent of Fader and Hardie (1996), who found that a complex non-parametric structure for the so-called brand-specific constants could be explained more parsimoniously – and with greater managerial meaning – using a parametric approach and known brand attributes.

Estimates of household response parameters appear in Table 3. The estimated marketing mix coefficients for the proposed models are primarily in the expected direction.[9] For ketchup, insignificant coefficients on price (for two supports) and display (for one support) correct themselves while going from the MNL to the proposed (parametric) model, i.e., they become significant and signed in the expected direction. This suggests that the proposed model, by more fully capturing the dimensions of households' choice behavior, is capable of correcting for some types of distortion, due to misspecification bias, in the MNL model. In the peanut butter category, two out of four supports exhibit significant effects of inertia (-4.2 and -2.5),

[8] The SBC, which penalizes highly parameterized models, is given by $SBC = -2*LL + n*ln(T)$, where n is the number of parameters and T is the number of observations.

[9] The estimated display coefficient is wrongly signed (i.e., negative) for three out of four supports for peanut butter.

collectively accounting for 68% of peanut butter buyers. Similarly, in the ketchup category, three out of four supports exhibit significant effects of inertia (-1.94, -0.78 and -6.1), collectively accounting for 77% of ketchup buyers.

Inter-Product Similarity Effects

Insofar as the pairwise product similarity matrix is concerned, brand name is revealed to be the most influential attribute in the peanut butter product category (with a "part worth" of 0.72, as opposed to 0.27 for product type and 0.00 for product size) while product size is the most influential attribute in the ketchup category (with a "part worth" of 0.85, as opposed to 0.13 for brand name). This suggests that brand name not only has a direct effect on households' product choices (as captured by the intercept term in the MNL formulation), but also has a strong indirect effect due to inter-product similarities (as captured in the state dependence formulation) in the peanut butter category. Taken on its own, this suggests that a peanut butter manufacturer may do well to consider an 'umbrella' brand name (e.g., "Peter Pan") for each of its product variants within the peanut butter product line. This may not be quite so critical in the ketchup category, where the effects of brand name on inter-product similarities are far less pronounced.

We report the full matrix of similarity parameters for the nonparametric version of the proposed model in Table 4. For comparability, we construct the corresponding similarity matrix for the parametric model (based on the "part-worth" estimates for underlying attributes) and report it in the lower-triangular ('southwest') portion of the similarity matrix. In the peanut butter category, since brand name largely drives inter-product similarities, we observe substantial inter-product similarity between all Peter Pan products (Peter Pan Creamy 18 oz., Chunky 18 oz. and Creamy 28 oz.); specifically, the average inter-product similarity is 0.82 (based on the parametric model). It may be worthwhile for the manufacturer to investigate the consequences of such inertial effects on the profitability of its product line. If cannibalization effects, due perhaps to inter-product similarities and inertia, overwhelm the benefits of an expanded product line, it may be prudent to consider pruning low share products (Peter Pan Chunky 18 oz. and Peter Pan Creamy 28 oz., with shares of 8.8% and 4.7%, respectively) from their product line and retain only the flagship product (Peter Pan Creamy 18 oz., with a share of 28.9%).

In the ketchup category, on the other hand, product size largely drives inter-product similarities ("part worth" of 0.85), whereas brand name does so only to a small degree ("part worth" of 0.13). In fact, based on the parametric model, the average inter-product similarity for Heinz's products within the ketchup line is only 0.15. Therefore, Heinz may well be exploiting the inertial benefits of having a wide product line by employing different product sizes (14 oz., 28 oz., 32 oz., 44 oz. and 64 oz.) within the category. In other words, Heinz is attempting to obtain as wide a reach in the category as possible by appealing to buyers of various product sizes. By offering limited product lines in terms of size, Hunts and Del Monte may be losing out on the opportunity to attract buyers of other product sizes. Of course, this assumes that these brands can obtain shelf space as well as produce these products cost effectively. It is interesting to note that 'size loyalty' effects were observed even in the earliest studies in the brand choice literature, such as Guadagni and Little (1983).

Market-Level Implications of Inertial Effects

In order to place the estimated inertia effects into perspective, we compute equilibrium market shares based on the proposed model and contrast these with those obtained by setting the state dependence parameter (V) to zero. We use a numerical simulation for this purpose[10]; the results of this comparison are given in Table 5. For peanut butter, based on the proposed model (parametric), we find that the three major products are Peter Pan Creamy 18 oz., Control Brand Creamy 18 oz. and Control Brand Chunky 18 oz., each with a market share of 22%. In the absence of inertial effects ($V = 0$), however, one is led to infer that Peter Pan Creamy 18 oz. is the clear market leader (with a share of 30%). This comparison indicates that inertial effects in the peanut butter category seem to counter the "equity-building" efforts of national brands and differentially favor private labels in the long run. For ketchup, based on the proposed model (parametric), we find that the three major products, in descending order of share, are Heinz 32 oz., Heinz 28 oz. and Control Brand 32 oz. with shares of 26%, 21% and 18% respectively. In the absence of inertial effects ($V = 0$), however, Control Brand 32 oz. appears to obtain an equilibrium share of 24% (at the expense of Heinz 32 oz. and Heinz 28 oz., whose equilibrium shares are 23% and 18% respectively).

This suggests that, in contrast to the analogous finding in the peanut butter category, a large national brand such as Heinz stands more to gain than a private label from inertial effects operating in the marketplace. However, a low share product, Heinz 14 oz., has an expected equilibrium share that is greater in the absence (11%) than in the presence of inertial effects (7%). Such an effect may come about for two reasons: first, its

[10] Household choices are simulated on the basis of the estimated response and heterogeneity parameters over a sufficiently long time horizon (40 weeks). The "stationary" market shares at the end of this time sequence are

low share may mean that it lacks an installed customer base sufficiently large to sustain the benefits of inertial effects in the long run; second, its unique product size (14 oz.), rather than being viewed in the positive manner unique features often are, may turn out to be a liability, because inertial households in the ketchup market assess inter-product similarities largely along product size, and switch accordingly. This pattern of effects is consistent with the steady-state analysis of Feinberg et al. (1992), which suggested that variety-seeking is a boon to small-share brands and a bane to large-share ones, albeit in an individual-level context lacking marketing mix variable effects.

Parametric vs. Non-Parametric Representations of Brand Attributes

Differences in equilibrium shares are hardly discernible between columns 3 and 4 in Table 5. In other words, if one employs the nonparametric approach, ignoring the effects of inertia seems to have few consequences on the predicted equilibrium shares of products. This is consistent with the nonparametric structure of the similarity matrix's overfitting the choice data, by picking up effects of the omitted inertia variable. Such a finding is similar to that of Erdem (1996), that a static model of market structure (e.g., one that ignores inertia and variety-seeking), can lead to biased inferences about product maps. *From the managerial standpoint of predicting products' equilibrium market shares, therefore, it appears necessary to explicitly parameterize the nature of inter-product similarities using observed product attributes, rather than merely estimate them in a non-parametric manner.* A non-parametric approach, while flexibly picking up the effects of omitted variables such as inertia, distorts inferences about inter-product competition. Comparisons of equilibrium shares between the proposed model and the MNL model show substantial differences in predicted equilibrium shares as well. For example, equilibrium shares of the largest-share products are overstated by as much as 0.07 and 0.12 points for peanut butter and ketchup respectively. We consider this an important finding, as the heterogeneous MNL is, by a wide margin, the most extensively applied choice model in marketing practice.

State Dependence and Pairwise Brand Competition

In order to investigate the consequences of state dependence on the estimated degree of inter-product competition for a given pair of products *i* and *j*, we compute the competitive measure $C_{i\to j}$ (= $P_{i\to j} - P_i$), as

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taken to be the equilibrium shares of products. Additional detail, including the full simulated time series, is available from the authors.

discussed previously. Recall that negative values of $C_{i\to j}$ indicate substitutability, whereas positive values suggest a complementary relationship. Since $P_{i|j}$ depends on the state dependence parameter V as well as on the inter-product similarity parameter c_{ij}, the estimated values of V and c_{ij} allow us to explicitly understand the effects of both state dependence and inter-product similarities on the estimated competitive measure. This stands in contrast with state dependence models that ignore inter-product similarities (such as the "mover-stayer" models of Givon 1984, Kahn et al. 1986), which force different products to be always complements for a variety-seeking household, and always substitutes for an inertial household[11]. In Table 6, we report the measures of inter-product competition $C_{i|j}$ for all pairs of products, computed at the average values of the brands' marketing variables over the study period, and weighted across the four supports of the heterogeneity distribution. $C_{i\to j}$ is listed in the (i^{th} row, j^{th} column) entry of the matrix in Table 6, so that rows, by definition, must sum to one. Note that, because any diagonal element in Table 6 estimates the competitive impact of a product on itself, all are positive, since the market is inertial and the inter-product similarity between a product and itself is one[12].

Symmetric and Asymmetric Substitutability

In the peanut butter category, the product that benefits most from inertial effects is Control Brand Chunky 18 oz., as its choice probability (conditional on its being bought on the previous purchase occasion) is 0.29 greater than the unconditional probability (i.e., in the absence of inertia). Two pairs of products are seen to be strong substitutes for one another in the product category: {Peter Pan Creamy 18 oz., Control Brand Creamy 18 oz.} with $C_{1\to2} = -0.12$ and $C_{2\to1} = -0.17$; and {Peter Pan Creamy 18 oz., Control Brand Chunky 18 oz.} with $C_{1\to4} = -0.08$ and $C_{4\to1} = -0.19$. Intriguingly, three pairs of products show strongly asymmetric substitutability, that is, one product heavily substitutes for the other but not vice versa: {Peter Pan Creamy 18 oz., Jif Chunky 18 oz.} with $C_{1\to7} = -0.01$ and $C_{7\to1} = -0.16$; {Control Brand Creamy 18 oz., Jif Chunky 18 oz.} with $C_{2\to7} = -0.01$ and $C_{7\to2} = -0.10$; and {Peter Pan Creamy 18 oz., Jif Creamy 28 oz.} with $C_{1\to8} = -0.00$ and $C_{8\to1} = -0.13$. Finally, two products are observed to strongly complement one another: {Jif Creamy 18 oz., Jif Creamy 28 oz.} with $C_{5\to8} = 0.09$ and $C_{8\to5} = 0.06$. However, this seemingly complementary relationship may be due largely to the fact that, because product size does not seem to matter in characterizing inter-product

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[11] In Givon's (1984) model, for example, $P_{j\to i} - P_j > 0$ if $V > 0$ and < 0 if $V < 0$.

[12] The reported measures in Table 6 are based on the parametric model. Those based on the nonparametric model are available from the authors.

similarities (c_3 = *0.00* in Table 3), the two products are perceived by households as being more-or-less identical.

In the ketchup category, the product benefiting most from inertial effects is Heinz 28 oz., as its choice probability (conditional on it being bought at the previous purchase occasion) is 0.23 greater than the unconditional probability (i.e., in the absence of inertia). As in the previous analysis for peanut butter, we observe pairs of brands characterized by both symmetric and asymmetric substitutability. Two product pairs appear to be strong substitutes: {Control Brand 32 oz., Heinz 14 oz.} with $C_{2\rightarrow6}$ = -0.06 and $C_{6\rightarrow2}$ = -0.11; and {Heinz 32 oz., Heinz 28 oz.} with $C_{1\rightarrow4}$ = -0.05 and $C_{4\rightarrow1}$ = -0.05. Three pairs evidence strongly <u>asymmetric</u> substitutability: {Control Brand 32 oz., Heinz 44 oz.} with $C_{2\rightarrow7}$ = -0.02 and $C_{7\rightarrow2}$ = -0.11; {Control Brand 32 oz., Heinz 64 oz.} with $C_{2\rightarrow8}$ = -0.01 and $C_{8\rightarrow2}$ = -0.11; and {Control Brand 32 oz., Heinz 28 oz.} with $C_{2\rightarrow4}$ = -0.03 and $C_{4\rightarrow2}$ = -0.12. Interestingly, unlike for the peanut butter category, we find no strongly complementary product pairs. However, for two product pairs we observe an asymmetry in whether they are perceived as consumption substitutes or complements: {Control Brand 32 oz., Del Monte 32 oz.} with $C_{2\rightarrow5}$ = 0.02 and $C_{5\rightarrow2}$ = -0.05; {Control Brand 32 oz., Hunts 32 oz.} with $C_{2\rightarrow3}$ = 0.02 and $C_{3\rightarrow2}$ = -0.03.

Complementarity and Substitutability as Brand-Level Constructs

Effects of consumption substitutability and complementarity due to inter-product similarities are ignored both by the MNL model (which ignores the effects of state dependence on product choices) as well as the "mover-stayer" formulations of state dependence (Givon 1984, Kahn et al. 1986), since they do not explicitly accommodate the effects of product attributes. The proposed modeling framework yields managerially actionable insights about substitutability and complementarity from a consumption perspective. Though our approach is decidedly different from that of the SKU-level choice model of Fader and Hardie (1996), both strive for a similar goal: a parsimonious and managerially expedient method to both characterize household choice in product categories with many relevant SKUs, as well as to better understand the effects of state dependence on household-level choice dynamics.

CONCLUSIONS

Although the vast majority of work in category management using scanner panel data has focused on competition between brands, firms concern themselves managing entire product lines. Such product lines can be viewed in several ways. Prominent among them is an ‘atomistic’ view: a product line is merely a collection of individual SKUs, which compete in a manner similar to that between brands. Another view is that individual products in a line differ not in brand, but in terms of overt, observable features or other attributes; that is, in terms of what they *offer* to consumers. Under either of these views, modeling how consumers with vastly different preferences make choices, over time, among numerous alternatives – characterized by brand, size and format – is complicated by the sheer number of possibilities, as well as the multitude of attributes which characterize them. In this paper, we approach the consumer ‘problem’ as one of dynamic attribute satiation. Specifically, households’ needs vary over time, and they will seek out the *attributes* which best meet them, in the form of a successive sequence of (perhaps different) products. One would therefore expect to see attribute satiation writ large in observed household-level switching patterns.

Among the problems in parsimoniously modeling household-level switching patterns is formalizing a notion of how similar two brands are, based on the attributes they share (if any). Although all previous models have grappled with the plain fact that households vary enormously in their preferences among brands, they have largely sidestepped the combinatorially more complex issue of how to represent different patterns of interbrand *similarity* across products and households. The dynamic model proposed in this paper has attempted to resolve this ‘similarity problem’ by taking account of a particular reality of the marketplace: while product preferences may differ markedly across households, product *positionings* will not. That is, although households may entirely disagree on the relative merits of two products, they are far more likely to agree on how similar they are. Construing this position-induced similarity as a function of observable product attributes allows for a remarkably parsimonious characterization of inter-product similarity that, like preferences, can differ across households.

The proposed model allows us to understand the statistical and managerial implications of employing choice models that hold aside the effects of one or more variables of known managerial importance: the marketing mix, state dependence (inertia/variety-seeking), unobserved heterogeneity, inter-product similarities, and observable product attributes. For example, the model handily outperforms the ubiquitous MNL model, which ignores the effects of both state dependence and interproduct similarities. Similarly, the parametric version of the model, which explicitly characterizes inter-product similarities in terms of their shared attributes, empirically outperforms the nonparametric version, which does not make use of product attribute information, instead estimating the similarity matrix. One might interpret this as a kind of "face validity", whereby observable attributes offer clear benefits in model formulation and parametric interpretation. Given that the parametric model is easier to interpret and can guide managerial policy-making in an intuitive way, this is an important finding for practitioners.

Application of the model to two frequently purchased consumer goods categories revealed intriguing differences between them. In the peanut butter category, it appears that brand name is a crucial determinant of how similarly two products are perceived. While, on the one hand, this suggests that manufacturers may be able to capitalize upon a strong brand name (for example, by umbrella branding their various products using a common name), it also suggests the possibility of products cannibalizing one another's sales if other attributes in the product category are perceived to be unimportant. One might expect that results for the ketchup and peanut butter categories might be substantively identical, or at least broadly analogous, given their seeming similarities (purchase frequency, price levels, shelf stability, etc.). However, in the ketchup category, we find that brand name is quite a bit less important than product *size* as a determinant of how similarly two products are perceived. This suggests that it is critical for a manufacturer to ensure that the product line contain a large enough variety of sizes to reap the benefits of households that switch *across* various brand names *within* a given product size (that is, households which are less 'brand loyal' than 'size loyal'). The data suggest that Heinz may be doing this successfully already, with a 61.5 % share of the market across its five product sizes. Based on the model, other manufacturers might do well to follow suit.

Simulating equilibrium market shares suggests inertia benefits a large private label in the peanut butter category and a large national brand in the ketchup category. Using a non-parametric approach to estimate the similarity matrix results in a model specification whose equilibrium shares are not sensitive to the accommodation of the effects of inertia. To the extent that this may due to the non-parametric similarity matrix picking up the effects of inertia, such an approach may lead to distorted inferences about inter-product competition. Once again, this supports the use of observed attributes in model specification.

The model allows one to better understand inter-product competition in terms of whether product pairs serve as consumption substitutes or complements, based on the estimated state dependence and inter-product similarity parameters. We are able not only to characterize products (pair-wise) as being substitutes or complements, but also to estimate the magnitude or degree of such substitutability or complementarity. Specifically, we find suggestive asymmetries in the degree of substitutability or complementarity between some pairs of products. These effects, which have no analogue in conventional models of choice (e.g., MNL, "mover-stayer" models of state dependence, etc.), are of great relevance to managers wishing to better understand how their products are positioned, relative to competitors, in their segment of the market. The ability to discern patterns of *asymmetric substitutability* is among the model's major strengths, and suggests that complementarity and substitutability should not be construed solely at the category level.

Several directions for future research suggest themselves. First, it is important to investigate whether the parametric version consistently outperforms the nonparametric version of the proposed model across a wide variety of product categories. If this turns out not to be the case, the pattern of products for which underlying product attributes provide a consistently interpretable structure may help generate a useful taxonomy. It may be the case, for example, that 'experience goods', or those for which consumers have a difficult time delineating the basis of their choices, do not especially benefit from the type of attribute-based modeling approach advocated here. Given the strength of our estimated attribute effects in this study, however, it is our belief that the parametric version will do well across a relatively broad range of product categories. Second, it may be useful to model state dependence and inter-product similarities in a random utility framework (*a la* Erdem 1996), and to compare such an effort to the proposed approach, which rests in a stochastic choice framework. Finally, it is intriguing to consider the effects of the marketing mix on inter-product similarities and state dependence. For example, two products that operate within a price tier (e.g., private labels) may be perceived to be more similar to one another than other pairs of products, all else being equal. Frequent price promotions within a category may induce a price-sensitive household to seek variety in the long run (since price promotions induce frequent switching between products, thus serving to reduce households' transaction costs of switching). We leave these as avenues for future research addressable in the context of structure-based models of dynamic choice.

TABLE 1: Descriptive statistics

A. Peanut Butter

Number of households = 488
Number of purchases = 4715

Brand	Price ($/oz.)	Display	Feature	Share
PP Creamy 18	0.0859	0.12	0.12	28.9%
CB Creamy 18	0.0628	0.11	0.16	28.0%
PP Chunky 18	0.0874	0.16	0.15	8.8%
CB Chunky 18	0.0636	0.11	0.16	17.0%
Jif Creamy 18	0.0952	0.03	0.07	7.6%
PP Creamy 28	0.0934	0.05	0.07	4.7%
Jif Chunky 18	0.0951	0.01	0.05	1.7%
Jif Creamy 28	0.0978	0.04	0.01	3.3%

B. Ketchup

Number of households = 529
Number of purchases = 5954

Brand	Price ($/oz.)	Display	Feature	Share
Heinz 32	0.0365	0.16	0.16	37.8%
Control 32	0.0254	0.19	0.11	17.6%
Hunts 32	0.0363	0.30	0.14	14.9%
Heinz 28	0.0510	0.05	0.06	10.7%
DelMonte 32	0.0363	0.25	0.29	6.0%
Heinz 14	0.0532	0.02	0.05	5.2%
Heinz 44	0.0419	0	0.15	5.7%
Heinz 64	0.0423	0	0.10	2.1%

TABLE 2: Fit Results

A. Peanut Butter

Fit criterion	Heterog. Proposed (Parametric) GBC-Hetero.	Heterog. Proposed (Nonparam.)	Heterog. MNL	Homog. Proposed (Parametric)	Homog. Proposed (Nonparam.)	Homog. MNL
Log-likelihood	-4569	-4548	-5141	-5289	-5076	-7004
SBC	9560	9730	10645	10696	10481	14092
# Parameters	50	75	43	14	39	10

B. Ketchup

Fit criterion	Heterog. Proposed (Parametric)	Heterog. Proposed (Nonparam.)	Heterog. MNL	Homog. Proposed (Parametric)	Homog. Proposed (Nonparam.)	Homog. MNL
Log-likelihood	-7165	-7112	-7757	-7941	-7703	-9136
SBC	14755	14875	15887	15994	15744	18358
# Parameters	49	75	43	13	39	10

TABLE 3: Household response parameter estimates[13]
(Four-support solution)

A. Peanut Butter

Parameter	Proposed model (Parametric)	Proposed model (Nonparametric)	MNL
α_1 (PP Cr. 18)	2.92, 2.45, 3.82, -2.49	1.86, 2.30, 3.52, -2.54	1.55, 3.70, 4.01, -2.42
α_2 (CB Cr. 18)	0.59, 2.52, -0.30, 1.86	-0.45, 2.60, -0.30, 1.08	-0.78, 4.35, 0.62, -1.75
α_3 (PP Ch. 18)	1.90, 1.99, -0.09, 0.56	0.83, 1.96, 0.12, -0.07	1.51, 2.44, 1.75, -1.53
α_4 (CB Ch. 18)	-0.34, 1.77, 2.62, -1.11	-1.41, 1.86, 2.49, -1.68	-1.20, 2.90, -1.74, -0.02
α_5 (Jif Cr. 18)	2.58, 1.32, -0.50, -2.74	1.33, 1.58, -1.30, -0.24	2.16, 2.36, 0.88, -3.14
α_6 (PP Cr. 28)	-0.27, 0.24, 2.13, -2.49	-0.13, 0.13, 1.90, -0.12	-1.48, 0.83, 2.66, -3.40
α_7 (Jif Ch. 18)	0.49, 1.04, -2.15, -2.59	-0.14, 1.11, -1.55, -0.60	0.48, 0.98, -1.53, -2.52
α_8 (Jif Cr. 28)	0	0	0
Price	-2.51, -5.78, 0.09, -0.98	-2.57, -5.78, -0.38, -0.36	-2.71, -4.64, -0.30,-3.53
Display	-0.47, -0.69, 0.63, -0.76	-0.45, -0.75, 0.31, -0.92	-0.49, -0.68, 0.11, -1.00
Feature	0.92, 0.81, 0.57, -0.07	0.83, 0.85, 0.68, -0.49	0.61, 0.65, 0.63, 1.04
V	-4.2, -2.5, insig., insig.	-3.9, -2.4, insig., insig.	NA
Support prob.	0.32, 0.36, 0.21, 0.11	0.33, 0.35, 0.19, 0.14	0.23, 0.36, 0.26, 0.14
c_{ij}	$c_o = 0.01$, $c_1 = 0.72$ $c_2 = 0.27$, $c_3 = 0.00$	See Table 4	NA

[13] All reported parameter estimates are significant at the 0.05 level of significance.

TABLE 3 (contd.)

B. Ketchup

Parameter	**Proposed model (Parametric)**	**Proposed model (Nonparametric)**	**MNL**
α_1 (Heinz 32)	2.66, insig, 1.34, insig	2.61, 2.68, 1.12, -0.87	3.01, 3.27, 1.35, insig
α_2 (CB 32)	-0.84, insig, -0.93, 1.19	-0.65, 1.82, -1.03, 0.73	insig, 3.67, -2.98, -1.96
α_3 (Hunts 32)	insig, insig, 2.67, insig	0.66, 2.25, 2.12, -0.50	1.55, 2.99, -1.24, 1.41
α_4 (Heinz 28)	1.65, 2.68, 2.85, insig	1.51, 2.05, 2.65, -1.09	1.98, 2.31, 0.46, 1.70
α_5 (DMonte 32)	-1.32, insig, -1.49, -1.25	insig, 1.68, -1.55, insig	0.64, 2.57, -3.15, -1.92
α_6 (Heinz 14)	0.47, 1.56, 1.74, 2.54	0.54, 1.55, 1.78, 1.32	0.78, 1.75, 1.69, -1.16
α_7 (Heinz 44)	1.40, 0.77, -1.41, 0.30	0.70, insig, -0.98, 0.49	0.98, insig, 1.69, -2.31
α_8 (Heinz 64)	0	0	0
Price	-0.88, -3.73, -0.41,-2.75	-1.54, -3.16, insig, -1.14	-2.18, -2.45,insig, insig
Display	0.54, 0.53, 0.45, 0.35	0.51, 0.37, 0.71, 1.24	0.51, 0.35, 0.91, insig
Feature	0.30, 0.44, insig, insig	0.25, 0.55, insig, -0.88	0.30, 0.36, -0.43, insig
V	-1.94, -0.78, -6.1, insig.	-3.6, -1.3, insig., insig.	NA
Support prob.	0.31, 0.38, 0.09, 0.22	0.36, 0.40, 0.11, 0.13	0.55, 0.27, 0.10, 0.08
c_{ij}	$c_o = 0.02$, $c_1 = 0.13$ $c_2 = 0.85$	See Table 4	NA

TABLE 4A: Similarity Matrix for Peanut Butter[14]

Product	PPC18[15]	CBC18	PPH18	CBH18	JC18	PPC28	JH18	JC28
PP Creamy 18	1	0.44	0.77	0.01	0.43	0.79	0.11	0.05
CB Creamy 18	0.28	1	0.02	0.59	0.03	0.00	0.00	0.01
PP Chunky 18	0.73	0.01	1	0.37	0.02	0.02	0.14	0.01
CB Chunky 18	0.01	0.73	0.28	1	0.06	0.01	0.18	0.04
Jif Creamy 18	0.28	0.28	0.01	0.01	1	0.01	0.01	0.18
PP Creamy 28	1.00	0.28	0.73	0.01	0.28	1	0.00	0.01
Jif Chunky 18	0.01	0.01	0.28	0.28	0.73	0.01	1	0.03
Jif Creamy 28	0.27	0.28	0.01	0.01	1.00	0.28	0.73	1

TABLE 4B: Similarity Matrix for Ketchup

Product	PPC18[16]	CBC18	PPH18	CBH18	JC18	PPC28	JH18	JC28
Heinz 32	1	0.33	0.39	0.53	0.37	0.33	0.73	0.24
CB 32	0.87	1	0.13	0.04	0.17	0.00	0.00	0.00
Hunts 32	0.87	0.87	1	0.12	0.36	0.01	0.02	0.04
Heinz 28	0.13	0.02	0.02	1	0.21	0.12	0.36	0.35
Del Monte 32	0.87	0.87	0.87	0.02	1	0.01	0.01	0.01
Heinz 14	0.15	0.02	0.02	0.15	0.02	1	0.00	0.01
Heinz 44	0.15	0.02	0.02	0.15	0.02	0.15	1	0.12
Heinz 64	0.15	0.02	0.02	0.15	0.02	0.15	0.15	1

[14] The northeast triangle represents similarity indices c_{ij} based on the nonparametric model, while the southwest triangle represents the similarity indices based on the parametric model.

[15] The acronyms in this row stand for the SKUs listed in the first column of the table in the same order. We have used acronyms here to save space.

[16] The acronyms in this row stand for the SKUs listed in the first column of the table in the same order. We have used acronyms here to save space.

TABLE 5A: Equilibrium Market Shares for Peanut Butter **(standard errors in parentheses)**

Product	Parametric (Unrestricted)	Parametric (V=0)	Nonparam. (Unrestricted)	Nonparam. (V=0)
PP Creamy 18	0.22 (0.04)	0.30 (0.04)	0.31 (0.04)	0.31 (0.03)
CB Creamy 18	0.22 (0.03)	0.24 (0.03)	0.27 (0.09)	0.28 (0.07)
PP Chunky 18	0.10 (0.02)	0.08 (0.02)	0.10 (0.03)	0.08 (0.02)
CB Chunky 18	0.22 (0.04)	0.19 (0.02)	0.11 (0.06)	0.10 (0.06)
Jif Creamy 18	0.10 (0.02)	0.09 (0.02)	0.08 (0.02)	0.09 (0.02)
PP Creamy 28	0.06 (0.01)	0.04 (0.01)	0.07 (0.01)	0.06 (0.01)
Jif Chunky 18	0.04 (0.01)	0.03 (0.01)	0.03 (0.01)	0.04 (0.01)
Jif Creamy 28	0.04 (0.01)	0.03 (0.01)	0.03 (0.00)	0.04 (0.01)

TABLE 5B: Equilibrium Market Shares for Ketchup **(standard errors in parentheses)**

Product	Parametric (Unrestricted)	Parametric (V=0)	Nonparam. (Unrestricted)	Nonparam. (V=0)
Heinz 32	0.26 (0.02)	0.23 (0.02)	0.36 (0.04)	0.33 (0.04)
CB 32	0.18 (0.02)	0.24 (0.03)	0.17 (0.04)	0.19 (0.04)
Hunts 32	0.11 (0.01)	0.09 (0.02)	0.16 (0.02)	0.15 (0.02)
Heinz 28	0.21 (0.02)	0.18 (0.02)	0.10 (0.02)	0.10 (0.02)
Del Monte 32	0.05 (0.00)	0.04 (0.01)	0.08 (0.02)	0.08 (0.01)
Heinz 14	0.07 (0.01)	0.11 (0.02)	0.06 (0.01)	0.07 (0.02)
Heinz 44	0.09 (0.01)	0.08 (0.01)	0.05 (0.01)	0.05 (0.01)
Heinz 64	0.03 (0.01)	0.03 (0.00)	0.02 (0.00)	0.03 (0.00)

TABLE 6A: Inter-product Competitive Measures for Peanut Butter ($C_{i \to j} = P_{i \to j} - P_j$)

Product	PPC18[17]	CBC18	PPH18	CBH18	JC18	PPC28	JH18	JC28
PP Creamy 18	0.17	-0.12	0.03	-0.08	-0.02	0.04	-0.01	-0.00
CB Creamy 18	-0.17	0.19	-0.05	0.03	-0.00	-0.01	-0.01	0.01
PP Chunky 18	-0.07	-0.14	0.24	-0.02	-0.04	0.04	0.004	-0.01
CB Chunky 18	-0.19	-0.05	-0.01	0.29	-0.02	-0.03	0.01	-0.01
Jif Creamy 18	-0.15	-0.07	-0.05	-0.06	0.19	0.01	0.04	0.09
PP Creamy 28	-0.02	-0.08	0.02	-0.05	-0.00	0.12	-0.00	0.01
Jif Chunky 18	-0.16	-0.10	0.01	-0.01	0.07	-0.02	0.13	0.07
Jif Creamy 28	-0.13	-0.05	-0.03	-0.05	0.06	0.01	0.02	0.16

TABLE 6B: Inter-product Competitive Measures for Ketchup

Product	PPC18[18]	CBC18	PPH18	CBH18	JC18	PPC28	JH18	JC28
Heinz 32	0.13	-0.04	0.04	-0.05	0.01	-0.05	-0.02	-0.01
Control Brand 32	-0.02	0.10	0.02	-0.03	0.02	-0.06	-0.02	-0.01
Hunts 32	0.03	-0.03	0.12	-0.05	0.03	-0.06	-0.02	-0.01
Heinz 28	-0.05	-0.12	-0.04	0.23	-0.01	-0.04	0.01	0.01
Del Monte 32	0.02	-0.05	0.05	-0.02	0.08	-0.06	-0.02	-0.01
Heinz 14	-0.03	-0.11	-0.03	-0.02	-0.01	0.20	-0.01	-0.00
Heinz 44	-0.04	-0.11	-0.01	0.01	-0.01	-0.03	0.19	0.01
Heinz 64	-0.01	-0.11	-0.02	0.01	-0.00	-0.03	0.01	0.16

[17] The acronyms in this row stand for the SKUs listed in the first column of the table in the same order. We have used acronyms here to save space.

[18] The acronyms in this row stand for the SKUs listed in the first column of the table in the same order. We have used acronyms here to save space.

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