A Brand Choice Model for the Analysis of New Product Positioning

Kyuseop Kwak
Lecturer, School of Marketing
University of Technology, Sydney
Phone: +61 2 9514 3150
Kyuseop.Kwak@uts.edu.au

Gary J. Russell
Henry B. Tippie Research Professor of Marketing
Henry B. Tippie College of Business
University of Iowa
Phone: 319-335-0993
gary-j-russell@uiowa.edu

Thomas S. Gruca
Henry B. Tippie Research Professor of Marketing
Henry B. Tippie College of Business
University of Iowa
Phone: 319-335-0946
thomas-gruca@uiowa.edu

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Kyuseop Kwak is lecturer (email: kyuseop.kwak@uts.edu.au), School of Marketing, University of Technology Sydney. Gary J. Russell is Henry B. Tippie Research Professor of Marketing (email: gary-j-russell@uiowa.edu) and Thomas S. Gruca is Henry B. Tippie Research Professor of Marketing (email: thomas-gruca@uiowa.edu), Marketing Department, Tippie College of Business, University of Iowa.
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ABSTRACT

Not all customers will consider buying a newly introduced product. Customers are likely to consider a new brand if it is similar to the brands currently in the consideration set or if it is close the customer’s ideal point. In this research, we develop a choice model which explicitly links the success of a new product introduction to consideration set structure. Our model is constructed in two steps. First, we use household purchase summaries to calibrate a joint-space (pick-any) map. This map has the property that proximity of a customer’s ideal point and brand positions increases the likelihood of the product being considered by the customer. Second, using this joint-space map and household purchase histories, we calibrate a mixture logit choice model in which distances between customers and products determine choice probability. We use our model to analyze new product introduction in the coffee market. Our analysis provides insights into the consideration set profile of the new entrant and provides a method for studying the impact of alternative product positioning decisions.

Keywords: New Product, Choice Modeling, Consideration Sets, Joint-Space Models
INTRODUCTION

Introducing a new product is a very expensive and risky undertaking for any consumer packaged goods (CPG) company. To reduce the chances for failure, companies often test market a new product in a few localized markets before it is introduced nationwide. Information obtained in this way allows the development of sales forecasts.

The methodology used to analyze test market information has evolved over time. In the 1960’s, diary panels were added to test market studies to provide additional information (such as trial and repeat rates) needed to improve the accuracy of long-run forecasts of sales volume (Fourt and Woodlock 1960) and market share (Parfitt and Collins 1968). The 1980’s saw the introduction of scanner-based test markets that combined detailed data on panelist behavior and backgrounds with information about the store environment (competitor’s prices, feature advertising and display activity). In some markets, cable TV allowed monitoring and targeting advertisements to individual households. However, models used to analyze test market data from scanner panels have advanced slowly. A notable exception to this statement is work by Fader et al. (2003) in which store environment information is used to improve the forecasting of new trial rates using scanner-based test marketing.

Product Consideration and Positioning

A desirable direction for improved analysis of test market data is the incorporation of key consumer constructs into the model formulation. It is well-known that consumers do not consider buying every product in a given category; they restrict themselves to a relatively small set of options. This empirical regularity is incorporated into models of consumer choice among established brands and into models to analyze data from simulated test markets (e.g., the Assessor model of Silk and Urban 1978). In some models, which utilize household level data
from scanner-based test markets, the assumption that all households consider the new product remains intact (Chintagunta 1999; Van Heerde et al 2004).

Effective positioning of a new product is a key determinant of product success because it is linked to the product being within the consideration set of a sufficiently large number of consumers. A series of experiments by Lehmann and Pan (1994) examined how various positioning strategies affect whether a new product gains membership into the consideration sets of consumers. Extending the research on the attraction effect (Huber and Puto 1983; Simonson and Tverski 1992), these researchers found that entrants that attained a dominant or compromise positioning were more likely to be included in customers’ consideration sets than those in extreme or dominated positions. Based on their experiments, Lehmann and Pan (1994) conclude that change in consideration set membership is “the primary impact of new brand entry” (page 372).

Research Agenda

The goal of this research is to develop a choice model for test market analysis which focuses on the interplay between product positioning and consideration set membership. The model is constructed in two steps. First, we use household purchase summaries to calibrate a joint-space map using the pick-any scaling method developed by Levine (1979). This map has the property that proximity of a customer’s ideal point to a given brand position increases the likelihood that the brand will be considered by the customer. Second, using this joint-space map and data from household purchase histories, we calibrate a mixture logit choice model in which distances between customers and products determine the value of brand intercepts for individual households. Accordingly, the observed choice share of a brand depends upon which customers actively consider the brand and how these customers respond to marketing activity.
This study contributes to the extant research on new product introduction in several ways. First, we add consideration set formation to existing models (e.g., Chintagunta 1999) to better understand customer’s new brand choice after entry. Second, we relate new brand positioning to consideration set membership using data from actual consumer choices in a real market. This is an improvement in external validity over the prior studies using experiments (e.g., Lehman and Pan 1994). Third, we formulate individual consideration set probabilities using household-level purchase histories (obtained from scanner panel data) in contrast to previous models which used aggregate approximate consideration sets (e.g., Silk and Urban 1978). To achieve these goals, our procedure merges research on joint-space mapping (Holbrook et al 1982; Levine 1979) with the consideration set formation research (Howard and Sheth 1969; Bronnenberg and Vanhonacker 1996). The joint-space map of consumer ideal points and product positions provides a basis for making inferences about consideration membership of newly introduced products.

The rest of paper is organized as follows. We begin by describing a model which links product positioning, consideration set composition, and brand choice. We develop a simulated maximum likelihood (SML) algorithm to calibrate model parameters, allowing for heterogeneity in both consideration set composition and marketing mix response across consumers. The model is then applied to test market data from the ground coffee market. This analysis provides information on the actual positioning of the new product entrant, generates diagnostic information on consideration set profile of each product, and clarifies the impact of new product entry on brand price competition. We also show how the model can be used to provide the marketing manager with insights into the likely market share consequences of alternative product positionings. We conclude with suggestions for new research.
MODEL DEVELOPMENT

Our approach rests upon the linkage between consideration set composition and brand choice probability. Conceptually, two steps are necessary in model construction. In the first step, we relate the likelihood of including a brand in the customer’s consideration set to the distance between brand and customer on a psychometric joint-space map. This map contains an ideal point for each customer and a location for each brand in the market. In the second step, we integrate the likelihood of brand consideration into a choice model which accounts for marketing mix effects. The result is a model in which brand positioning (as revealed by the joint-space map) impacts overall choice probability.

Modeling Consideration Probability

The key idea underlying our model is that brand positioning impacts the likelihood that a brand will be considered by a given customer. We assume that customers and brands can be located in a joint-space of ideal points and brand locations. Further, we assume that the consideration likelihood is inversely related to the distance between customer ideal point and brand position.

We first construct a joint-space map based on the pick-any algorithm developed by Levin (1979). Pick-any scaling is well-known technique in the marketing literature (Moon and Russell 2008; Gruca et al 2002; Moore and Winer 1987; Holbrook et al 1982). This procedure uses a customer-by-brand matrix in which elements represent number of purchases of a brand made by a customer over an initial time period. Using this matrix, an eigenvector analysis generates a map in which customers are located in the weighted center of brands chosen, and brands are located at the weighted center of customers who select a brand. Details on this algorithm are presented in the Appendix. The resulting joint-space map of ideal points and brand positions is
comparable to those generated by traditional perceptual mapping techniques (see Holbrook et al. 1982 for details).

Using the coordinates from this joint-space map, we construct a distance matrix, $D$, in which each element $d_{ij}$ represents Euclidean distance between a customer $i$’s ideal point and position of a brand $j$:

$$d_{ij} = \sqrt{\sum_{m} (i_m - j_m)^2}$$

where the summation runs over each of the dimensions of the joint-space map. We assume the probability that a customer $i$ considers brand $j$ is an exponential function of distance between her ideal point and the brand ($d_{ij}$) in the map.\(^1\) Specifically, the probability that customer $i$ considers brand $j$ is given by the relationship

$$\pi_{ij} = \exp\left(-\frac{d_{ij}}{\tau_i}\right), \text{ where } \tau_i \sim \text{log-Normal}(\bar{\tau}, \sigma_\tau)$$

The assumption of log-normal distribution for $\tau_i$ ensures that $\tau_i$ is always positive. Moreover, the form of equation (2) implies that two brands will have the same probability of being considered if the brands are equidistant from the customer’s ideal point.

Intuitively, the parameter $\tau_i$ determines how many brands are included in the household’s consideration set. This is due to the fact that $\tau_i$ controls the rate at which consideration probability declines as distance increases.\(^2\) The larger the value of $\tau_i$, the more likely a customer considers brands located further away from her ideal point. Conversely, if $\tau_i$ is small, the customer only considers brands very close to the ideal point. Since both distance measures $d_{ij}$

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\(^1\) In our empirical work, we tested other functional forms (such as Gaussian) to represent spatial relationships. The exponential kernel used here was found to yield the best fit.

\(^2\) This parameter is defined as bandwidth in the spatial statistics literature.
and range parameters $\tau_i$, vary across customers, our model allows for a high degree of household-
level heterogeneity in consideration set formation

< Insert Figure 1 about Here >

In Figure 1, we illustrate the consideration set membership probability, $\pi_{ij}$ (represented by
the height of the curve) for two households $(i_1,i_2)$ having the same ideal point but different range
parameters: one with small $\tau_i$ and the other with large $\tau_i$. Because two households have a
different range parameter, brand A is more likely to be in the consideration set of the household
having the larger $\tau_i$. However, notice that the consideration likelihood of brand A for the small $\tau_i$
household is almost same as that of brand B for large $\tau_i$ household, although brand B is further
away from the household’s ideal point. Consequently, the model takes into account that every
household has a different consideration set due to differences in distances and range parameters.
A brand whose position is on top of a customer’s ideal point is always considered, i.e., $d_{ij} = 0$
implies that $\pi_{ij} = 1$.

A Choice Model Incorporating Consideration Probability

Consistent with standard random utility theory, we assume that a customer compares the
utilities ($U_{ijt} = \alpha_{ij} + \beta_i'X_{ijt} + \epsilon_{ijt}$) of brands that are in the consideration set and chooses the brand
with the largest utility. Let us now introduce a variable $\psi_{ij}$ indicating whether or not a brand $j$ is
in a customer $i$’s consideration set. Simply put, if a brand $j$ is not in the consideration set, a
customer $i$ ignores the brand while making a choice. Thus, the analyst can eliminate the brand
from the construction of choice model at a given time with certainty, if the consideration
membership is known to the analyst a priori.
Incorporating this consideration membership $\psi_{ij}$ and assuming that random errors, $\varepsilon_{ijt}$, are independent draws from an extreme value distribution, the probability of customer $i$ choosing brand $j$ at time $t$ is given by the logit model

$$
\theta_{ijt} = \frac{\psi_{ij} \exp\left(\alpha_{ij} + \beta'_j X_{ijt}\right)}{\sum_{k=1}^{J} \psi_{ik} \exp\left(\alpha_{ik} + \beta'_k X_{ikt}\right)}
$$

where $\psi_{ij} = 1$ if brand $j$ is in customer $i$’s consideration set, otherwise zero. Here, $\alpha_{ij}$ is a brand specific intercept, $X_{ijt}$ is a vector of marketing mix variables of brand $j$ at time $t$; and $\beta_i$ is a corresponding household specific parameter vector.

The model in equation (3) assumes that the consideration set of each customer is known with certainty. Thus, when the item or brand is not available in a consumer’s mind, the choice probability of the item becomes zero and the denominator of the choice model changes correspondingly. In our study, if the brand is very far from the ideal points, the brand is considered not available to the consumer for choice decision. However, because our model in equation (2) only permits us to know the probability that a brand will be considered, we restate the choice model, applying a fuzzy consideration set logic (see, e.g., Bronnenberg and Vanhonacker 1996; Wu and Rangaswamy 2003). This leads to the logit choice model

$$
\theta_{ijt} = \frac{\pi_{ij} \exp\left(\alpha_{ij} + \beta'_j X_{ijt}\right)}{\sum_{k=1}^{J} \pi_{ik} \exp\left(\alpha_{ik} + \beta'_k X_{ikt}\right)}
$$

where $\pi_{ij}$ is a probability of considering brand $j$ by customer $i$ defined in equation (2).

To allow for heterogeneity in customer response, brand intercepts ($\alpha_{ij}$) and marketing mix parameters ($\beta_i$) are assumed to follow normal distributions and marketing mix parameters (i.e., $\beta_i$) are allowed to be correlated with each other. Specifically, we assume that the relationships
characterize the consumer population.

The resulting model (equations (2) thru (5)) has several appealing features. First, in contrast to some previous studies (Andrews and Srinivasan 1995; Chiang et al. 1999), we do not need to enumerate all possible $2^n-1$ consideration sets. That is, the model is estimable for any arbitrary size of the universal consideration set. Second, although the consideration probabilities of a given customer do not vary over time, brand choice probabilities are not stationary because marketing mix variables change over time. Third, as brand locations (product positions) shift on the joint-space map, both the probability of brand consideration and choice probability change. As we show in our empirical work, these features allow the model to provide the manager with many insights into choice behavior.

The model is different from market map analysis (Erlo and Keane 1995, Harris and Keane 1999). Previous market map analyses assume unobserved product attributes (e.g., quality) are to be modeled using random errors in the utility structure. Although it is possible to infer product positions from this approach, consumer ideal points are not explicitly represented. In contrast, our two-step procedure (first, build a map, and then embed the map in a choice model) provides a representation of both product positions and customer ideal points. In addition, our procedure uses distance measure between ideal point and product position based on their coordinates. Thus, our procedure allows us to understand the interplay between product strategy and customer segmentation.

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3 Reorganizing elements in equation (4), we can rewrite logit choice model as $\theta_{ij} = \frac{\exp(\alpha_i + \beta' X_{ij} + \log \{\pi_{ij}\})}{\sum_k \exp(\alpha_k + \beta' X_{ik} + \log \{\pi_{ik}\})}$, where $\pi_{ij}$ is based upon distance measure from a joint-space map.
Impact of New Product Entry

Because our model is intended to examine the impact of new product entry, it is necessary to make assumptions about how customer choices are modified by new product entrants. We assume that the parameters in (2) determining consideration probabilities and the parameters in (4) determining choice probabilities do not change when a new brand enters the market. This assumption is widely accepted and consistent with the empirical evidence (e.g., Chintagunta 1996). We further assume that customer ideal points and brand positions of existing brands do not change substantially in the period after new entry. This assumption is also supported by existing empirical studies (Chintagunta 1996, Gruca et al 2002).

Consistent with this logic, we assume that the new product entrant adds two new components to the model: a new location on the existing product map, and a new brand intercept in the choice model. Formally, the probability of buying the new product entrant \( q \) is given by

\[
\theta_{iq} = \frac{\pi_{iq} \exp\left(\alpha_{iq} + \beta_i'X_{iqt}\right)}{\pi_{iq} \exp\left(\alpha_{iq} + \beta_i'X_{iqt}\right) + \sum_{k=1}^{J} \pi_{ik} \exp\left(\alpha_{ik} + \beta_i'X_{ikt}\right)}
\]

where the marketing mix parameters \( \beta_i \) are the same as in equation (4). The only new parameter shown in (6) is the brand specific intercept \( \alpha_{iq} \) of the new entrant. Implicit in this expression -- though not shown in the notation -- is the need to add a new brand location for the entrant on the existing joint-space map. This is needed to properly define all the consideration set probabilities \( \pi_{ij} \) in the period after new product introduction. During model calibration, we treat the new entrant brand intercept and map location coordinates as additional parameters to be estimated.

Model Calibration

To calibrate the model, we use information from panel choice histories that spans a time period before and after a new product enters the market. The complete model specification
(equations (2), (4) and (6)) includes the following parameters: marketing mix parameters ($\beta$), brand intercepts (for incumbents and new brands), range parameters ($\tau_i$), and the new brand position on the joint-space map. We define a vector of parameters $\xi = (\xi_1, \xi_2)$, where $\xi_1$ contains the marketing mix parameters, incumbent brand intercepts ($\alpha_i$), and range parameter ($\tau_i$) and $\xi_2$ contains the new brand intercepts and location on the joint-space map.

Let $\delta_b$ be an indicator variable taking on the value of one for time periods before introduction and zero after introduction. Let $y_{ijt} = 1$ if customer $i$ purchases brand $j$ at time $t$, otherwise zero. Then, the likelihood for each household, $i$, is given by

$$L_i(y_i; \xi_1, \xi_2) = \prod_{r=1}^{T} \left( \prod_{j=1}^{J} \Theta_{ij}^r (\xi) \right)^{y_{ij}} \left( \prod_{j=1}^{J} \Theta_{ij}^{r} (\xi, \xi_2) \right)^{1-y_{ij}} f(\xi) f(\xi_2) d\xi d\xi_2$$

where $\Theta_{ij}(\xi)$ is choice probability with corresponding parameter vector $\xi$. The integration shown in this expression reflects the fact $\xi = (\xi_1, \xi_2)$ contains parameters that randomly vary across customers.

We used a simulated maximum likelihood (SML) procedure to estimate the parameters since the likelihood function contains multi-dimensional integrals (Train 2003, Erdem 1996).

Using R random numbers for each household, we can approximate equation (7) as

$$\tilde{L}_i(y_i; \xi_1, \xi_2) = \frac{1}{R} \sum_{r=1}^{R} \prod_{j=1}^{J} \Theta_{ij}^{(r)} (\xi_1^{(r)})^{y_{ij}} \left( \prod_{j=1}^{J} \Theta_{ij}^{(r)} (\xi_1^{(r)}, \xi_2^{(r)}) \right)^{y_{ij}^{(r)}} \left( \prod_{j=1}^{J} \Theta_{ij}^{(r)} (\xi_1^{(r)}, \xi_2^{(r)}) \right)^{1-y_{ij}^{(r)}}$$

In this expression, the R draws are taken from the heterogeneity distributions assumed earlier: $\tau_i$ has a log normal distribution with mean $\tau_{i\_bar}$ and standard deviation $\sigma_{\tau}$; and brand intercepts and marketing coefficients have the normal distributions shown in equation (4). The final log-likelihood function for the customer population has the form
The SML estimates of model parameters are obtained by maximizing equation (9).

\[
LL(y; \xi_1, \xi_2) = \sum_{i=1}^{n} \log \tilde{L}_i (y; \xi_1, \xi_2)
\]

**APPLICATION**

To illustrate our approach, we consider new product entry in the ground caffeinated coffee category in early 1980’s. During this period, Folgers (P&G) and Maxwell House (General Foods) were the two main competitors along other small brands. After the successful introduction of the Folgers Flaked in 1977 (O’Connor 1979), General Foods introduced three variants (i.e., grinds) of the Master Blend brand in 1981 (Fanelli 1981). Within a year, Master Blend achieved a national market share of five percent, making it one of the most successful new product launches in the retail coffee market in many years (Maxwell 1982).

Our analysis is intended to answer several questions. *What made Master Blend successful? Were all of the variants of Master Blend equally successful? If not, what made the difference? What would have happened if these new products were positioned differently?* As we show below, our model addresses these questions by relating brand positioning to consideration set probability.

**Data Description**

The data used in this study are taken from the Marion, Indiana IRI scanner panel data for ground caffeinated coffee category spanning the period March 24, 1980 to August 30, 1981, a total of 75 weeks. A total of 49 weeks of data are available prior to the introduction of Master Blend. In this product category, there are three large national brands (Folgers, Maxwell House and Chase/Sanborn) prior to the new product entry. We represent an aggregate of private brands...
with the label SPL. Following previous research (Moore and Winer 1987), each brand was further classified in terms of grind (regular, drip, and electric perk). After eliminating households with very low category consumption, a total of 251 households were available for analysis. Additional information about the Marion coffee market can be found in Gruca et al. (2002).

Table 1 describes market shares and prices of the ground coffee brand both before and after the introduction of the three grind variants of Master Blend. Note that Folgers Flaked has the largest share during both periods and, in general, Drip was the most popular grind. Almost all incumbents lost some amount of market share to Master Blend. All brands reduced their prices when the new entrant (Master Blend) joined the market. Other marketing mix variables, not presented here, showed a similar but somewhat mixed pattern.

< Insert Table 1 about here >

The initial 21 weeks of data are used to prepare a joint-space map of existing brands and customer ideal points. All subsequent periods (weeks 22 through 75) were used to estimate the parameters of the choice model. The introduction of Master Blend into the market occurs in week 50.

Joint-Space Map

Figure 2 is a graphical representation of first two-dimensions of the joint space map the market prior to the introduction of the three Master Blend variants. Following the algorithm discussed in the Appendix, we generated a three-dimensional joint-space map to model the probability of brand consideration.\(^4\) It is obvious that private brands (SPL) and national brands

\(^4\) According to Levine (1979), as the eigenvalues ($\lambda$) decrease in size, the difference between the mean sum of squares (MSS) based on data and true MSS increases by the factor of $(1-\lambda)^2/\lambda^2$, which we define as a \textit{misrepresentation index}. Our choice of a three-dimensional solution is based upon both this index and the interpretability of the resulting joint-space map.
are separately located in different quadrants. Moreover, brands with same grind are clustered
together indicating that the type of coffee maker has a strong influence on which brands/grinds
are considered. As expected, popular brands are considered by many customers, whose ideal
points are represented by open circles. Based on this map, the 251 customer by 14 brand
distance matrix \( (D) \) was computed using the three dimensional coordinates; the elements of the
distance matrix (i.e., \( d_{ij} \)) were used as input for the consideration likelihood model (equation (2)).

< Insert Figure 2 about here >

**Choice Model Calibration**

Model parameters were estimated using simulated maximum likelihood with 125 Halton
quasi random draws for each household. (See Bhat (2001) and Train (1999) for a discussion on
the use of Halton sequences in statistical analysis.) Results are presented in Table 2. To
illustrate the performance of our formulation, a model assuming that all consumers consider all
brands (called “All Consideration”) is presented as a comparison. Mean and standard deviations
of all parameters are presented. All marketing mix parameters of both models have the correct
signs and are statistically significant. Average range parameter, \( \tau \) is about 0.0684 \((\log(\tau) = -2.684)\), implying that people may be able to consider products in very short range on joint-space
map. Further detail analyses about consideration probability will be presented shortly.

< Insert Table 2 about here >

Our proposed model fits the data much better than a model that ignores consideration set
heterogeneity. All the fit measures \((\rho^2, AIC \text{ and } BIC)\) favor our model. This result might be
expected because new information (i.e., distance between ideal point and brand location) from a
joint-space map is incorporated into the analysis. However, the consideration set model also
changes the magnitude of marketing mix effects. For example, the value of the price parameter
is much larger when consideration sets are explicitly represented in the model formulation (-0.577 vs. -1.295). This strongly suggests that the impact of marketing elements is misstated when consideration sets are ignored by the researcher.

Model fit can also be assessed by examining the ability of the model to recover market shares in the period following new product introduction. Using the observed customer heterogeneity in model coefficients, we constructed upper and lower bounds for shares. Results are presented in Figure 3. Clearly, the model recovers share very well: actual market share falls within upper and lower bounds (i.e., dotted line) of our estimated market share.

< Insert Figure 3 about here >

**Customer Heterogeneity**

In order to use the model to provide diagnostics about the impact of new product entry, it is necessary to assign specific parameter values to specific households in the panel data. Following Greene (2003), we can recover an individual household’s posterior parameter estimates using the expression

\[
\hat{\xi}_i | \xi, \sigma, \Sigma = \frac{\sum_{r=1}^{R} L_i \left( \xi^{(r)}_i \right)}{\sum_{r=1}^{R} L_i \left( \xi^{(r)}_i \right)}
\]

That is, by taking draws from the population heterogeneity distribution and weighting the draws by the associated likelihood of the household, we can infer the choice model parameters that characterize a particular household. We make use of these posterior estimates in the scenario and elasticity analyses presented below.

An example of this procedure -- for the price coefficient and the consideration set range parameter ($\tau_i$) -- is presented in Figure 4. The mean of the price parameters is approximately -1.3,
in agreement with mean price coefficient found in Table 2. Moreover, the consideration set range parameter distribution is highly skewed toward small values. Using this distribution, the joint-space map and the consideration set probability expression in equation (2), we can infer that the average size of a customer’s consideration set is approximately 2.8 brands.\textsuperscript{5} That is, the average customer only considers about three brands among the total 17 brands (including the three new brands). This finding (small consideration set size) is expected in consumer packaged goods markets (Bronnenberg and Vanhonacker 1996) and serves to validate the model structure presented here.

< Insert Figure 4 about here >

Analysis of Product Positioning

As noted earlier, model calibration includes the estimation of the product locations of the new product entrants. In Figure 5, we display the locations of the three grind variants of Master Blend in relation to the product locations of existing products. For clarity, customer ideal points have been removed from the plot. Although the three grinds of Master Blend end up close to their corresponding competing grinds, the locations are not all in the middle of the of the clusters where many households ideal points are located.

< Insert Figure 5 about here >

To study the implications of positioning further, we computed individual household consideration probabilities for each brand. As mentioned earlier, the consideration set depends on brand positioning and, thus, affects brand choice. Using equations (2) and (10), we can recover an individual household’s consideration probabilities for each brand. Histograms

\textsuperscript{5} The expected number of brands considered is computed by summing the consideration probabilities for all brands within each customer. Averaging this number over customers yields the average consideration set size for the population.
showing the number of households with different consideration set probabilities are presented for the three Master Blind grinds in Figures 6A, 6B and 6C. For purposes of comparison, we also present the consideration set profiles for the incumbent brands in each plot.

< Insert Figures 6A, 6B and 6C about here >

All brands show a decided skew in the consideration set profile toward lower probabilities. This is consistent with previous literature showing that any given consumer only actively considers a small number of brands. In comparing the Master Blend profile to those of the incumbent brands, we see striking similarities across brands for both regular and electric perk grinds (Figures 6A and 6C). In contrast, Master Blend Drip has a pronounced skew toward lower consideration probabilities relative to the incumbent brands.

These patterns strongly suggest that the positioning of Master Blend Drip is relatively weak and could be improved. We analyze this possibility further by considering what would have happened if Master Blend had achieved a different positioning. This can be done by considering scenarios in which the Master Blend locations on the map are moved, consideration probabilities are recomputed, and then aggregate market shares are forecasted.

We consider two different scenarios. In the first scenario, we moved the three Master Blend variants to the middle of each of the respective grind clusters. In the second scenario, we set coordinates of Master Blend to be the same as the three Folgers grinds. The first scenario illustrates what would have happened if Master Blend were located closer to the average ideal point of customers in each grind cluster. The second scenario illustrates what would have happened if Master Blend achieved the same positioning as Folgers.

Figure 7 shows the market share forecasts based on different scenarios compared to actual market share. Master Blend Regular and Drip variants would have been better off with
Analysis of Brand Price Competition

Our model also allows us to investigate how new product entry impacts brand price competition in the coffee category. Following Russell and Kamakura (1994), aggregate measures of own ($\eta_{ij}$) and cross price elasticity ($\eta_{jk}$) have the form

$$\eta_{ij} = \frac{\% \Delta MS_j}{\% price_j} = \left[ \frac{\sum_{i=1}^{N} \beta_{ij} \theta_j \left(1 - \theta_j \right)}{MS_j} \left/ \frac{1}{N} \right. \right] price_j$$

(11)

$$\eta_{jk} = \frac{\% \Delta MS_j}{\% price_k} = \left[ \frac{\sum_{i=1}^{N} \beta_{ij} \theta_j \theta_k}{MS_j} \left/ \frac{1}{N} \right. \right] price_k, j \neq k$$

where the summation runs across the N households in the dataset. Here, we focus on the changes in aggregate own price elasticities due to new product entry.

In Table 3, we present a comparison of own price elasticity before and after new product entry. Note that the price elasticities of almost all incumbent brands are lower in magnitude after new brand introduction. Such results are not typically observed because we generally expect that lower share following entry will translate into high price elasticity (cf. Russell and Kamakura 1994). However, in this market, two variables changed simultaneously after Master Blend entered the market: shares fell, but average prices also fell (see Table 1).
We can easily see that these two forces working in opposite directions in our data. In Table 3, we decompose elasticities into two components: Entry Effect and Price Effect. To carry out this decomposition, we computed the three sets of elasticities: Before, After and No-Reaction. The Before column shows the elasticities of the incumbent brands based upon the average marketing mix variables for each brand prior to new product entry. The After column shows the final elasticities for both new and incumbent brands, using the average marketing mix variables following Master Blend entry. The No-Reaction column entries are the elasticities predicted by the model if prices of the incumbent brands had remained stable after Master Blend entry.

We define the Entry Effect as the difference between No-Reaction elasticity and Before elasticity, and the Price Effect as the difference between No-Reaction elasticity and After elasticity. These calculations are shown on the right hand side of Table 3. The net result of these comparisons is that the Entry Effect varies by brand: some brands become more price sensitive, and other become less price sensitive. However, the Price Effect is unambiguous: lowering prices leads to a less elastic demand. Because the Price Effect dominates in this market, the net effect of product entry is lower price elasticity for incumbent brands. For the Master Blend variants, the post entry elasticities suggest that the new brands are among the most price sensitive brands in the market.

Price elasticity analyses across various positioning scenarios also confirm why Master Blend Drip would have gained significant market share with different positioning (Figure 7). Figure 8 shows that with two national brand positioning strategies, Master Blend Drip’s own price elasticity become very low compared to that with actual position. Combining with the findings from consideration profile (i.e., higher consideration likelihoods of other brands), lower
price sensitivity explains why new positioning would have been better off for Master Blend Drip. Other variants’ own price elasticities are not much different from actual ones.

**Summary**

This analysis shows how our model can be used to study the impact of new product entry in a market. First, it provides insights into the positioning of the new product entrant relative to competitors. Second, it yields a profile of the entrant in terms of likelihood of consumer consideration. Third, it provides a method of computing the changes in the pattern of price sensitivity due to new product entry. Collectively, these elements allow the analyst a rich set of diagnostics to judge the success of the entrant.

**CONCLUSIONS**

This research develops a logit choice model which provides insights into the impact of new product introduction into a test market. By linking product positioning on a joint-space map to the probability of brand consideration, the model allows the researcher to understand the positioning of the new product relative to competitors, the consideration set profile of the both new and incumbent brands, and the impact of product entry on brand price competition. The model also allows for a scenario analysis in which the demand implications of new product positioning can be studied.

An empirical analysis of the ground coffee category provided insights into the impact of the entry of Master Blend. Through scenario analyses, we showed that changing brand position changes market share forecasts. Among the three new brands, two brands would have been better off with new positions (i.e., congruent to Lehman and Pan (1994)’s assimilation), while the other would not. The most dramatic change in share forecasts is attributed to Master Blend
Drip, a brand whose consideration set profile has a pronounced skew toward lower consideration probabilities than competitors. Our model implies that improved positioning boosts brand consideration and therefore leads to higher share. We also found that the price elasticities of incumbent brands fell following entry due to simultaneous price decreases. Interestingly, the observed price elasticities of Master Blend are lower (closer to zero) than would be expected if the incumbents had not reacted with decreased prices. However, the Master Blend brands are collectively one of the more price sensitive brand groups in the market.

Methodologically, this research provides an approach for adding additional information from a joint-space map based upon an initial dataset into choice models. With this map, we are able to model consideration probability as a function of the distance between customer ideal point and brand location. Heterogeneity in consideration sets is then implicitly dependent upon both the customer’s ideal point location and upon a range parameter representing how quickly consideration likelihood decreases as distance increases. This approach provides a parsimonious way of linking brand positioning to product choice.

Our model is based upon a few assumptions, some of which could be usefully relaxed in future research. First, our study assumes that consumers have stationary consideration sets. Some researchers argue that the consideration set varies depending upon in-store marketing mix variables (Allenby et al 1995; Bronnenberg et al 1996). Another possibility is that consideration probabilities are updated as the customer gains more experience in the category. Second, because our model is based upon choice models, our analysis is focused on market share. A model based upon sales could be explored to create a stronger link between model forecasts and brand profitability. Finally, our analysis provides short-term forecasts based upon the assumption that mix parameters and brand positions do not change. For a long-run analysis, it
would be necessary to investigate the long-term competitive equilibrium induced by the competitive reaction of incumbents.
APPENDIX

Generating a Joint-Space Map by Modified Pick-Any Scaling

Pick-any scaling is a psychometric procedure developed by Levine (1979). It has seen several applications in the marketing science literature (Moon and Russell 2003; Gruca et al 2002; Holbrook et al 1982; Moore and Winer 1987). The method is designed around a data collection procedure (called “pick-any” choice) in which respondents are allowed to select as many objects as they desire out of a set of objects presented by the researcher. In marketing, the objects are typically products, and customers are asked to select those products that match certain criteria. In the research reported here, we define the pick-any set of products as those products that the customer has already purchased in the past. Further, we slightly modify Levine’s (1979) procedure by taking into account how often the customer has picked the product.

Pick-any scaling (Levine 1979) creates a map with two properties: customers are located in the center of the products that they select; and products are located in the center of customers who select them. In our modified algorithm, however, the location of both products and customers are weighted by number of purchases. So, the customer is located closer to brands that are more frequently purchased, and the brand is located closer to the customers who are heavy purchasers.

The mapping algorithm can be formulated as an eigenvalue problem as follows. Let \( N \) be the number of customers and \( K \) be the number of products. Define \( E \) as a symmetric matrix of dimension \( N+K \) with the following form:

\[
E = \begin{bmatrix}
\phi_N & B \\
B' & \phi_K
\end{bmatrix},
\]

(A.1)
The original pick-any algorithm defines $B$ as an $N$ by $K$ matrix of zeros and ones with elements $b_{ij}$ indicating the choice of product $j$ by respondent $i$. In contrast, we define $B$ as an $N$ by $K$ matrix of zeros and positive integers with elements $b_{ij}$ indicating number of purchases of product $j$ by respondent $i$ given period of time. Both $\varphi_N$ ($N$ by $N$) and $\varphi_K$ ($K$ by $K$) are null matrices.

Next, $D$ is defined as a diagonal matrix of order $N+K$ with diagonal elements

\begin{equation}
  d_{ii} = \sum_{j=1}^{N+K} e_{ij}
\end{equation}

For $I \leq N$, $d_{ii}$ represents the number of products chosen by person $I$, and for $N+1 \leq I \leq N+K$, $d_{ii}$ is the number of customers choosing product $i-N$, in original pick-any mapping. In our approach, however, $d_{ii}$ represents the number of total purchases made by person $i$, and the number of purchases of product $i-N$, respectively. It can be interpreted as weighted version of original $D$ matrix, where the weights are the number of purchases of each brand by each person at a given time. Finally, let $x_r$ be a column vector of $N+K$ coordinates for the $N$ respondents (first $N$ rows) and $K$ products (last $K$ rows) or the $r$-dimension of the joint space.

Using this notation, Levine’s (1979) procedure solves the eigenvalue problem.

\begin{equation}
  \lambda_r x_r = D^{-1} E x_r
\end{equation}

where $\lambda_r$ and $x_r$ are the $r^{th}$ eigenvalue and eigenvector (respectively) of the non-symmetric matrix $D^{-1}E$. In words, this states that a customer’s coordinate on dimension $k$ of the map must be proportional (through $\lambda_r$) to the centroid of the products he/she selected. Simultaneously, a product’s coordinate on dimension $r$ of the map must be proportional (through $\lambda_r$) to the centroid of the customers who selected the product.

For computational simplicity, this problem is restated as

\begin{equation}
  \lambda_r \left( D^{1/2} x_r \right) = D^{1/2} \left( D^{-1} E \right) x_r = W \left( D^{1/2} x_r \right)
\end{equation}
where $W = D^{1/2}ED^{1/2}$. This formulation is a symmetric eigenvalue problem where $\lambda_r$ and $D^{1/2}x_r$ are eigenvalues and eigenvectors (respectively) or the symmetric matrix $W$. The coordinates of the products and customers can therefore be obtained by calculating the eigenvalues of $W$, and then pre-multiplying them by $D^{-1/2}$ to obtain $D^{-1/2} (D^{1/2}x_r) = x_r$. 
REFERENCES


**TABLE 1**

Market Share and Price Changes After Master Blend Introduction

<table>
<thead>
<tr>
<th>Brands</th>
<th>Market Share</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Before Entry</td>
<td>After Entry</td>
</tr>
<tr>
<td>Folgers Regular</td>
<td>0.0506</td>
<td>0.0513</td>
</tr>
<tr>
<td>Folgers Drip</td>
<td>0.1208</td>
<td>0.0932</td>
</tr>
<tr>
<td>Folgers Elec Perk</td>
<td>0.1019</td>
<td>0.0814</td>
</tr>
<tr>
<td>Folgers Flaked</td>
<td>0.1876</td>
<td>0.1861</td>
</tr>
<tr>
<td>Max Hse Regular</td>
<td>0.0208</td>
<td>0.0108</td>
</tr>
<tr>
<td>Max Hse Drip</td>
<td>0.1571</td>
<td>0.1319</td>
</tr>
<tr>
<td>Max Hse Elec Perk</td>
<td>0.0563</td>
<td>0.0402</td>
</tr>
<tr>
<td>Chs-San Regular</td>
<td>0.0104</td>
<td>0.0075</td>
</tr>
<tr>
<td>Chs-San Drip</td>
<td>0.0270</td>
<td>0.0387</td>
</tr>
<tr>
<td>Chs-San Elec Perk</td>
<td>0.0255</td>
<td>0.0316</td>
</tr>
<tr>
<td>SPL Regular</td>
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<td>0.0301</td>
</tr>
<tr>
<td>SPL Drip</td>
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<td>0.0502</td>
</tr>
<tr>
<td>SPL Elec Perk</td>
<td>0.0482</td>
<td>0.0613</td>
</tr>
<tr>
<td>SPL Bean</td>
<td>0.1046</td>
<td>0.0778</td>
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<tr>
<td>Mast-Bln Regular</td>
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<td>0.0115</td>
</tr>
<tr>
<td>Mast-Bln Drip</td>
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<td>0.0688</td>
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<tr>
<td>Mast-Bln Elec Perk</td>
<td>-</td>
<td>0.0276</td>
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</table>

* Unit of price is dollar per pound
### Table 2

Parameter Estimates

<table>
<thead>
<tr>
<th>Parameters</th>
<th>All Consideration</th>
<th>Proposed Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>s.e.</td>
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<tr>
<td>Folgers Regular</td>
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<td>-</td>
</tr>
<tr>
<td>Folgers Drip</td>
<td>0.164 (0.132)</td>
<td>2.145* (0.134)</td>
</tr>
<tr>
<td>Folgers ElecPrk</td>
<td>-0.557* (0.152)</td>
<td>2.014* (0.120)</td>
</tr>
<tr>
<td>Folgers Flaked</td>
<td>-1.951* (0.279)</td>
<td>4.413* (0.235)</td>
</tr>
<tr>
<td>Max Hse Regular</td>
<td>-1.510* (0.188)</td>
<td>1.249* (0.163)</td>
</tr>
<tr>
<td>Max Hse Drip</td>
<td>-0.450* (0.178)</td>
<td>3.164* (0.186)</td>
</tr>
<tr>
<td>Max Hse ElecPrk</td>
<td>-1.271* (0.195)</td>
<td>2.199* (0.153)</td>
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<td>Chs San Regular</td>
<td>-2.091* (0.250)</td>
<td>0.975* (0.178)</td>
</tr>
<tr>
<td>Chs San Drip</td>
<td>-0.933* (0.213)</td>
<td>1.251* (0.167)</td>
</tr>
<tr>
<td>Chs San ElecPrk</td>
<td>-1.229* (0.235)</td>
<td>1.769* (0.177)</td>
</tr>
<tr>
<td>SPL Regular</td>
<td>-1.813* (0.302)</td>
<td>1.875* (0.205)</td>
</tr>
<tr>
<td>SPL Drip</td>
<td>-0.149 (0.185)</td>
<td>0.864* (0.124)</td>
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<tr>
<td>SPL ElecPrk</td>
<td>-0.540* (0.215)</td>
<td>1.396* (0.133)</td>
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<tr>
<td>SPL Bean</td>
<td>-0.040 (0.464)</td>
<td>1.687* (0.284)</td>
</tr>
<tr>
<td>MastBln Regular</td>
<td>-1.051* (0.253)</td>
<td>-0.685* (0.269)</td>
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<tr>
<td>MastBln Drip</td>
<td>0.058 (0.237)</td>
<td>2.184* (0.272)</td>
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<td>-0.510* (0.195)</td>
<td>-1.018* (0.190)</td>
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<tr>
<td>$\beta_{\text{price}}$</td>
<td>-0.577* (0.236)</td>
<td>3.658* (0.185)</td>
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<tr>
<td>$\beta_{\text{feat}}$</td>
<td>1.765* (0.086)</td>
<td>-0.569* (0.106)</td>
</tr>
<tr>
<td>$\beta_{\text{disp}}$</td>
<td>0.692* (0.139)</td>
<td>0.057 (0.120)</td>
</tr>
<tr>
<td>$\log(\tau)$ †</td>
<td>-</td>
<td>-</td>
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<tr>
<td>$\rho_{\text{price,feat}}$</td>
<td>0.511* (0.116)</td>
<td>0.101 (0.123)</td>
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<tr>
<td>$\rho_{\text{price,disp}}$</td>
<td>-0.995* (0.169)</td>
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<td>$\rho_{\text{disp,feat}}$</td>
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<tr>
<td>Log-Likelihood</td>
<td>-5705.05</td>
<td>-5103.00</td>
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</table>

* indicates significance at 1 percent level
† $\tau$ is following log-normal distribution
TABLE 3
Analysis of Own Price Elasticity

<table>
<thead>
<tr>
<th></th>
<th>Elasticity</th>
<th>Elasticity Decomposition</th>
<th></th>
<th></th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Before</td>
<td>After</td>
<td>No Reaction*</td>
<td>(After-Before)</td>
<td>Entry Effect</td>
</tr>
<tr>
<td>Folgers Regular</td>
<td>-2.33</td>
<td>-1.89</td>
<td>-2.02</td>
<td>0.44</td>
<td>0.31</td>
</tr>
<tr>
<td>Folgers Drip</td>
<td>-2.09</td>
<td>-1.89</td>
<td>-2.07</td>
<td>0.20</td>
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</tr>
<tr>
<td>Folgers Elecprk</td>
<td>-2.17</td>
<td>-1.80</td>
<td>-1.93</td>
<td>0.37</td>
<td>0.24</td>
</tr>
<tr>
<td>Folgers Flaked</td>
<td>-1.10</td>
<td>-1.01</td>
<td>-1.04</td>
<td>0.09</td>
<td>0.06</td>
</tr>
<tr>
<td>MaxHse Regular</td>
<td>-3.89</td>
<td>-3.65</td>
<td>-3.91</td>
<td>0.23</td>
<td>-0.03</td>
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<tr>
<td>MaxHse Drip</td>
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<td>-1.70</td>
<td>-1.95</td>
<td>-0.06</td>
<td>-0.31</td>
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<tr>
<td>MaxHse Elecprk</td>
<td>-3.36</td>
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<td>0.18</td>
<td>-0.24</td>
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<tr>
<td>ChsSand Regular</td>
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<td>0.09</td>
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<tr>
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<td>0.16</td>
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<td>-2.81</td>
<td>0.29</td>
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<tr>
<td>SPL Bean</td>
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<td>-0.69</td>
<td>-0.73</td>
<td>-0.04</td>
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</tr>
<tr>
<td>MastBln Regular</td>
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<td>-</td>
<td>-</td>
<td>-</td>
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<td>MastBln Drip</td>
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<td>MastBln Elecprk</td>
<td>-3.17</td>
<td>-4.31</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

# No Reaction is based on the assumption of no incumbent's reaction (i.e., no price reduction).
* (After-Before) = Entry Effect + Price Effect
** Entry Effect = No Reaction – Before
*** Price Effect = After – No Reaction
Figure 1 – Consideration Set Membership Probability
Figure 2 -- Joint-Space Map of Incumbent Brands
Figure 3 – Comparison of Share Forecasts to Actual Share
Figure 4 – Heterogeneity Distributions

Price Coefficient

Consideration Set Range Coefficient
Figure 5 – Estimated Position of Master Blend Entrants
Figure 6A -- Consideration Set Probability Distributions

Regular Coffee
Figure 6B -- Consideration Set Probability Distributions

Drip Coffee

![Graph showing consideration set probability distributions for different brands of drip coffee, including Folgers, MaxHse, ChsSan, and MastBn. The x-axis represents the probability range from 0.1 to 1, and the y-axis represents the number of consumers. The graph compares the probability distributions for each brand, with Folgers showing the highest probability distribution.](image-url)
Figure 6C -- Consideration Set Probability Distributions

Electric Perk Coffee

![Probability Distributions Graph]
Figure 7 – Market Share Forecasts for Various Scenarios

- Actual Position
- Average National Brand Position
- Same Position as Folgers

MastBln Regular
MastBln Drip
MastBln Elecprk

Y-axis: (%)
X-axis: MastBln Regular, MastBln Drip, MastBln Elecprk
Figure 8 -- Own Price Elasticity across Various Scenarios