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Modelling the Effect of Purchase Quantity on Consumer Choice of Product Assortment

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ABSTRACT

The authors develop a model to predict consumer selection of product assortment and its relationship to category purchase quantity. Brand and variety choice decisions are modelled with a nested logit. A shopper's vector of choice probabilities—and hence likely assortment selection—directly depends on his or her purchase quantity. The purchase quantity decision is modelled with a Poisson regression which is, in turn, integrated with the nested logit. The full model permits investigators to assess the impact that quantity—and the marketing activity that affects it—has on the assortment of items chosen at the point of purchase. It should provide a decision aid for both manufacturers and retailers seeking to understand and forecast demand for item assortment. The authors illustrate their modelling approach with scanner panel data for yogurt. The results show that panellists' assortment selection is significantly related to purchase quantity, but the overall magnitude of the effect is small when compared to other factors that predict item sales. © 1998 John Wiley & Sons, Ltd.

KEY WORDS choice models; scanner data analysis; demand forecasting

INTRODUCTION

In many product categories consumers regularly purchase multiple items on their shopping trips and select an assortment of flavours or varieties among those items (e.g. yogurt, ice cream, soup, frozen entrées, baby foods). Recently, several studies in marketing have presented evidence that consumers demand a wider assortment of flavours or varieties when they buy a larger number of units (Simonson, 1990; Simonson and Winer, 1992; Walsh, 1995). A behavioural rationale offered for this phenomenon is that buying a greater quantity lengthens the consumption horizon, thereby raising uncertainty about preferences at future consumption occasions.

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Shoppers handle this uncertainty by broadening the assortment of items that they select at the time of purchase.

This aspect of consumer demand has ramifications for manufacturers and retailers. For example, to ensure adequate product supplies in the distribution channel (i.e. avoid out-of-stock conditions), manufacturers and retailers need to forecast whether short-term fluctuations in overall demand (e.g. due to short-term promotions, holidays, or other events) are associated with changes in demand for the *mix* of items available within a product class. Indeed, forecasting the effect that changes in purchase quantity will have on demand for product assortments is likely to be increasingly important to retailers and manufacturers as they strive to trim inventory levels in the distribution channel.

While studies in marketing have presented reasons *why* purchase quantity may have an effect on assortment selection, no models currently exist to forecast *how much* the demand for a product mix is likely to change. For example, Simonson's (1990) study presents evidence from a controlled experiment. Two other studies—Simonson and Winer (1992) and Walsh (1995)—present empirical evidence from scanner data, but neither develops or tests a model suited for use in demand forecasting.

An additional limitation of previous scanner-based studies is that the assortment effect is documented with tests that are based on correlating the observed number of different flavours or varieties purchased at a given shopping occasion with the total number of units purchased (Simonson and Winer, 1992; Walsh, 1995). Even when no assortment effect actually takes place—i.e. there is no change in consumer preference across the product mix as quantity changes—the expected number of different flavours or varieties a consumer will select still increases with the total number of items bought. (One can think of a shopper as simply taking more draws from the multinomial distribution with the probabilities remaining the same.) Thus, models of the quantity-assortment effect need to distinguish between true shifts in demand mix (i.e. the relative proportions or shares for the various flavours or varieties) versus a 'draws from the urn effect'. Said another way, the true assortment effect means that manufacturers and retailers need to adjust the *relative proportions* of different items available in the distribution channel; the 'draws from the urn effect' implies no change in proportions.

Our objective in this paper is to propose, illustrate, and test a simple modelling approach that will predict assortment selection and the impact that purchase quantity has upon it. Our model places the 'assortment effect' in the context of other key factors influencing choices made by shoppers at the point of sale. For example, we incorporate the effects that marketing-mix activity has on quantity and choice alongside the impact that quantity has on assortment. The model captures (1) the effect of quantity on flavour/variety choice, (2) the effects of price, promotion, and flavour choice on brand choice, and (3) the effect of price and promotion on purchase quantity.

We construct our model at the level of the decisions made by individual shoppers at store visits in which a category purchase occurs. (Since our focus is on purchase quantity and the assortment of items chosen, we do not model the category purchase (buy/no buy) decision here.) The overall model has two primary components: (1) a (truncated) Poisson regression to predict category purchase quantity and (2) a nested logit to predict choice of brand and the flavours/varieties of that brand. In the nested logit, the flavour/variety choice is nested within brand choice. The lower branch of the nested logit models the shopper's choice of flavour or variety as a function of purchase quantity. The upperbranch models brand choice as a function of price, promotion, and the consumer's utility from the flavour/variety choice decision.

Our approach represents the demand for assortment by the information contained in the consumer's flavour/variety choice probabilities. Demand for a broader (or narrower) range of items is manifested by an increase (or decrease) in the dispersion of each panelist's flavour/variety choice probabilities. Our modelling approach captures the assortment effect by linking changes in purchase quantity to changes in the consumer's vector of flavour/variety choice probabilities. This is what gives rise to changes in relative demand within a product mix as purchase quantities fluctuate up and down. Our objective is to model and forecast the changes in consumer demand for assortment by using existing, well-tested probabilistic choice models that incorporate the (potential) link between quantity and flavour/variety choice. The goal is to provide a good 'first cut approximation' to this problem. Thus, we do not attempt to model the formal decision process undertaken by the consumer, but seek a representation that enables us to quantify the assortment effect.

We also wish to note that our focus is on assortment, not variety seeking. We consider variety seeking to refer to consumer selection of different items (e.g. yogurt flavours, frozen dinner entrées, soup varieties) over *multiple* purchase occasions. We consider assortment to refer to consumer selection of different items on *a single* purchase occasion. This distinction is important because the underlying consumer behaviour driving the phenomena is presumed to be different. For example, models of variety seeking have traditionally held that satiation on item characteristics (McAlister, 1982) or desire for balanced consumption over time (Lattin, 1987) lead consumers to seek variety. On the other hand, consumers select an assortment of items on a single purchase occasion to maintain flexibility in their future consumption of the product. As noted above, consumers seek this flexibility to accommodate uncertain future tastes (Koopmans, 1964; Kreps, 1979; Walsh, 1995) and/or to avoid decision conflict and thus put off ultimate choice until later (Simonson, 1990).

In the marketing literature, there is an extensive history of modelling work on variety-seeking behaviour. These studies have looked at variety seeking manifested at both *consumption* decisions (McAlister, 1982; Lattin, 1987) and *purchase* decisions (e.g. Givon, 1984; Kahn, Kalwani, and Morrison, 1986; Bawa, 1990). Work on assortment, however, has not been as extensive. McAlister (1979) studied the problem of portfolio choice. The more recent work by Simonson (1990), Simonson and Winer (1992), and Walsh (1995) focused on the effect of purchase quantity on the breadth of assortment selected.

Another related study in marketing is Harlam and Lodish (1995). They propose a model of consumer choice for multiple items purchased on a shopping trip. Their approach uses within-shopping trip information to help predict the flavours or varieties of subsequently selected items. For example, if blueberry is placed in the shopping trolley first, subsequent selections would be less likely to be blueberry and more likely to be other flavours. One limitation of their approach is that it is based on the assumption that the within-trip selection of items proceeds sequentially and that this order is known to the modeler.[1]

Our approach differs from the Harlam and Lodish model in two key respects. First, unlike Harlam and Lodish, we explicitly model the impact of purchase quantity on assortment selection. Second, we do not assume an ordering for item selection on a store visit. Our model yields the same results regardless of the within-trip item ordering used in the estimation. Since the item

[1] Harlam and Lodish (HL) assume that the sequence follows a consumer's preferences in decreasing order. In their application, HL test the robustness of this assumption for two alternative selection sequence orderings. But literally hundreds of possible orderings exist for typical purchase occasions. For example, in the case of six different items, there are 6! or 720 possible selection orders.

selection sequence is not part of available data, our approach may be better suited to the actual information provided by scanner panels.

In the next section, we describe our modelling approach in more detail and provide mathematical specifications for the model components. A subsequent section presents the results from an empirical application of our model to the yogurt scanner panel data provided by A. C. Nielsen. Following this, we assess the forecasting performance of the model and discuss how the model can be used to decompose the impact of price on brand choice, purchase quantity, and assortment selection. We close with our conclusions.

MODELLING APPROACH

Consumer purchase behaviour

Our model seeks to represent the following purchase behaviour of scanner panelists. On a given shopping trip, and given that a purchase takes place in the product category, a consumer decides how many units to buy. This quantity decision is influenced by consumer needs, and by marketing activities such as price and promotion. The shopper then decides how the total number of units are to be allocated across the available brands and flavours/varieties.[2] The brand choice decision is affected by consumer brand preferences, brand marketing activities, and each brand's attractiveness to the consumer based on the flavours available on the shelf. Given brand choice for a particular item, the consumer decides which flavour/variety to select. The flavour decision is affected by the shopper's flavour preference and by category purchase quantity. Note that we have made our model conditional on category purchase incidence (i.e. a non-zero number of units are purchased) since the focus of our investigation is item choice and purchase quantity.

To represent the purchase behaviour just described, our model brings together three components of consumer choice: (1) category purchase quantity, (2) brand choice, and (3) flavour choice. While these three decisions could be modelled separately, we are interested in capturing the dependency of brand on flavour and of both on purchase quantity. To do this, we combine the model components to obtain the expected number of units that a panelist purchases of flavour/variety v of brand i on a store visit and category purchase that takes place at time t. Mathematically, the model is given by

$$E[Q_{ivt}^h] = \sum_{q_t^h=1}^{\infty} q_t^h P_t^h(Q_t^h = q_t^h) P_t^h(i \mid q_t^h) P_t^h(v \mid i, q_t^h) \tag{1}$$

where

$E[Q_{ivt}^h]$ = expected number of units that household h buys of brand i, flavour/variety v, at time t

$P_t^h(Q_t^h = q_t^h)$ = probability that h buys q units in the category at time t

$P_t^h(i \mid q_t^h)$ = probability h chooses brand i for an item at time t, given q units are purchased in the category

$P_t^h(v \mid i, q_t^h)$ = probability h chooses flavour/variety v at time t, given q units are purchased in the category and brand i is chosen.

[2] We use the terms 'flavour' and/or 'variety' to refer to the multiple product offerings within a brand's line in a given product class.

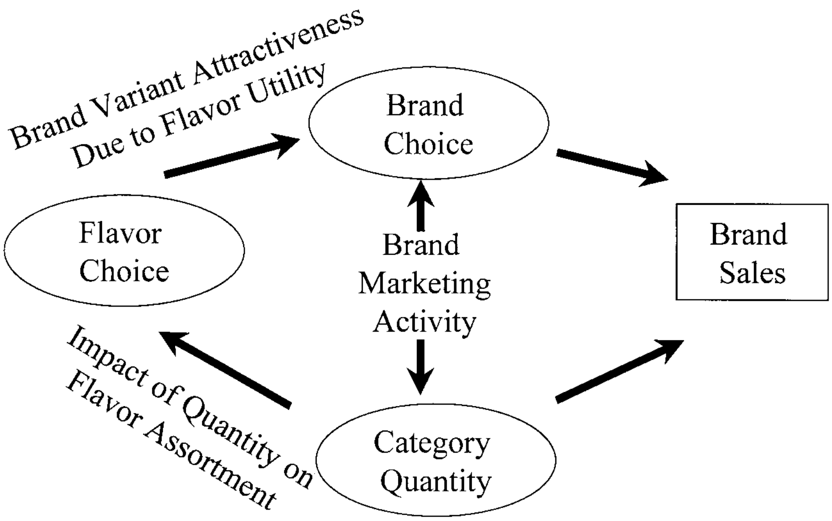

Figure 1. Conceptual framework

The category quantity probability, $P_t^h(Q_t^h = q_t^h)$, is modelled with a truncated Poisson regression (i.e. only the non-zero outcomes are considered). The brand and flavour choice probabilities, $P_t^h(i \mid q_t^h)$ and $P_t^h(v \mid i, q_t^h)$, are modelled with a nested logit (e.g. Guadagni and Little, 1998). Detailed specifications are presented in the next subsection.

Figure 1 depicts the conceptual framework for our modelling approach. We wish to highlight two aspects of the framework. First, the three model components are interdependent. Category quantity affects the consumer's flavour choice (assortment effect), which in turn affects brand choice (through the brand variant attractiveness term of the nested logit). Second, a change in a brand's marketing activity, such as price, has three simultaneous effects on brand sales:

(1) Brand marketing activity has a direct influence on brand choice and hence brand sales.
(2) Brand marketing activity has a direct influence on category quantity and hence brand sales.
(3) Brand marketing activity's effect on category quantity also influences flavour choice and, in turn, brand choice and brand sales.

Modelling these effects together permits their relative impact on brand sales to be assessed and the magnitude of the 'assortment effect' to be quantified. In this modelling framework, category quantity directly affects flavour choice, but only indirectly affects brand choice via the nested logit. Our model captures the effect of quantity on flavour/variety assortment but does not explicitly consider the effect of quantity on 'brand assortment'. We leave the study of this phenomenon to future research because the purchase of multiple brands on a given shopping trip is an infrequent occurrence in the yogurt category (95% of purchase occasions involve only a single brand).

Category quantity model

We begin our specification of the model components with category purchase quantity. To represent the probability that a panelist purchases a particular number of units, we employ a Poisson regression. The Poisson regression is a well-established approach for modelling count data in econometric studies (e.g. El Sayyad, 1973; Hausman, Hall, and Griliches, 1984) and applications of the Poisson regression to model purchase quantity have recently appeared in Chintagunta (1993) and Wedel *et al*. (1993). The Poisson regression always predicts a non-negative purchase quantity—something a conventional linear regression cannot guarantee. The Poisson regression also provides a natural fit with the brand and flavour choice models since the unit purchase probabilities can be readily combined with the brand and flavour probabilities to form an integrated likelihood (see equation (1)).

Since our model is conditional on category purchase, we seek the probability that household h buys $q_t^h = 1, 2, \ldots, n$ units in the category on purchase occasion t. To eliminate the no-purchase outcome, we truncate the zero point in the Poisson model. The truncated Poisson model is given by

$$P_t^h(Q_t^h = q_t^h) = \frac{(\lambda_t^h)^{q_t^h} \exp(-\lambda_t^h)}{(1 - \exp(-\lambda_t^h))q_t^h!} \tag{2}$$

where λ_t^h is the purchase rate of panelist h at time t. The purchase rate is a function of household-specific variables and marketing activity. It is given by

$$\lambda_t^h = \exp(\theta \mathbf{X}_t^h) \tag{3}$$

where $\mathbf{X}_t^h$ is a vector of household and marketing variables and θ is a vector of parameters to be estimated. Specifying λ_t^h as an exponential function of the explanatory variables ensures that the purchase rate will be non-negative.

A potential limitation of the Poisson regression is the mean-variance restriction that accompanies a single-parameter distribution. Two factors mitigate this limitation here. The first is that λ_t^h varies both across panelists (due to usage rate heterogeneity) and over time (due to the effects of marketing activity). Thus, the mean-variance restriction applies only to a single observation at a time. The second is that the truncation of the no-purchase outcome eliminates the spike at the zero point. The non-zero observations follow a smooth, unimodal distribution that is well approximated by the Poisson.

Nested logit hierarchy

The brand choice and flavour/variety choice components of the model are linked together in a nested logit. We have assumed a brand–flavour hierarchy in which we placed the flavour/variety choice decision at the bottom of the tree and the brand choice decision at the top. Conceptually, this seems more appropriate for most non-durable product categories than a flavour–brand hierarchy. A given brand's varieties are more often displayed together in supermarkets than a given variety's brands (see, e.g., the discussion in Simonson and Winer, 1992). This suggests that consumers are more likely to follow a brand → flavour sequence than a flavour → brand sequence. In the empirical application we also explicitly test our hierarchy assumption by setting up a nested logit for both decision sequences.

Flavour/variety choice model

Starting at the bottom of the nested logit tree (i.e. given that brand i has been selected), the probability that household h buys flavour/variety v on occasion t is given by the multinomial logit model

$$P_t^h(v \mid i, q_t^h) = \frac{\exp(VU_{ivt}^h)}{\sum_{v' \in i} \exp(VU_{iv't}^h)} \tag{4}$$

The deterministic component of the variety utility, VU^h_{ivt}, is written as

$$VU^h_{ivt} = \alpha_{iv} + \beta \mathbf{Y}^h_{ivt} \quad (5)$$

where α_{iv} are brand and flavour/variety specific constants, $\mathbf{Y}^h_{ivt}$ is the vector of explanatory variables, and β is the vector of parameters to be estimated.

An important feature of the model in equation (4) is that the summation is taken over only those varieties v' that are both offered by brand i and stocked by the store visited at time t. This means that the choice set of flavour/varieties entering the model may vary by brand and by store. In the nested logit, this type of variation can affect inclusive value (the log of the denominator in equation (4)) and therefore the brand choice probabilities. Thus, the model permits brands to be more or less attractive to consumers depending upon the varieties that they offer and those that are carried by the retailer.

A key objective of our modelling approach is to parsimoniously capture the impact of purchase quantity on flavour choice (and therefore the assortment of flavours selected). Our approach begins with the notion that each panelist has a baseline set of zero-order choice probabilities for the various brand-flavours. A good predictor of these probabilities is the historical preferences of the panelist for the brand-flavours. Following the logit modelling tradition established in marketing (e.g. Guadagni and Little, 1983), we label these historical preferences brand-variety loyalties, or *BVLOY*'s. Each panelist has a vector of *BVLOY*'s for each brand and the elements of each of these vectors sum to one.

In a model of the quantity–assortment phenomenon, the purchase of a larger than normal number of units should be associated with higher entropy in the choice probability vector (i.e. large probabilities become smaller and small probabilities become larger). Similarly, a smaller than normal number of units should be associated with lower entropy in the vector. Thus, increases (decreases) in quantity should raise (lower) the probability that the shopper selects less-preferred flavours. To model this, we make the influence that the *BVLOY*'s have on utility a function of the changes in purchase quantity. We propose that the *BVLOY*'s enter variety utility not simply as $\beta_1 BVLOY^h_{iv}$, as in a conventional logit approach, but as

$$(\beta_1 + \beta_2(q^h_t - \bar{q}^h))BVLOY^h_{iv}$$

where q^h_t is the actual category quantity, in units, bought by household h on occasion t and $\bar{q}^h$ is the average category quantity bought by the household. We expect $\beta_1 > 0$, $\beta_2 < 0$ and $|\beta_1| > |\beta_2|$. In the hold-out forecast test reported later in this paper (in which we do not know actual quantities purchased), we specify $\bar{q}^h_t$ as the *expected* category quantity that is estimated from the Poisson regression component of the model, or $\hat{q}^h_t$.

To further explain the rationale for our modelling approach in flavour choice, consider the case in which the consumer buys an above average number of units, i.e. $q^h_t > \bar{q}^h$. If β_2 is negatively signed, the quantity effect 'shrinks' the impact that the brand-variety loyalties have on flavour choice. As the influence of the loyalties drops, the consumer's preferences become more dispersed across the available flavours. This leads to a wider assortment of flavours selected. Conversely, purchase of a below-average number of units, i.e. $q^h_t < \bar{q}^h$, enhances the impact of the brand-variety loyalties. This increases the probability that more preferred flavours will be chosen, narrowing the breadth of the assortment selected.

Our approach assesses the impact of quantity on assortment selection by examining the change in the flavour choice probability vector that occurs with a change in purchase quantity. Note that this vector of flavour choice probabilities remains the same for all items purchased on a given shopping occasion. In this respect, our approach may be thought of as zero-order within-trip. In contrast to Harlam and Lodish (1995), no choice probabilities are affected by other flavour selections made on the same shopping trip. Given that the item-selection sequences are not revealed in scanner panel data, we feel that this is an appropriate modelling approach.

Brand choice model

The upper part of the nested logit tree is the brand choice model. The probability that household h buys brand i at time t, conditional on a purchase in the category is given by

$$P_t^h(i) = \frac{\exp(U_{it}^h)}{\sum_k \exp(U_{kt}^h)} \tag{6}$$

where the deterministic component of the utility is

$$U_{it}^h = u_i + \gamma \mathbf{Z}_{it}^h \tag{7}$$

Along with a vector of marketing and household-specific variables $\mathbf{Z}_{it}^h$, the model includes brand-specific intercepts u_i and a vector of response coefficients γ to be estimated.

Since the flavour choice model is nested within the brand choice model, one of the explanatory variables in equation (7) will be the inclusive value from the flavour choice model. We label the inclusive value *brand variant attractiveness*, or BVA_{it}^h. This variable is the maximum expected utility available to household h from buying a variety or flavour within brand i on purchase occasion t. Mathematically, this is equal to the log of the denominator of the flavour choice probability (McFadden, 1981; Ben-Akiva and Lerman, 1985), or

$$BVA_{it}^h = \ln\left[\sum_{v' \in i} \exp(VU_{iv't}^h)\right] \tag{8}$$

The nested logit model is derived from a theory of stochastic utility maximization and has been applied to a number of marketing problems (e.g. Kannan and Wright, 1991; Grover and Srinivasan, 1992; Bucklin and Gupta, 1992). It also provides a natural link between the consumer's flavour choice and brand choice decisions. Like the conditional flavour choice probabilities, $P_t^h(v \mid i, q_t^h)$, the brand choice probabilities, $P_t^h(i \mid q_t^h)$, are also zero-order within-trip (i.e. they remain constant across all items purchased on a given shopping occasion).

Model estimation

We use maximum likelihood to estimate the parameters of the model. To form the likelihood function for a given household, we consider all the shopping trips made by the household for which a category purchase is made. Within each trip, the information entering the likelihood function involves the number of units purchased, and the brands and varieties of each unit selected. Since our model is zero-order within-trip, the brand and flavour components of the likelihood are constant across items at a given purchase occasion. This approach leads to the following likelihood function specification for the household's purchase history:

$$L^h = \prod_t \left[\prod_i \prod_v \{P_t^h(v \mid i)\}^{q_{ivt}^h} \right] \left[\prod_i \{P_t^h(i)\}^{q_{it}^h} \} \right] [P_t^h(Q_t^h = q_t^h)] \tag{9}$$

where q_t^h is the category quantity, q_{it}^h is the brand i quantity, and q_{ivt}^h is the quantity of variety v of brand i, all bought by household h on shopping trip t. Here

$$\sum_{v \in i} q_{ivt}^h = q_{it}^h \quad \text{and} \quad \sum_i q_{it}^h = q_t^h$$

Equation (9) specifies that information about the brand and flavour of *each individual item* purchased (e.g. tubs of yogurt, jars of baby food) enters the likelihood function. Note, however, that our likelihood specification does not vary within a panelist's store visit (unlike the specification proposed by Harlam and Lodish, 1995).

For estimation, we use the log likelihood function taken over all households in the sample. The final log likelihood used in model estimation is given by

$$LL = \sum_h \ln L^h \tag{10}$$

We use the Davidon–Fletcher–Powell algorithm in GQOPT to maximize the log likelihood function and obtain parameter estimates and standard errors. All parameters are estimated simultaneously.

APPLICATION

In this section we present an application of our model using scanner panel data for the yogurt category. We begin by describing the characteristics of the data set. Next, we specify variables for each of the three model components. This is followed by the estimation results.

Data

The data for this study are drawn from the A. C. Nielsen scanner panel records for households in Sioux Falls, South Dakota, for the period 1986–1988. The last 52 weeks of the data were used for model calibration and the preceding 61 weeks for initializing model variables. Households were qualified for inclusion in the sample if they made 10 or more purchases of yogurt during the initialization and calibration periods (113 weeks). Out of the qualified households, 300 were randomly selected for model calibration. Over the course of the 52-week calibration period, the sample of 300 households made a total of 30,791 store trips across 13 stores in Sioux Falls. A total of 3215 store trips resulted in yogurt category purchases of which 82% were for multiple units.

We limited our study to the top-seven selling yogurt brands in the Sioux Falls market. Together, these accounted for 84% of category sales in dollars, and 89% in units. These brands, their market shares by units, and average prices are given below:

Brand	*Market share*	*Average price (cents)*
Nordica	0.22	39.1
Yoplait	0.19	58.1
Private Label	0.14	36.7
Dannon	0.11	67.1
W.B.B.	0.09	41.1
Weight Watcher's	0.07	60.8
QC	0.07	35.8

The private-label brand is offered in one chain of stores only. Each brand was offered in one size with all brands available in 8-oz containers except for Yoplait and Nordica, which were available in a 6-oz container. Each of these yogurt brands offered multiple flavours with a high degree of overlap across brands. We included flavours in the analysis that either exceeded 2% of the overall market or accounted for more than 10% of a single brand's sales. This resulted in a total of 18 different flavours for the study. Table I presents the unit market share for these 18 flavours computed over the estimation sample.

Model variables

We now turn to the specification of variables for the three components of our model.

Category quantity

The Poisson parameter for household h on purchase occasion t is given by

$$\lambda_t^h = \exp(\theta_0 + \theta_1 PR^h + \theta_2 CPRICE_t^h + \theta_3 CPROMO_t^h) \tag{11}$$

where

PR^h = historical purchase rate for household h
$CPRICE_t^h$ = category price level for household h at time t
$CPROMO_t^h$ = category promotion level for household h at time t
$\theta_0, \theta_1, \ldots, \theta_3$ = parameters to be estimated.

Table I. Share of yogurt flavours in the calibration data

Flavour	% share	Flavour	% share
Strawberry	15.2	Cherry	3.4
Raspberry	15.1	Pina colada	2.8
Peach	9.2	Orange	2.5
Blueberry	8.7	Cherry vanilla	2.3
Mixed berry	8.4	Plain	2.0
Black cherry	8.4	Boysenberry	2.0
Strawberry-banana	7.8	Dutch apple	1.5
Vanilla	4.3	Apple Granola	1.5
Lemon	4.2	Banana	0.7

Purchase rate, PR^h, is defined as the average number of units of yogurt purchased by household h, given that a yogurt purchase was made on a shopping trip. It is computed as the total number of units purchased in the initialization period divided by the number of yogurt purchase occasions (trips with a category purchase). This variable is designed to capture heterogeneity in purchase quantity across households. A household with a high purchase rate is likely to buy more units on a given purchase occasion than a household with a low purchase rate. We expect θ_1 to be positive.

We define category price, $CPRICE^h_t$, and category promotion, $CPROMO^h_t$, as weighted averages of brand prices and promotions at time t. We use household-specific brand loyalties, BL^h_{iv}, as weights, rather than market-level brand shares, in order to obtain more precise household-level estimates of these variables. The variables are computed as

$$CPRICE^h_t = \sum_i BL^h_i \times PRICE_{it} \tag{12}$$

$$CPROMO^h_t = \sum_i BL^h_i \times PROMO_{it} \tag{13}$$

Brand loyalties, brand prices, and promotion are more specifically defined in the brand choice section below. The household-specific weighting implies that the price and promotion activity of more preferred brands will have a greater effect on the category quantity decision than the activity of less preferred brands. We expect θ_2 to be negative and θ_3 to be positive.

Flavour choice

We model the brand-variety utility for household h, brand i, variety v at time t as

$$VU^h_{ivt} = \alpha_{iv} + (\beta_1 + \beta_2(q^h_t - \bar{q}^h))BVLOY^h_{iv} + \beta_3 LVP^h_{ivt} \tag{14}$$

where

$BVLOY^h_{iv}$ = brand-variety loyalty of household h for brand i's variety v
q^h_t = category quantity for household h at time t
$\bar{q}^h$ = average category quantity previously purchased by household h
LVP^h_{ivt} = 1 if brand-variety iv was selected on the last purchase occasion and 0 otherwise
$\{\alpha_{iv}\}$, β_1, β_2, β_3 = parameters to be estimated.

Brand-variety loyalty, $BVLOY^h_{iv}$, is a household-specific variable designed to capture heterogeneity in households' preferences for different brand-variety combinations. Analogous to the loyalty variable used in logit brand choice models, this variable is computed based on the actual purchases households make in the initialization period. Because of the large number of brand-variety combinations and sometimes limited number of purchases per household, a simple within-household share measure for $BVLOY^h_{iv}$ is unstable. To add stability to the measure, we create this variable as follows. First, we compute a variety loyalty variable, $VLOY^h_v$, *across all brands* using the within-household flavour shares in the initialization period. We then compute $BVLOY^h_{iv}$ by using $VLOY^h_v$ as a prior with the expression

$$BVLOY^h_{iv} = \frac{VLOY^h_v + r^h_{iv}}{1 + r^h_i} \tag{15}$$

where r_{iv}^h is the number of units of brand i, variety v purchased by household h and r_i^h is the total number of units of brand i purchased, both from the initialization period, and

$$r_i^h = \sum_v r_{iv}^h$$

This formulation is equivalent to using a Dirichlet prior with a sample size of one.

As explained in the previous section, the second term in equation (14) incorporates the effect of quantity on flavour choice via the increase or decrease in the net impact of flavour loyalties on utility. A panelist who buys above-average quantity on a purchase occasion is expected to seek a wider assortment while a panelist who buys a below-average quantity is expected to seek a narrower assortment. A negative β_2 will confirm this hypothesis.

We also include an indicator variable for whether or not the brand-variety was among those selected at the panelist's previous purchase occasion. A negative sign for β_3 could indicate that variety-seeking behaviour was taking place across purchase occasions. However, Simonson and Winer (1992) note that variety seeking is unlikely to be observed in the yogurt category due to the long duration of average interpurchase times. Finally, marketing variables are not included in the flavour choice model for yogurt since all flavours within a brand are priced and promoted together.[3]

Brand choice

We specify the deterministic component of utility for brand i at time t as

$$U_{it}^h = u_i + \gamma_1 BL_i^h + \gamma_2 LBP_{it}^h + \gamma_3 PRICE_{it} + \gamma_4 PROMO_{it} + \gamma_5 BVA_{it}^h \tag{16}$$

where

BL_i^h = loyalty of household h to brand i
LBP_{it}^h = 1 if brand i was purchased last time, 0 otherwise
$PRICE_{it}$ = shelf price of brand i at time t
$PROMO_{it}$ = promotional status of brand i at time t
$\{u_i\}, \gamma_1, \ldots, \gamma_5$ = parameters to be estimated.

Brand loyalty and last brand purchased are household-specific variables, while price and promotion are store-specific variables. BL_i^h is computed as the within-household market share of each brand during the 61-week initialization period. Note that brand loyalty varies across households but remains constant for a given household across time, capturing cross-sectional heterogeneity.[4] Last brand purchased is the time-varying component of a household's preference and is designed to capture purchase event feedback. Our measure for price, $PRICE_{it}$, is the actual shelf price of the brand (including temporary discounts) in cents per ounce. Our measure for promotional status, $PROMO_{it}$, is an indicator variable set equal to one if the brand is featured or displayed on occasion t and zero otherwise. We expect a negative sign for price and a positive sign for promotion.

[3] When a variable shares an identical value for all the alternatives in a logit model, it has no effect on the choice probabilities since it cancels from the numerator and denominator.
[4] Other methods of handling heterogeneity have appeared in the marketing literature (e.g. Kamakura and Russell, 1989; Rossi and Allenby, 1993). We choose to capture heterogeneity via the brand loyalty term (Guadagni and Little, 1983) because of the robustness of this approach.

In the nested logit framework, the attractiveness of brand i (due to the utility derived by a household from the various flavours available for that brand) is captured by brand variant attractiveness, BVA_{it}^{h}. As discussed earlier, brand variant attractiveness is equal to the log of the denominator of the flavour choice probability. To be consistent with stochastic utility theory, the estimated parameter for brand variant attractiveness, γ_5, should lie between zero and one (Ben-Akiva and Lerman, 1985).

Testing the brand–flavour hierarchy

Our nested model assumes a brand–flavour hierarchy where flavours are nested within the brands. This is consistent with the assumption that consumers first decide on which brand to buy and then decide on the flavours within that brand. The choice hierarchy, however, could be reversed, i.e. it may be flavour $\rightarrow$ brand in which brands are nested within the flavours. To test these alternative structures, we estimated two nested logit models consistent with each of the hierarchies. For purposes of this analysis, we did not include the purchase quantity component of the model or the effect of purchase quantity on flavour choice (i.e. β_2 in equation (14) was constrained to zero).

In order to make the two nested logits directly comparable in the information entering the estimation, two slight modifications were made to model variables. Variety loyalty was used in place of brand-variety loyalty and last variety purchased became non-brand-specific. This permits the flavour/variety choice model of equation (14) to make sense in either the top or bottom of the nested logit hierarchy. Both models have a total of 30 parameters each: six brand-specific constants, 17 flavour-specific constants, two flavour utility parameters, four brand utility parameters, and a parameter for inclusive value (which is either brand attractiveness or flavour attractiveness). The brand–flavour hierarchy fit the data better than the flavour–brand hierarchy with log likelihood values of $-30{,}708.8$ and $-30{,}788.9$, respectively. This provides empirical support for the hierarchy we use in the nested logit (see Ben-Akiva and Lerman, 1985).

Estimation results

We present the parameter estimates and fit of the proposed model in Table II. We also present results from estimation of a nested model that omits the effect of category quantity on flavour choice (i.e. constrains β_2 to zero). The results indicate that the proposed model, with one additional parameter, fits the data significantly better than the nested model ($\chi_1^2 = 163.8$, $p < 0.001$). In other words, incorporating the effect of purchase quantity on flavour choice significantly improves the model.

Table II also shows that all model parameters are in the hypothesized direction and are statistically significant. The brand variant attractiveness parameter, γ_5, also satisfies the stochastic utility theory constraint of falling between zero and one, indicating that the nested logit specification is an appropriate representation of the choice behaviour. No constraints were imposed in the estimation of the brand variant attractiveness parameter, γ_5.

The household heterogeneity variables (purchase rate, brand loyalty, and brand-variety loyalty) have the largest t-values, indicating that there is considerable heterogeneity in households' purchase rates, brand preferences, and flavour preferences. Brand prices and promotions have a significant impact on both brand choice and category purchase quantity. Most importantly for our purposes, category quantity has a significant effect on flavour choice ($\beta_2 = -0.421$, $t = -12.40$). The negative coefficient indicates that a purchase of above-average quantity shrinks

Table II. Parameter estimates for the proposed and nested model[a]

Variables	Proposed model Parameters	Proposed model *t*-values	Nested model Parameters	Nested model *t*-values
1. Category quantity model				
θ_1 (purchase rate)	0.263	22.62	0.263	22.61
θ_2 (category price)	−0.034	−6.34	−0.034	−6.30
θ_3 (category promotion)	0.073	3.40	0.073	3.40
2. Brand choice model				
γ_1 (brand loyalty)	2.071	31.71	2.052	31.67
γ_2 (last brand purchased)	1.062	22.86	0.992	20.89
γ_3 (brand price)	−0.548	−18.39	−0.554	−18.47
γ_4 (brand promotion)	1.264	22.90	1.250	22.54
γ_5 (brand variant attractiveness)	0.658	9.12	0.821	10.74
3. Variety/flavour choice model				
β_1 (brand-variety loyalty)	4.027	55.12	3.656	55.65
β_2 (effect of category quantity on variety choice)	−0.421	−12.40		
β_3 (last variety purchased)	1.137	36.95	1.151	37.17
Log-likelihood	−32,267.4		−32,349.3	

[a] Model constants are not presented.

flavour choice towards less-preferred flavours, thereby expanding the assortment selection that is predicted by the model.

The magnitude of the parameter estimates for β_1 and β_2 also provide some insight into the workings of the quantity–assortment phenomenon. The ratio β_1/β_2 gives the number of units above the panelist's average that need to be purchased before brand-variety loyalty no longer has an impact on choice. In this case $\beta_1/\beta_2 = -9.57$, indicating that a panelist would need to buy approximately 10 units of yogurt above his or her average in order for the term $\beta_1 + \beta_2(q_t^h - \bar{q}^h)$ to become zero and cause idiosyncratic preferences to become irrelevant. In this data set the average number of units bought at a purchase occasion is a little under three and purchases of more than nine tubs are extremely rare. Thus, the scale of the assortment effect, as captured by the estimated model parameters, appears reasonable.

Forecasting performance

The foregoing results on the effect of purchase quantity on assortment choice were obtained by calibrating the nested logit component of the model using actual purchase quantity, q_t^h. Thus, the model as developed thus far is *conditional* on knowing purchase quantity. From a forecasting perspective, however, actual purchase quantities are not known and would have to be estimated based on anticipated changes in marketing activity (e.g. price and promotion) or other aspects of the shopping situation (e.g. holidays, seasonal events, store-wide promotions, etc.). This raises the question of how well the assortment effect could be captured by an unconditional model.

To investigate this, we divided the 52-week estimation period into two parts: a 39-week calibration period and a 13-week hold-out period. We re-estimated all model parameters using only the purchases occurring in the 39-week period. (They remained substantially the same for both the proposed and null models.) We then proceeded to use the new model parameters to forecast sales in the hold-out period.

To assess the model's forecasting performance we used the following procedure. First, the parameters from the Poisson regression component of the model were used to generate the probability vector for the number of units purchased on each occasion. A random draw from this vector provided the forecast number of units bought on that occasion, $\hat{q}_t^h$. Second, in our proposed model, this predicted quantity was used in the flavour choice model in the adjusted $BVLOY$ term with the parameter β_2. This step is not needed for the null model, since quantity does not enter the flavour choice component. Third, following equation (1), we then multiplied $\hat{q}_t^h$ by the predicted brand and flavour choice probabilities to obtain the predicted number of units for each brand-flavour, $\hat{q}_{ivt}^h$. To ensure that the forecasts did not depend on any information available on actual purchases, the last brand purchased and last variety purchased variables, LBP_{it}^h and LVP_{vt}^h, were also generated by random draws from the respective probability vectors. For both the null and proposed models, we used a Monte Carlo procedure, repeating the forecast period simulation 100 times.

We assessed the performance of the unconditional model in the hold-out period using three model fit criteria: (1) log likelihood, (2) mean squared error (MSE), and (3) mean absolute deviation (MAD). Likelihood values were computed over the observations in the hold-out sample using the parameters from the 39-week period estimation and the expected quantities obtained from the Poisson regression. MSE and MAD were computed for the same time period as follows:

$$\text{MSE} = \frac{1}{T}\sum_t \frac{1}{BV}\sum_{i,v}(\hat{q}_{ivt}^h - q_{ivt}^h)^2$$

$$\text{MAD} = \frac{1}{T}\sum_t \frac{1}{BV}\sum_{i,v} |(\hat{q}_{ivt}^h - q_{ivt}^h)|$$

where T is the number of trips in the hold-out period (885) and BV is the total number of brand-varieties available on occasion t. We contrast the performance of the proposed model with that of the null model with no quantity-assortment effect. In Table III, we report the results of the forecast comparison of the two models. The reported values are averages from the 100 Monte Carlo simulations. According to each fit criterion, the proposed model provides better hold-out forecasts than the null model.

QUANTIFYING THE ASSORTMENT EFFECT

In this section we discuss how the model may be used to quantify the assortment effect on product mix demand. To illustrate how the model can be used to predict changes in assortment

Table III. Model performance in hold-out period forecasting

Fit criterion	Proposed model	Nested model
Log-likelihood	−10,235.2	−10,271.3
Mean squared error (MSE)	0.140	0.146
Mean absolute deviation (MAD)	0.095	0.097

Table IV. Flavour choice probabilities from nested and null models

Flavour	$P_t^h(v \mid i, q_t^h)$ estimated by Proposed model	Nested model
Strawberry	0.073	0.062
Raspberry	0.048	0.037
Blueberry	0.050	0.040
Mixed berry	0.053	0.040
Peach	0.065	0.054
Strawberry-banana	0.057	0.044
Black cherry	0.535	0.617
Boysenberry	0.026	0.020
Cherry	0.063	0.062
Vanilla	0.030	0.022

demand, we begin by examining the flavour choice probabilities of a randomly selected panellist on one of his or her purchase occasions. On this occasion, the expected quantity obtained from the Poisson regression is approximately three units higher than the average quantity (i.e. $\hat{q}_t^h - \bar{q}^h = 2.96$). In Table IV, we present the choice probabilities predicted by the proposed model and by the nested null model.

A comparison of the probabilities predicted by the two models illustrates the impact of taking into account the above-average quantity purchased at this occasion. The choice probability for the most preferred flavour, black cherry, is substantially reduced while the difference is redistributed across the other available flavours.[5]

While the above illustrates how the model works to obtain improved predictions at the level of the individual transaction, the potential value of the model to retailers and manufacturers lies in its ability to provide forecasts *aggregated* over large numbers of panelists. For purposes of illustration, we show how the model can be used to predict the changes in relative item demand when a substantial increase in purchase quantity is anticipated (e.g. due to a large promotional event such as a two-for-one offer or due to seasonal or holiday-related spikes in demand). To do this, we simulated a 50% increase in purchase quantity across all shopping occasions in the estimation sample.[6] For example, if a shopper had actually purchased four units, $q_t^h = 4$, we substituted a purchase quantity of six units, $q_t^h = 6$. This illustrates how much item sales proportions would be altered if there were to be a substantial, but not enormous, increase in category unit sales.

In Table V, we report results from this simulation for the 18 flavours and the brand–flavour combinations for the top-two selling brands, Yoplait and Nordica. The results show modest changes in the share positions for the flavours. As one would expect, higher-share flavours tend to lose sales to lower market-share flavours. Although the absolute change in market share is largest for the biggest flavours, the percentage impact is greater for the smallest flavours.

[5] Note that 10 flavour choice probabilities are reported, not the full 18 capable of being handled. Because the brand chosen stocked only these flavours in the store visited, other flavours did not enter the choice set and therefore have choice probabilities equal to zero.

[6] One could also simulate the assortment effect via a price or promotion change. Our illustration is intended to be a straightforward way of measuring the effect when a very large promotion is able to influence *category quantity*.

Table V. Impact of category quantity on flavour and brand choice

Flavour	Fitted share based on actual quantity	Fitted share based on 50% increase in quantity	% change in share
(A) Flavours			
Strawberry	15.04	14.57	−3.11
Raspberry	15.40	14.63	−5.02
Peach	9.04	9.23	2.03
Blueberry	8.47	8.50	0.24
Mixed berry	8.15	8.22	0.86
Black cherry	7.92	7.88	−0.44
Strawberry-banana	7.65	7.95	3.91
Vanilla	4.60	4.51	−1.85
Lemon	4.85	4.79	−1.13
Cherry	3.52	3.52	−0.11
Pina colada	2.75	2.91	5.77
Orange	2.30	2.26	−1.18
Cherry vanilla	2.46	2.65	7.47
Plain	2.03	2.13	4.62
Boysenberry	1.98	2.10	6.00
Dutch Apple	1.68	1.82	8.29
Apple Granola	1.47	1.61	9.44
Banana	0.67	0.71	6.00
(B) Brand–flavour combinations			
Yoplait Raspberry	17.00	16.03	−5.71
Yoplait Strawberry	15.48	14.87	−3.94
Yoplait Lemon	9.00	8.97	−0.33
Yoplait Blueberry	9.08	9.02	−0.66
Yoplait Strawberry-banana	7.83	8.28	5.75
Yoplait Plain	7.07	7.38	4.38
Yoplait Mixed Berry	7.17	7.26	1.26
Yoplait cherry	7.86	7.43	−5.47
Yoplait Peach	5.71	5.96	4.38
Yoplait Cherry Vanilla	5.44	5.77	6.07
Yoplait Apple Granola	3.60	3.93	9.17
Yoplait Banana	2.32	2.47	6.47
Yoplait Boysenberry	2.45	2.64	7.55
Nordica Strawberry	16.39	15.97	−2.56
Nordica Raspberry	16.31	15.51	−4.90
Nordica Mixed Berry	12.67	12.66	−0.08
Nordica Black Cherry	11.58	11.58	0.00
Nordica Strawberry-Banana	11.45	11.79	2.97
Nordica Peach	11.23	11.40	1.51
Nordica Blueberry	8.88	8.90	0.23
Nordica Cherry	3.93	4.15	5.60
Nordica Vanilla	3.93	4.19	6.62
Nordica Boysenberry	3.62	3.86	6.63

In panel (A) of Table V, the effects are computed across brands. Since manufacturers and retailers also need to assess the impact of shifting flavour positions within brands, we also report these for Yoplait and Nordica in panel (B) of Table V. The pattern of results again shows bigger flavours losing share and smaller flavours gaining share. Thus, the model may be used as an input to the production and ordering decisions of manufacturers and retailers. This information could be particularly valuable in perishable product categories (i.e. refrigerated products such as yogurt and, to a lesser extent, frozen products such as ice cream or prepared entrées). While all categories share the problem that ordering too little of a particular item risks an out-of-stock condition, perishable products have the additional problem that ordering too much risks spoilage.

CONCLUSION

In this study we have developed and illustrated a model that integrates the consumer's category purchase quantity decision with the selection of product assortment at the point of sale. Our quantity model is based on a truncated Poisson regression and our assortment representation is based on a nested logit model of brand and variety choice. We model the flavour/variety choice decision to depend upon the consumer's quantity decision: above-average quantity increases the predicted assortment of items a panelist selects while below-average quantity decreases the predicted assortment.

In an application to 300 panelists purchasing in the yogurt category, we compare the fit of our proposed model (purchase quantity affects flavour choice) versus the fit of a nested null model (purchase quantity constrained to have no effect on flavour choice). The proposed model fits the data significantly better than the nested model and the additional estimated parameter is correctly signed and strongly significant. We also present results from a hold-out forecast in which the model predictions are not conditional on known purchase quantities. Again, the proposed model provides a better fit than the null model.

A key feature of our modelling approach is the representation of assortment based on the estimated consumer choice probabilities for flavours or varieties. In our approach, we capture assortment by the dispersion in the elements of the predicted choice probability vector. The dispersion in probabilities—and therefore the breadth of assortment demanded—may be easily examined. This approach permits us to take advantage of the parsimony and robustness of a probabilistic choice model and to examine the assortment phenomenon alongside other factors influencing item sales.

Our approach to modelling assortment and assessing the magnitude of the quantity–assortment effect is based on changes occuring to the vector of flavour choice probabilities. If changes in quantity have no impact on these probabilities, then we maintain that there is no 'assortment effect'. Even though there is no assortment effect taking place, the expected number of flavours that a panelist will buy on a shopping occasion increases with purchase quantity. (See, for example, the scanner data measures used by Simonson and Winer, 1992, and Walsh, 1995.) This is simply because the purchase of more units means more draws from the multinomial distribution, raising the likelihood of *observing* the selection of less-preferred flavours on a given purchase occasion.

Models that predict assortment selection should carefully distinguish between the 'draws from the urn effect' and the change in consumer preferences that is related to a change in purchase quantity. Models which do not make this distinction may overstate the magnitude of the assortment effect or suggest that it is present when in fact it is not. While our modelling results strongly support the *theories* advanced by previous researchers (Simonson, 1990; Walsh, 1995), they also validate and quantify the effect in secondary data via an approach that avoids the potential problem of the 'draws from the urn' effect.

Simonson (1993) suggests that a manufacturer may be able to use promotions to disproportionately increase the sales of slower-selling variants. Our findings show that the size of the assortment effect in the yogurt category is modest even with a 50% increase in total quantity bought. Thus, managers may not be able to use the assortment effect to appreciably increase the sales of less popular varieties. Although assortment effects are small in this yogurt data set, effects could be larger in other product categories. An intended contribution of this research is to provide investigators with a tool for forecasting this effect in their specific categories and markets of interest.

We consider our efforts to bring the behavioural phenomenon of 'assortment seeking' into a model of consumer choice analogous to the first attempts to model the impact of variety-seeking behaviour on preference and choice. Like the early development of the variety-seeking literature, we hope that this study will stimulate further modelling work on the assortment phenomenon. We also hope that it will lead to further work to bring additional aspects of consumer behaviour into probabilistic choice models. One particular issue that we have left for future research is the modelling of 'brand assortment' in addition to that of flavour/variety assortment. Potentially interesting categories in which to investigate brand and variety assortment include ready-to-eat cereals and premium varietal wines.

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