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The Impact of Promotion and Advertising: A Latent Class Approach

Timothy J. Richards

ABSTRACT

Typically, marketers define market segments by their demographic characteristics, assuming that these segments represent consumers with relatively homogeneous buying patterns. A more managerially useful definition, however, groups consumers of similar behavior directly and then seeks to find demographic commonalities among them. This study uses a latent class analysis technique to segment consumers based on their responsiveness to a set of marketing variables, finding that a multiple-segment model provides a better fit to the data, and that these segments differ significantly in their responsiveness. By targeting marketing activities to their most responsive segments, the efficiency of commodity promotion can be dramatically improved.

Key Words: *advertising, apple, demand, latent class analysis, multinomial logit, segmentation.*

By segmenting a market into groups of relatively homogeneous consumers, marketing managers hope to be able to increase the efficiency of promotional programs directed towards those segments. However, the usefulness of this method relies upon the implicit assumption that consumers that share similar demographic profiles also share similar buying habits. In many cases this is clearly a very strong assumption and one that is not likely to hold up to deeper scrutiny. It would seem more logical, if behavior is of primary interest, to segment consumers on the basis of similar behaviors and then search for any demographic commonalities among them. The ability to segment consumers directly into groups that respond similarly to various marketing tools (price, promotion, advertising) is even more powerful if these segments are defined specific to their decision-stage.

It is now common in the marketing research literature to differentiate between the three decisions consumers make when purchasing a branded consumer product: when to buy (category choice), what to buy (brand choice), and how much to buy (purchase quantity) (Gupta 1988). However, the particular methods used in this literature, and the insights they allow, have not been used to gain a greater understanding of consumers' choice from among different categories of perishable products and from among varieties within those categories. In particular, fresh fruit is one of the most profitable departments in a retail grocery store, so this knowledge is becoming critical as overall store margins come under increasing pressure. In many respects a consumer's choice among fruits is analogous to the choice of branded products. On each trip to the store consumers must decide whether to buy a particular type of fruit or not, and if they

Timothy J. Richards is Associate Professor, Morrison School of Agribusiness, Arizona State University East.
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do what particular variety to buy. The focus of this study is on the decision of whether to buy apples, and conditional on the choice of apples, whether to buy Red Delicious, Golden Delicious, Granny Smith, or some other variety. Recently, studies of branded product choice have refined this multi-stage approach to identify segments of consumers that appear to be similar in their response to the usual set of marketing variables.

Because unique response-segments are likely to exist at each stage, it is necessary to both estimate the size and membership in these segments as well as estimate the response parameters in each (Bucklin, Gupta, and Siddarth). Several studies demonstrate the usefulness in estimating market segment sizes and unique segment-specific response parameters using household scanner data for consumer packaged-product purchases (Grover and Srinivasan 1987; Kamakura and Russell; Bucklin and Lattin; Bucklin and Gupta; Grover and Srinivasan 1992; Krishnamurthi and Raj; Bucklin, Gupta and Han; Bucklin, Gupta and Siddarth). However, none of this work addresses the unique characteristics of fresh fruit. Perishability, frequency of purchase, variable quality and a lack of true brands are each likely to influence consumers' choice between varieties of a particular fruit and the decision to buy a particular type of fruit on each trip to the store. This type of analysis is now possible with the development of household scanner panel data sets for what were once nonscanable products.

The objectives of this research are, therefore, to first determine whether there exist segments of fruit consumers whose members respond similarly to marketing variables such as price, promotion, and advertising. If such segments exist, a second objective is to determine the factors that drive the choice of a particular type of fruit (category choice) and fruit variety (variety choice) within each segment. By estimating the probability that each household belongs to each segment, this research also determines segment membership and, using household demographic data, describes each segment's typical demographic profile. Ultimately, therefore, the overall objective of this research is to establish and demonstrate a method of evaluating the effectiveness of promotion in a managerially relevant way.

To this end the paper begins with an explanation of the empirical model of variety and category choice and introduces the notion of multiple response segments. The next section describes the methods required to estimate this model as well as the particular determinants of choice at each stage. A third section describes the household scanner data used to demonstrate our particular application of this method to apple-variety and fruit-category choice. The fourth section presents results from estimating the model and provides a discussion of their relevance to marketing managers. A final section provides some conclusions and implications for how these methods of analysis may be able to improve the effectiveness of commodity promotion.

An Empirical Model of Variety Choice, Category Choice and Market Segmentation

The underlying rationale for separating variety choice from category choice, or the timing of category purchase, is the realization that consumer behavior is likely to differ according to the stage of the decision-making process. In particular, many argue (Tellis; Bucklin and Gupta; Dillon and Gupta) that the probability of a consumer buying within a category of products (ie. bananas or apples) depends upon a different set of factors than those that determine the probability of variety choice. These authors show that while the former may be determined by a real or perceived need as measured by such things as family size, inventory level, or the intensity of category advertising, the latter is more likely to reflect prices, promotion, tastes or loyalties. By applying the approach taken by Bucklin and Gupta in estimating a nested discrete choice model of fruit category and choice of apple variety, this study tests whether these factors are also important to a different type of product than previously considered. Despite the advantage of obtaining unique parameters for each decision, many of these authors assume (somewhat implausibly) that different consumers share a common vector of response parameters.

Rather, it is more likely that a market consists of groups, or segments of consumers who are relatively similar to each other in how they respond to marketing variables such as prices, price-promotions, or advertising campaigns. Being able to identify these segments promises not only a more accurate characterization of the market, but is also far more useful to marketing managers who are attempting to target consumer segments for various marketing campaigns. The problem is, therefore, how to identify these segments? Because consumers' response parameters are unobservable *a priori,* segments of homogeneous consumers are also unobservable or "latent classes" (Grover and Srinivasan 1987; Lazarsfeld and Henry). By using a finite mixture estimation method (Titterington, Smith, and Makov), the probability that a household belongs to each latent class becomes a parameter that can be estimated. Irrespective of how segment membership is estimated, the multiple-segment approach is being used extensively in the consumer packaged-goods literature. However, there are many reasons to believe that the packaged-goods results will not necessarily hold for the case of fruit purchases, thus providing a motivation for this research.

First, marketers of consumer goods are better able to build strong brand awareness and loyalty through promotion and advertising programs. Further, they are often able to maintain such brand equity by monitoring and controlling product quality and providing a consistent, year-round supply of the good. Fruit sales, on the other hand, are subject to wide variations in quality due to changes in growing conditions, fluctuations in supply driven by both seasonality and weather, and the inherent variability of taste and appearance of a grown as opposed to a manufactured product. Although each of these features makes branding fruit and establishing customer loyalty certainly more difficult, it is not impossible. Second, fruits are, in general, highly perishable foods. As such, long-term inventory behavior is not likely to be an issue, but short-term consumption rate and stockpiling are. For example, it may be the case that visits to the produce aisle are driven by the need to buy more bananas (a highly perishable fruit), but apples are not purchased because the existing stock is still viable. Third, fruit is not often promoted directly by the manufacturer (grower), but usually by a distributor, commodity association, or grower cooperative. Each of these unique qualities means that the body of accepted results found in the packaged-goods segmentation literature may not apply to fruit marketing. On the other hand, consumer demand studies that address the peculiarities of fruit demand using a utility-maximization demand-system approach are typically conducted at an aggregate level, thereby ignoring most of the insights provided by the variety choice/category choice approach (Lee, Brown, and Seale; Alston *et al.*). Consequently, an empirical model that retains both the theoretical consistency of more aggregate models and the power of individual choice models is preferred.

Specifically, the variety choice model developed here builds upon McFadden's (1974) random-utility assumption and, as such, is very similar to random-utility models of brand choice such as Guadagni and Little, or Bucklin and Gupta or the Christmas tree choice model of Davis and Wohlgenant. While this study follows Grover and Srinivasan (1987, 1989, 1992); Bucklin and Gupta; and Dillon and Gupta in developing a model of choice where consumers belong to one of several mutually exclusive response segments, the economic model initially assumes only one segment for clarity of exposition. For this single response-segment, the random-utility model assumes that a consumer faces a choice between goods that are effectively perfect substitutes. With linear indifference curves, the usual income-constrained utility-maximization process guarantees that only one of the goods will be purchased (Deaton and Muellbauer; Pudney). The empirical model, therefore, seeks to explain the probability that a consumer chooses the particular variety $i \in I$ of fruit $k \in K$ that provides maximum utility from discrete alternatives within each set of I (varieties) and K

(fruits). If consumers choose sequentially from among product categories, and then from within each category according to the multistage budgeting process of Gorman, the total probability that a consumer chooses variety i from category k is the product of the conditional probability of choosing i given k and the marginal probability of choosing category k. Therefore, the unconditional probability of household h choosing variety i from category k at time t is given by:

$$(1) \qquad P_t^h(i, k) = P_t^h(i|k)P_t^h(k),$$

where $P_t^h(k)$ is the probability of buying fruit from category k on a given shopping trip t, and $P_t^h(i|k)$ is the probability of purchasing variety i conditional on the choice of category k. Because the probability of each variety and category choice is determined by the relative utility derived from each compared to its alternatives, implementing (1) requires the definition of formal random utility models at each decision stage.

While the logic underlying discrete choice models is common to both the economics and marketing literature, the specification of utility functions differs greatly. Models appearing in the marketing literature tend to go beyond prices and expenditure to include factors that are more intimately related to the actual decision being made, and thus provide insight into consumers' decision-making processes that are unavailable to standard economic models. For example, whereas the probability of buying a particular category of goods is determined by factors related to a household's need or ability to purchase (income, inventory level, recent purchase history, or generic advertising), variety choices are more likely to be influenced by variables such as relative prices, variety preference, variety loyalty, or retail promotions (Dillon and Gupta).

Of the various models of probabalistic choice, the nested multinomial logit model (NMNL) of McFadden (1981) provides an approach that is both consistent with the logic of fruit-buying as a two-stage decision process, akin to Gorman's budget-tree, and avoids the implausible "independence of irrelevant alternatives" (IIA) property of single-stage multinomial logit models (Currim).[1] To understand the logic of the NMNL model, suppose that a household gains utility from choosing both a type or category of fruit and then from a particular variety of fruit in a hierarchical structure. Assuming that the household's utility is composed of a deterministic and random component, the total utility from both choices is given by:

$$(2) \qquad U_{ik}^h = V_{ik}^h + \epsilon_{ik}^h = u_{ik} + \beta_i' \boldsymbol{X}_{ik}^h + \alpha_i \boldsymbol{Y}_k^h + \epsilon_{ik}^h,$$

where u_{ik} represents a choice-specific preference parameter, $\boldsymbol{X}_{ik}^h$ consists of a set of household and variety attributes that can vary by product category, $\boldsymbol{Y}_k^h$ is a set of category-specific variables, and ϵ_{ik}^h is a random error term. Assuming this error term is type I extreme value distributed at each stage (McFadden 1981), the conditional variety-choice probability in (1) is written as:

$$(3) \qquad P^h(i|k) = \frac{\exp(\beta_i \boldsymbol{X}_{ik}^h)}{\exp(I_k^h)},$$

while the probability of choosing category k is given by:

$$(4) \qquad P^h(k) = \frac{\exp(\alpha_k \boldsymbol{Y}_k^h + \gamma_k I_k^h)}{\sum_{j=1}^{T} \exp(\alpha_j \boldsymbol{Y}_j^h + \gamma_j I_j^h)},$$

where

$$I_k^h = \log\left(\sum_{i=1}^{N_k} \exp(\beta_i \boldsymbol{X}_{ik}^h)\right)$$

is defined as the "inclusive value" or, in this application, the "category value" term (Ben-Akiva and Lerman; Bucklin and Gupta) for T categories and N varieties. In this sense, category value is interpreted as the maximum amount of utility from the variety-choice

[1] The IIA property means that the probability of choosing one variety within a particular category relative to another variety in that category is independent of all other choices. This assumption is clearly implausible for varieties of the same type of fruit.

stage, or, because it represents the maximum utility from choosing from among varieties specific to one type of fruit, it also measures the degree of overall category attraction. Therefore, it is expected to have a positive effect on the probability that a household chooses a particular category (Bucklin and Gupta). More importantly, however, including this term in the category-choice model insures that the product of the variety and category choice probability models represents the unconditional probability of variety purchase. Such disaggregation provided by the nested multinomial logit model offers other attractive features beyond theoretical consistency, particularly when estimated across multiple market segments.

Whereas the choice model in (1) assumes that all households share a common vector of response parameters, assume instead that there are a finite number of consumer segments that are relatively homogeneous in terms of both their variety (r) and category (s) response. In this case, the unconditional probability that a household h buys variety i from category k in (1) can be rewritten as a weighted average, or mixture of the variety and category choices across segments of each (Bucklin and Gupta):

$$(5) \qquad P^h(i, k) = \sum_r \sum_s \pi_{rs} P_r^h(i|k) P_s^h(k),$$

where π_{rs} = the size of the rs variety choice and category choice segment. Because these segments are mutually exclusive, it must be the case that

$$0 \leq \pi_{rs} \leq 1, \quad \text{and} \quad \sum_r \sum_s \pi_{rs} = 1.$$

A particular household may belong to any one segment, so membership in the rs segment places a household in one cell of an $R \times S$ segment matrix. Therefore, the choice probabilities for a household h in (3) and (4) are now conditional on which segment it belongs to, and the choice parameters now vary by segment. These probabilities are thus given by:

$$(6) \qquad P_r^h(i|k) = \frac{\exp(\beta_{ir} X_{ik}^h | r)}{\exp(I_k^h | r)}, \quad \text{and}$$

$$(7) \qquad P_s^h(k) = \frac{\exp(\alpha_{ks} Y_k^h + \gamma_k I_k^h | s)}{\sum_{j=1}^{T} \exp(\alpha_{js} Y_j^h + \gamma_j I_j^h | s)},$$

for the variety and category choice, respectively. With this extension of the basic nested multinomial logit model, each of the variety or category choice models described above are now conditional on segment membership. Consequently, the estimation method must provide segment-specific response parameters at each stage, as well as the size of each segment.

Model Estimation

Random coefficient models can address heterogeneity among consumers, but a more managerially relevant solution is to recognize that segments of consumers may indeed be relatively homogeneous in their response to marketing variables. Whereas much of the empirical market segmentation research defines segments on an *a priori* basis, according to either demographic or purchase history information (Krishnamurthi and Raj 1991), recent work estimates consumers' response elasticity and their response-segment membership simultaneously. This section provides the details on how the EM algorithm is used to estimate the endogenous probabilities of latent-class, or segment membership of each household. Although this description is in terms of the variety choice model, the method used to estimate the category choice model differs only in the form of the likelihood function.

The EM algorithm initiates the expectation/maximization iteration with the expectation stage. In this stage, a initial values for the sample average weights are chosen by selecting reasonable values for π_r such that $0 \leq \pi_r \leq 1$ and initial values for the model parameters (θ) are found by estimating a single-segment version of (6). With these values, initial estimates of the household-specific segment probabilities are found from Baye's Rule as:

$$(8)\qquad w_r^h = \frac{\pi_r L_r^h}{\sum_r \pi_r L_r^h},$$

where w_r^h is the household-specific probability of belonging to segment r, π_r is the estimated sample-average segment probability, and L_r^h is the value of the likelihood function for household h in segment r.

Following Dillon and Gupta, the maximization step proceeds by introducing a binary indicator variable where: $I_{hr} = 1$ if household h belongs to segment r and is zero otherwise. Determining whether a household belongs to segment r or not depends on whether it is more likely to belong to r than any other segment. Consequently, a household is deemed to belong to segment r if $w_r^h > 0.5$. Assuming the conditional distribution of I_{hr} is multinomial distributed:

$$(9)\qquad \Pr(I_{h1}, \ldots, I_{hR} \mid \pi_1, \ldots, \pi_R) = \prod_r \pi_r^{I_{hr}},$$

the unconditional log-likelihood function for the variety choice decision over all households is given by:

$$(10)\qquad L = \sum_h \sum_r I_{rh} \ln \pi_r + \sum_h \sum_r I_{rh}\left(\ln \prod_i P_r^h(i \mid k)\right)^{\delta_i^h},$$

where $\delta_i^h = 1$ if the household buys variety i on a given shopping occasion. Maximizing (10) provides estimates of all choice parameters, which are then used to recalculate household and segment-specific likelihood function values: L_r^h. These estimates are then used in equation (8) to find new estimates of each household's segment probabilities. If the probability of belonging to segment r is greater than 0.5, the indicator variable is updated by setting $I_{rh} = 1$ and the maximization step proceeds anew. Iteration between the E and M steps continues until the likelihood function value changes less that 0.001 between iterations. A similar procedure is used to find the category choice segment sizes and parameters, where the likelihood function at this level is modified by writing:

$$(11)\qquad L = \sum_h \sum_s I_{sh} \ln \pi_s + \sum_h \sum_s I_{sh}\left[\ln \prod_j P_s^h(k)^{\delta_j^h}(1 - P_s^h(k))^{(1-\delta_j^h)}\right],$$

where $\delta_j^h = 1$ if household h chooses category j on a particular shopping trip. Applying this procedure to the combined variety choice-category choice problem requires either simultaneous or sequential estimation.

Although estimating the variety and category choice models simultaneously is the most efficient approach, it is common to exploit the hierarchical structure of the NMNL model and choose to estimate it sequentially. Not only does this simplify the estimation method compared to the simultaneous approach of Dillon and Gupta or Grover and Srinivasan (1992), but Bucklin and Gupta argue that the resulting parameter and standard error estimates differ little from those estimated with a fully simultaneous approach. Because the apple-choice example developed here consists of a relatively large set of choice and explanatory variables, the variety and category modes are estimated sequentially, but unlike Bucklin and Gupta, category-segment membership is independent of variety choice segment membership. Consequently, we first estimate the response parameters and segment probabilities at the variety-choice level, and then use the inclusive values from this stage to estimate both the category response parameters and category segment probabilities. In order to carry out this estimation procedure, it is necessary to define the specific arguments of both the variety and category utility functions.

Data and Variable Definition

Variable Definition

The primary advantage to using a nested multinomial logit model of choice is its ability to differentiate between the factors that drive discrete choices among several varieties from those that influence category choice. At the variety-choice level households are assumed to choose from a set of apple varieties, conditional on their choice of the apple category.

These varieties include Red Delicious, Golden Delicious, Granny Smith, and a set of other or "specialty varieties."[2] In making this choice, the deterministic component of a household's utility from the first-stage or variety choice, V_i^h, consists of variables reflecting attributes of both the household and its particular choice:

$$(12) \quad V_i^h = u_i + \beta_i X_i^h$$
$$= u_i + \beta_{i1} P_i + \sum_{j \neq i} \beta_{ij} P_j + \beta_{i5} LP_i^h$$
$$+ \beta_{i6} LOY_i^h + \beta_{i7} DL_i + \beta_{i8} P_i \cdot LOY_i^h$$
$$+ \beta_{i9} DL \cdot LOY_i^h + \beta_{i10} EXP,$$

where: P_i = adjusted price of choice i facing the household; P_j = adjusted price of apple varieties not chosen by household; DL = binary variable indicating whether the product is on a promotional deal; LOY = binary variable indicating whether the household is variety loyal; LP = binary variable indicating whether household made same choice on last trip; $P \cdot LOY$ = interaction variable between LOY and PR_i; $DL \cdot LOY$ = interaction variable between LOY and DL_i; EXP = household expenditure on fruit category per shopping trip.

This specification is similar to Bucklin and Gupta, but reflects many features unique to the fruit-choice data. First, prices for the same brand are commonly assumed to be identical for all sample households. Although this may be a valid assumption for single-market household samples buying national brands of packaged consumer products, this study includes households from six major U.S. metropolitan markets buying fruit that often vary in local quality, availability, size, grade and outlet. To control for the variability in price due to unobservable or "quality" characteristics, this study uses the hedonic method of Cox and Wohlgenant to create quality adjusted fruit prices.[3] Prices are also net of any promotional deals so the reported price is that which is actually paid. By subtracting the value of promotional deals from the shelf-price, we are able to include a separate variable that captures the independent effect of price-promotions on variety choice (*DL*). Further, the utility index for each choice is consistent with the theory of constrained utility maximization as it also includes the price of each alternative variety.

Second, models of variety and category choice typically find that loyalty is the most important explanatory variable (Guadagni and Little; Tellis; Gupta; Bucklin and Lattin). Operationalizing the notion of "loyalty," however, is subject to considerable controversy. Bucklin and Lattin and Tellis define the category-share of a household's expenditure on a particular brand as a continuous measure of loyalty. Krishnamurthi and Raj (1991) simplify this approach by defining *loyalty* in terms of a binary variable. With this measure, a household is defined as loyal if the dominant brand share within a given category is greater than 50 percent, but their results are insensitive whether 50, 60, or 70 percent is used as the threshold rate. We apply this measure to define loyalty to apples in general (*ALOY*, which enters the category model below) and a particular variety of apples, *LOY*. Because this definition of *loyalty* becomes a characteristic of each household, it is often thought of as a long-term measure of loyalty.

However, Grover and Srinivasan (1992) and Bucklin and Gupta include a second, short-term measure of loyalty. In practice, marketing managers are more likely to use a measure of repeat-purchase behavior to define a loyal consumer. Specifically, if a consumer buys the same variety on two adjacent trips to the store, then this is a strong indicator of variety loyalty. Roy, Chintagunta and Haldar interpret this variable as an indicator of "state dependent" variety choice—or whether current behavior is disproportionately influenced

[2] The choice of several varieties on one trip is not included in order to simplify the estimation procedure and because of the relative infrequency of this option—only 1.4% of all observations included the purchase of more than one apple variety. Therefore, the bias introduced by ignoring these observations is likely to be small.

[3] The arguments of the hedonic model include a set of household demographic as well as groups of binary market and week variables.

by more recent memories of past purchases. In this study we follow Bucklin and Gupta and define this variable as LP in the model above.

Research that explicitly defines loyal and non-loyal buyers commonly finds a significant difference in price response between the two groups. To capture this effect, this study defines two variables that relate loyalty and price and loyalty and promotional deal. It is expected that loyal households will be less sensitive to changes in price than non-loyal segments. Similarly, it is also expected that promotional deals will be less likely to induce variety switching behavior among loyal as compared to non-loyal buyers. Whereas Bucklin and Lattin show that such "opportunistic" variables have a profound effect on variety choice, category choice tends to follow patterns of need. Such needs, both real and perceived, are in turn influenced by a different set of variables, reflecting consumers' usage rates, stockholdings, and underlying information about a product category.

To capture these effects, the vector $\boldsymbol{Y}$ in the category model includes some variables that are unique to this decision-stage. Specifically, the category-utility for household h is written as:

$$
\begin{aligned}
(13) \quad V_k^h &= \alpha' \boldsymbol{Y}_k^h + \gamma_k I_k^h \\
&= \alpha_0 + \alpha_1 PA_k + \alpha_2 PO_k + \alpha_3 LP_k \\
&\quad + \alpha_4 ALOY_k + \alpha_5 CR_k + \alpha_6 INV_k \\
&\quad + \alpha_7 AAD_k + \alpha_8 OAD_k + \alpha_9 EXP_k + \gamma_k I_k,
\end{aligned}
$$

where the explanatory variables introduced here include: PA = price of purchased apples; PO = price of other fruit; LP = 1 if household purchased in same category on last trip; $ALOY$ = category loyalty; CR = consumption rate, in pounds per day; INV = household inventory; AAD = apple advertising; OAD = other fruit advertising; EXP = total expenditure on fruit on this shopping trip; I = category value from variety choice stage.

As in the variety choice model, category choice is hypothesized to be driven by the own-category price, a price index of alternative fruit available in a particular market on a particular week, and total expenditure on the fruit category as a whole. Further, including last purchase and loyalty variables accounts for both the short- and long-term notions of loyalty defined above for the variety model. As in the variety model, we expect both of these variables to be significant, positive determinants of category choice. For purposes of the category model, a household is "category loyal" if it purchases more than 50 percent of its fruit needs, by expenditure, from either the apple, banana, grape, or soft fruit categories. In applying a model of product choice to fresh fruit it is also critically important to account for household inventory because fruit typically has a high purchase frequency, is only somewhat storable, and is relatively bulky. Estimating a household's stock on hand, however, is subject to much debate in the literature. Whereas Guadagni and Little and Tellis estimate a moving average of calculated household stocks, smoothed with an exponential decay process, this study follows Bucklin and Gupta by calculating inventory from:

$$(14) \quad INV_t^h = INV_{t-1}^h + Q_{t-1}^h - CR^h T_{t,t-1},$$

where INV_t^h is the inventory of household h at time t, Q_{t-1}^h is the amount purchased on the previous shopping trip, CR^h is the average daily category consumption rate, calculated from the entire purchase history of household h, and $T_{t,t-1}$ is the interval between successive purchases, measured in days.[4] In theory, the probability of category purchase should decline in household inventory as the likelihood of a stock-out between shopping trips falls. On the other hand, a household's consumption rate should have a positive effect on category purchase. Whereas each of these variables represents an actual need for the product by each household, advertising reflects a household's perceived need for the product category.

Generic advertising is more likely to affect category rather than variety choice. Because very little apple advertising differentiates among varieties, there is no reason to presume that it would affect variety choice stage as de-

[4] As in Bucklin and Gupta, inventory is initialized at zero.

fined here. Increasingly, however, the choice of what type of fruit to buy is dependent upon the amount of advertising growers of domestic fruit or importers of bananas invest in. For purposes of this study, advertising includes the total amount of market-specific expenditure from all sources on television, radio, newspapers, and outdoor advertising as reported by Competitive Media Reporting, Inc. (CMR). Because CMR reports their findings on a monthly basis only, and the unit of observation here is the shopping-trip day, the amount of advertising exposure is assumed to be constant for all shopping trips taken within a particular month.[5]

Data Sources

Except for the CMR data, all data are from the AC Nielsen HomeScan database collected July–December, 1997. For this study, the category sample consists of observations covering over 38,000 shopping trips wherein consumers bought either apples, bananas, grapes, or soft fruit (nectarines, peaches, plums, or pears).[6] Although the data include many other types of fruit, they are not in the final sample due to infrequency of purchase. This sub-sample consists of 9510 purchase occasions after excluding households that make fewer than two fruit purchases per month. Although this may be a source of sample-selection bias, it is common in this literature and necessary to implement the loyalty and inventory variables with any degree of confidence. Each observation includes the date of the purchase, price paid, quantity purchased, use of a promotional deal, shopping outlet, metropolitan area, and a variety of household demographic data. Prices paid for fruits not purchased are calculated for each week and market using the first-order procedure for imputing missing prices described by Cox and Wohlgenant.[7] With these data, all estimation results are obtained using maximum likelihood methods. The following section presents and discusses these results, first in terms of the adequacy of model specification and then in terms of the marketing problems at hand.

Results and Discussion

Of course, a multiple-segment model is only preferable to a single-segment alternative if it provides a better fit to the data. At both the variety and category levels, likelihood ratio (LR) tests compare the fit of the two alternatives.[8] In the variety model, a LR of 2,793.03 strongly supports the superiority of the two-segment model so these results form the basis for interpreting the estimated parameters. However, both segments must be large enough that the difference in estimated responses are more than a statistical curiosity, but have managerial relevance as well. As Table 1 shows, Segment 1 consists of over 57 percent of the sample households with the remainder in Segment 2, so it may indeed be both feasible and profitable to attempt to reach both. In this section the first set of results concern the variety choice stage, while the category choice results follow.

Variety Choice Results

In Table 1 the variety choice parameters are interpreted as marginal utilities with respect to

[5] While this may seem to be a strong assumption, it is not wholly inaccurate as the Washington Apple Commission plans advertising budgets on a monthly basis. Due to the lags inherent in consumers' response to advertising, it is rare to see firms make radical changes to their advertising budgets on a shorter, weekly basis.

[6] Because purchases are only recorded when some type of fruit is bought, the purchase of "no fruit" is not an option. Therefore, all estimation results are conditional on fruit consumption and the conclusions drawn only apply to fruit consumers.

[7] Dong, Shonkwiler, and Capps argue that the method of Cox and Wohlgenant produces biased results because it does not account for the likely simultaneity of expenditure and prices. However, their corrected results (estimated for a single-equation meat-expenditure model rather than the more complicated model of demand used here) show the estimated unit values to differ little between methods.

[8] The likelihood ratio test statistic is $LR = 2(LLF_u - LLF_r)$, where LLF_u is the value of the unrestricted log-likelihood function (two-segments) and LLF_r is the value of the restricted log-likelihood function. With 28 parameter restrictions, the critical chi-square value at a 5 percent level is 41.337.

Table 1. Variety Choice Parameters by Response Segment

	Choice Segment 1				Choice Segment 2			
Variable:	Red[1]	Gold	Granny	Special	Red	Gold	Granny	Special
Constant	−2.524*	−3.064*	−1.628*	2.116*	−2.284*	−2.535*	−1.489*	0.843*
	(−8.799)	(−9.231)	(−4.222)	(7.094)	(−7.776)	(−6.599)	(−3.875)	(2.696)
PR	−1.335*	1.628*	0.311	0.834*	−0.307	0.769*	0.454	0.384*
	(−8.049)	(7.938)	(1.421)	(4.987)	(−1.894)	(3.712)	(0.224)	(2.299)
PGD	0.647*	−2.311*	0.778*	0.769	−0.031	−0.748*	0.415*	0.133
	(4.274)	(−10.872)	(3.638)	(0.471)	(−0.202)	(−3.685)	(2.154)	(0.106)
PGN	0.465*	1.377*	−1.248*	−0.781*	−0.032	0.669*	−0.363*	0.556*
	(2.887)	(5.904)	(−5.522)	(−4.803)	(−0.185)	(3.080)	(−2.707)	(3.267)
PS	1.165*	1.448*	0.576	−1.914*	0.408*	0.354	0.549*	−1.489*
	(7.769)	(7.278)	(0.281)	(−12.053)	(2.703)	(1.778)	(2.788)	(−9.230)
LP	0.473*	0.484*	0.343*	0.749	0.318*	0.499*	0.309*	0.282
	(8.716)	(6.192)	(4.434)	(1.285)	(5.591)	(6.411)	(3.999)	(0.456)
DL	0.116	0.118	0.139	0.155	0.175	0.222	0.138	0.091
	(0.638)	(0.516)	(0.711)	(0.804)	(0.969)	(0.934)	(0.652)	(0.471)
LOY	1.567*	1.355*	0.134	1.378*	0.592*	0.463	1.018*	1.502*
	(10.364)	(7.001)	(0.652)	(8.515)	(3.810)	(0.235)	(5.034)	(8.987)
P*LOY	−1.326*	−1.382*	0.121	−1.676*	−0.394*	−0.612	−1.107*	−1.664*
	(−10.261)	(−8.591)	(0.679)	(−11.878)	(−3.047)	(−0.372)	(−6.012)	(−11.736)
DL*LOY	−0.215	0.025	0.254	0.139	−0.116	0.537	0.256	0.564
	(−1.800)	(0.095)	(0.119)	(0.656)	(−0.582)	(0.201)	(0.111)	(0.263)
EXP	0.002	0.004*	0.004*	0.008	0.002	0.003*	0.004*	0.008
	(0.134)	(2.576)	(3.094)	(0.778)	(0.224)	(2.278)	(2.804)	(0.698)
π_R		0.576				0.424		
		$LR^2 = 2{,}793.031$				$\chi^{2}_{o}{}^{3} = 195.163$		

[1] T-ratios are in parentheses. A single asterisk indicates significance at a 5% level.

[2] The test statistic comparing the two segment and one segment models is: $LR = 2(LLF_U - LLF_R) \sim \chi_q$, where q is the number of parameter restrictions, LLF_U is the unrestricted (two segment) log-likelihood function value and LLF_R is the restricted (single segment) value. the critical chi-square value with 44 degrees of freedom at 5% is 68.401.

[3] The statistic χ^2_o compares the log-likelihood function value of the estimated model and a null model where $\beta = 0$. Rejecting the null hypothesis that all model parameters are not significantly different from zero provides an indication of the goodness of fit of the multinomial logit model. The critical chi-square value at 5% and 88 degrees of freedom is 110.898.

each regressor. Although the signs of these parameters are the same from Segment 1 to Segment 2, they differ considerably in magnitude. Recall that u_i represents the intrinsic preference for each apple variety. Segment 2, therefore, can be described as having a slight relative preference for all varieties (except for specialty varieties) compared to Segment 1. Whereas other variety, or brand choice studies assume constant response parameters for each choice (Bucklin and Gupta), the model used here provides choice-specific response parameters for each marketing variable. This is important because packers commonly face variety-specific shipment decisions, even though marketing strategy is generic. Table 1 also shows that Segment 1 households are typically more price responsive than those in Segment 2 in terms of marginal utility—a result that Table 3 confirms with respect to their price elasticity. A higher elasticity of demand in one segment suggests that price discrimination may be profitable, depending on the ability to identify the sample attributes (i.e. demographic variables) of each segment and prevent resales between them. In addition to own- and cross-price effects, both short-term (LP) and long-term (LOY) measures of loyalty tend to be important determinants of variety choice.

Whereas the short-term definition of loyalty embodied in LP tends to be a more important determinant of Red Delicious choice in Segment 1 than Segment 2, the same is not necessarily true for the other varieties. Segment 2 thus may consist of less traditional or variety seeking households compared to those in Segment 1. With respect to the long-term definition of *loyalty,* consumers in Segment 1 appear to be more loyal to Red and Golden Delicious apples than those in Segment 2, but the opposite is the case for the other two varieties. Roy, Chintagunta, and Haldar interpret this as suggesting that product samples or demonstrations are likely to be more effective for Granny and Specialty varieties in Segment 2. Comparing these results to those of the DL variable for both segments supports the superiority of alternative types of promotion besides price-deals. In fact, none of the variety/segment results show promotional deals to have a significant effect on choice when coupon value is already deducted from the shelf price. Although some claim that the "announcement effect" of having a product on promotion is sufficient to generate volume even without the effect of the price reduction, this result does not appear in the fresh fruit data. Such price changes are also likely to have different effects on variety-loyal as opposed to non-loyal buyers.

Although Grover and Srinivasan (1992) show that promotions have a greater effect on loyal versus non-loyal consumers, this study finds virtually no corroboration of their result. In particular, despite the fact that the effect is not different from zero at usual levels of significance, the point estimates are more often positive across all segments and varieties. However, the effect of loyalty on price sensitivity does appear to be greater for households in Segment 1 than for those in Segment 2. Specifically, for three of the four varieties, the variety choice of loyal buyers is more sensitive to changes in price than are non-loyal buyers. Note that this difference is strongest in the case of Red Delicious apples, so this somewhat surprising result is likely due to the fact that Reds are not only the low-price option, but often low quality as well. Because Reds are the dominant apple variety, many people are likely to appear loyal simply because they buy the lowest price alternative on each shopping trip. However, higher prices cause consumers to switch between varieties as they search for a more favorable price/quality tradeoff.

In Table 2 the reported elasticities appear to draw a sharper distinction between the two segments. Not only is Segment 1 uniformly more price elastic than Segment 2 but, after allowing for both effects of price-promotion (directly on choice and mitigated by variety loyalty), the point-estimates in this table indicate that Segment 1 may become more deal-sensitive as well. This suggests that although households in this segment tend to switch varieties in response to differences in price they are also more likely to exhibit strong short- and long-term variety loyalty. Moreover, this result implies that Segment 1 households may

Table 2. Variety Choice Elasticities by Response Segment

	Choice Segment 1				Choice Segment 2			
Var:	Red[1]	Gold	Granny	Special	Red	Gold	Granny	Special
PR	−0.528	1.158	0.408	0.243	−0.134	0.415	0.025	0.421
PGD	0.351	−1.481	0.432	0.222	0.063	−0.427	0.275	0.047
PGN	0.292	0.887	−0.824	−0.519	0.055	0.506	−0.159	−0.418
PS	0.658	0.848	0.828	−1.402	0.456	0.422	0.154	−1.105
LP	0.144	0.268	0.207	0.027	0.109	0.175	0.109	0.013
DL	0.007	0.021	0.029	0.013	0.003	0.016	0.009	0.012
LOY	0.598	0.487	0.295	0.949	0.461	0.214	0.268	0.718
EXP	0.014	0.152	0.151	0.021	0.019	0.132	0.129	0.025

[1] Elasticities calculated using the expression: $\varepsilon_i = (x_{ij}/\hat{P}_i)\cdot(\partial\hat{P}_i/\partial x_{ij})$ for each variety i and variable j.

be easier to attract with low prices, but once they buy a particular variety habitually, they are less likely to switch than Segment 2 members. These differences are particularly valuable if it is possible to identify the segments by various demographic characteristics, as we do below. Further, because loyalty is expected to have differing effects on the probability of category choice compared to variety choice, the multi-segment category choice model includes these variables as well.

Category Choice Results

Whereas many response-segmentation studies define several segments—sometimes up to five or more (Gupta and Chintagunta)—Zenor and Srivastava suggest that this many individual segments may indeed lead to suspicion of their being "figments of the model's imagination" (p. 374). Moreover, for practical purposes many segments are difficult to interpret as no clear pattern of distinction arises across the entire set of parameters. Therefore, the category-choice model, as with the variety-choice model, consists of two segments. As the chi-square likelihood ratio test statistic in Table 4 shows, a two-segment model represents a significant improvement over the single-segment alternative.

Similar to the variety choice results, the parameters in this table provide estimates of the marginal utility of each variable in choosing whether to buy in the apple category. In interests of parsimony, variables that reflect likely differences in a household's "need" for apples and, therefore, candidates to appear in Equation (13), that were initially found to be insignificant were not included in the estimated version. These variables include such demographic variables as the household size, age and education of the household head, and household income.[9] Among the remaining variables, Segment 1 consumers appear to be less price-responsive than those in Segment 2. This is also true for total category expenditure. Further, both definitions of loyalty are important determinants of whether or not an apple is purchased on each trip for each segment. Households in Segment 1, however, are more loyal in both the short-term and long-term sense. A household's consumption rate also has a greater impact on its utility in Segment 1 than in Segment 2. Segment 1 households are also slightly more responsive to stocks of apples on hand, so these segments appear to be relatively homogeneous with respect to their "need" for apples. Consequently, a retailer contemplating a temporary price reduction need worry less about Segment 2 households stockpiling against future consumption as they are less averse to acquiring inventory. Segment 1 consumers are, however, less amenable to direct advertising as the response parameter is almost half that of Segment 2 consumers.

[9] The fact that these demographic variables are not significant is perhaps not surprising given that the model controls for behavioral heterogeneity between households by including the INV, CR, and loyalty variables. These measures likely explain the same variation in choice as would the demographic variables.

Table 3. Category Choice Nested Multinomial Logit Model: Single and Multi-Segments

Variable:[1]	Model 1: One Segment	Model 2: Two Segment Segment 1	Segment 2
Constant	−0.762*	−0.681*	−0.699*
	(−4.123)	(−3.563)	(−2.705)
PA	−0.216*	−0.147*	−0.237*
	(−3.042)	(−2.251)	(−2.552)
PO	0.029	0.322	0.029
	(0.361)	(1.365)	(1.244)
LP	1.834*	1.984*	1.563*
	(29.464)	(25.262)	(17.416)
ALOY	1.130*	1.149*	0.894*
	(12.920)	(10.414)	(7.315)
CR	0.043*	0.044*	0.031*
	(11.623)	(8.856)	(6.115)
INV	−0.003	−0.003*	−0.002
	(−1.992)	(−2.295)	(−1.858)
AAD	0.026*	0.021*	0.040*
	(4.666)	(3.591)	(2.514)
OAD	0.001	0.002	−0.001
	(0.071)	(0.285)	(−0.673)
EXP	0.021*	0.022*	0.027*
	(2.254)	(2.069)	(2.550)
CV	0.153	0.161*	0.114*
	(1.627)	(2.228)	(2.853)
Segment Size	1.000	0.643	0.357
LR[2]		2418.412	

[1] Variables are defined as PA = apple price; PO = Stone's index of other fruit prices; LP = last purchase was of same category; ALOY = category loyalty defined as historical purchase-share greater than 50%; CR = daily consumption rate in pounds; INV = inventory on shopping date in pounds; AAD = apple advertising expenditure by market in $ '000; OAD = advertising expenditure on bananas, grapes, and soft fruit, by market, in $ '000, EXP = total expenditure on fruit category; CV = category value from variety choice model. A single asterisk indicates significance at a 5% level.

[2] Comparing the two LLF values with a likelihood ratio test statistic gives the chi-square value of 2418.412. At a 5% level with thirteen restrictions the critical chi-square value is 22.362, so the null hypothesis of equal parameters is strongly rejected.

Such comparisons, however, are more useful if expressed in terms of elasticities.

Table 4 contains the category response elasticities for each explanatory variable. Again, the elasticities are broadly supportive of the marginal utility results, but elasticities have the advantage of allowing comparisons of the relative strength of each explanatory variable. With this in mind it is apparent that Segment 1 consumers are indeed less price-responsive when expressed in terms of elasticities. This suggests that if price discrimination between these two groups were possible, it would be profitable to do so. Moreover, these results show that loyalty is strongest as a short-term phenomenon. Although the difference is less for Segment 2 households, this means that what consumers purchased on the last shopping trip is more important in determining whether they purchase in the apple category than what they habitually buy. Category managers, therefore, should focus more resources on initiating new purchases, rather than attempting to reinforce established patterns. Segment 2 purchasers are also more sensitive to the rate of household consumption, but less so with respect to inventories. The fact that the consumption rate elasticity is greater than the inventory elasticity suggests that these households buy in anticipation of need

Table 4. Category Choice Model Response Elasticities by Segment

Variable:	Segment 1	Segment 2	t-ratio
PA[1]	−0.152*	−0.240*	2.784
PO	0.201*	0.180*	2.211
LP	1.034	1.052	−0.212
ALOY	0.152*	0.337*	−3.388
CR	0.219*	0.686*	−4.695
INV	−0.056*	−0.043*	−2.515
AAD	0.046	0.064	−1.443
OAD	0.006*	−0.005*	2.367
EXP	0.133	0.139	−1.588

[1] A single asterisk indicates mean elasticities are significantly different from each other at a 5% level of significance. Null hypothesis in each case is defined as: H_0: $\varepsilon^j_1 - \varepsilon^j_2 = 0$, where ε^j_n is the elasticity with respect to variable j in segment i.

with little regard to how much of a product they have on hand. This result is to be expected because the unit of observation here is the shopping trip and not a fixed unit of time. Often, there are many days between shopping trips, so households clearly anticipate shortages during interim periods. Consistent with their pattern as the "sensitive segment," households in Segment 2 are also more responsive to mass apple advertising, although this difference is not statistically significant at 5 percent. They are also more responsive to other fruit advertising. In fact, households in Segment 1 seem to regard messages promoting other fruit as complementary to their apple choice. Of course, this entire segmentation exercise, particularly with respect to advertising, is only useful if a manager is able to identify segment members and direct marketing efforts appropriately. The next section shows how this is possible by characterizing each segment according to a few demographic and geographic attributes.

Demographic Segment Description

As a final step in the analysis we characterize the demographics of each response-segment using household-specific data describing household size, income, age, education, and shopping-trip frequency. Table 5 provides this comparison across both variety choice and category choice segments.

With respect to variety choice, households in the "more responsive" segment (1) have slightly, yet statistically significant, lower incomes, larger households, are older, and are slightly less educated than their less-responsive counterparts. They appear to shop approximately the same number of times per week, however. Combining this result with the response elasticities invites characterizing a typical household in the first segment as an "easy sell," one that is highly receptive to incentives to change varieties, and more prone to continue buying a variety of apple that it likes. These profiles differ slightly from those defined for the category-choice model.

Although households in Segment 2 in the category choice model are not uniformly more sensitive than Segment 1, these households ap-

Table 5. Demographic Characteristics by Variety Choice and Category Choice Response Segment

	Variety Choice			Category Choice		
Variable:	Segment 1	Segment 2	t-ratio	Segment 1	Segment 2	t-ratio
Income[1]	$61,415.00	$62,508.00	−2.547*	$62.830.00	$59,690.00	4.296*
HH Size	2.870	2.718	4.564*	2.735	2.625	3.467*
Age	45.62 yrs.	43.16 yrs.	6.724*	47.05 yrs.	45.05 yrs.	37.430*
Education	15.39 yrs.	15.58 yrs.	−7.988*	15.55 yrs.	14.90 yrs.	28.709*
Frequency	18.52×	18.05×	1.852	18.37×	22.33×	−12.462*

[1] A single asterisk indicates a significant difference in means at 5%. The null hypotheses tested in this table is that the segment one average for the indicated attribute less the segment two average is equal to zero. Variable definitions are as follows: Income = annual household income; HH Size = number of people in the household; Age = age in years of the eldest of the male or female head; Education = years of education; Frequency = number of store visits over sample period in which fruit is purchased.

pear to be smaller, have less income, are significantly younger, are less educated, and shop much more frequently than the households in Segment 1. Given the difference in average age and household size of members in these two segments, households that may be relatively easy to switch from some other type of fruit to apples may not have as much discretionary income as those that are willing to experiment with new varieties. The importance of the long-term definition of loyalty (*ALOY*) to these people suggests that free samples or demos are likely to be less effective in building category volume than programs that reward continued purchase of a preferred variety. Further, and perhaps more importantly, the size of the elasticity with respect to short-term loyalty (*LP*) suggests that apple advertising may be effective in building the apple category if it induces initial purchases. These initial trials are reinforced through the other definition of loyalty to generate long-term incremental sales. Perhaps the relative effectiveness of advertising is to be expected given the greater amount of time devoted to mass media—television, magazines, radio, and newspapers—among these consumers.

Conclusion and Implications

The central hypothesis of this paper is that marketing activities, particularly price-promotions and media advertising, have different effects on consumers' choice of fruit-variety compared to their effect on consumers' decision to buy a particular type or category of fruit on a given shopping trip. Defining apple-varieties as analogous to brands, and apples as the product category of interest, this study tests this hypothesis using a nested multinomial logit (NMNL) approach to estimating brand and category choice that is now common in the consumer products marketing research literature. Estimates of the discrete-choice model are obtained using data consisting of fruit choices, prices, and demographic variables gathered from a large sample of A.C. Nielsen scanner-enabled households on a shopping-trip basis over the final six months of 1997. Further, this research maintains that there exists unique segments of consumers that are likely to be more or less amenable to being influenced by marketing activities. To identify these segments and to estimate segment-specific response parameters, the study applies the NMNL model in a general finite mixture distribution, or latent class, framework. Because these segments are latent, or unobserved, models at each decision stage are estimated sequentially using an EM (expectation/maximization) approach. Once households are assigned to each segment based on their posterior probabilities of segment membership using Baye's Rule, demographic data for each household are used to construct response-segment profiles.

With this approach, the paper finds a significant value to differentiating between factors that drive consumers' variety and category choices. Whereas factors such as variety-specific preferences and prices are important in a household's choice of apple variety, need-based factors such as consumption rate and level of household inventory are more important in determining whether consumers purchase apples as opposed to another type of fruit on a particular trip to the store. Moreover, indicators of loyalty and memory of recent purchase history are shown to be important at both levels. In addition to the measures of actual need, as an indicator of perceived need, mass advertising is a significant determinant of the probability that a household buys apples on a given shopping trip. Importantly, the direct elasticity of apple advertising is far greater than the cross elasticity of category choice with respect to banana, soft fruit, and grape advertising. Moreover, this result holds true for all market segments.

The results also show that a two-segment model provides a far better fit to the data than a single-segment version at each decision stage. At the variety-choice stage, households in one segment are shown to be more responsive to changes in price and individual measures of variety-loyalty compared to the other. A typical household in this segment is larger, has a lower income, is older, and has less education than one in the less-responsive segment. At the category level, members of the more responsive segment share the income and education characteristics of the variety-choice responsive segment, but are smaller, significantly less educated and shop much more frequently than the less-responsive segment.

There are several potential benefits to disaggregating consumer response to marketing variables in this way. First, commodity promoters are beginning to recognize that market share within category is not sufficient to generate increased grower returns when competition for "stomach share" becomes all important. Whereas modeling variety choice aids tactical decisions in particular markets, the long-term effectiveness of commodity promotion depends critically on the ability to generate incremental category volume. Second, as grower margins shrink in the face of increasing retail and middle-market concentration, efficiency in mounting promotion programs becomes more important. Targeting market segments with tools that have proven effective for particular segments represents just one way in which this analysis can contribute to marketing efficiency. Finally, with increasing use of category management, efficient consumer response (ECR), and other methods that rely on micro-level scanner data, techniques must be developed that make the best use of this information.

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