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The Impact of Advertising on Product Choice, Purchase Frequency and Purchase Quantity: Washington Apples

Timothy J. Richards and Paul M. Patterson

ARIZONA STATE UNIVERSITY

POLYTECHNIC CAMPUS

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Table of Contents

Executive Summary

- Marketing research in consumer packaged goods shows that consumers' brand choices, category choices, and purchase volumes are all affected by different factors and in different ways by price-promotions and advertising. Research also suggests that brand-loyalty, purchase rates, and inventory behavior are important determinants of category choice. These findings are likely to be true of apples as well.

- Households in high income market segments tend to purchase double the amount of specialty apple varieties (Fuji, Gala, Braeburn, Jonagold, etc.) than do lower income groups. Consumers in Los Angeles are most likely to buy specialty apples, while those in Baltimore and San Antonio are both heavy consumers of Red Delicious apples and the primary competing product - bananas.

- Medium-sized households tend to consume more apples than either smaller households or larger households. Households with older heads tend to consume more of specialty apple varieties than younger families. These consumers appear to substitute soft fruit for grapes and bananas during the summer fruit season, and not apples.

- Consumers with more education tend to consume greater amounts of specialty apple varieties and lesser amounts of bananas and soft fruit compared to those with less. Hispanic and Asian consumers prefer non-Red Delicious apple varieties and consume more bananas and grapes than White consumers, while African Americans prefer soft fruit to bananas.

- Apple-loyal buyers tend to consume three times the amount of apples as non-loyal buyers, while they consume 30% less bananas and half as much grapes and soft fruit.

- Apple consumers' choice of variety is modeled as depending upon prices, promotional activity, two measures of variety-loyalty, and a combination of price and loyalty. Estimates of the variety choice model show that consumers' of all varieties are unlikely to switch varieties due to changes in price and loyal buyers are even less likely - nearly never likely - to switch.

- Category choice, or the probability of buying apples as opposed to any other fruit on a given shopping trip, is determined by prices, promotion, consumption rates, inventory, product-loyalty, and advertising. Product choice is highly sensitive to changes in price and the use of price-promotions for both loyal and non-loyal consumers. Banana buyers are more sensitive to price than apple buyers. Apple and banana advertising have nearly offsetting rivalrous effects on the probability of buying within a given category.

- Consumers who are relatively price-sensitive in category choice tend to have higher incomes, are younger, and are better educated than non-responsive consumers. These consumers are more likely to be African American and to live in Chicago. Advertising-responsive consumers tend to have higher incomes, larger families, are slightly older and more likely to be white than non-responsive.

- With respect to consumers purchase quantity, apple buyers are more price-elastic than are consumers of other fruits but are less likely to increase purchases in response to a price-promotion. A 10% increase in advertising expenditure increases household purchase quantity by an average of

0.34% across all sample markets.

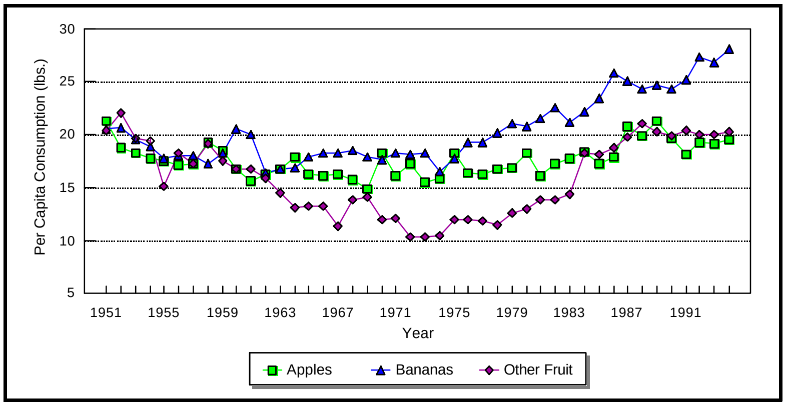
- Households that are relatively price-responsive tend to have higher incomes, larger families, and are younger and better educated than the largest response-segment. These consumers are more likely to be white and to live in N.Y. than non-price responsive households. This same pattern is similar to those who respond strongly to price-promotions. Advertising has its greatest impact on those households with lower income, smaller families, and those who have older and less-educated heads. Advertising was most effective in late 1997 in New York and San Antonio than elsewhere.

- The primary implications of this analysis for WAC marketing strategy are: (1) growth-segments (young consumers, more educated, hispanic, LA) tend to favor specialty apple varieties over traditional varieties, suggesting that these segments be targeted in future promotions for these varieties; (2) consumers' choice of variety is largely determined by loyalties and are insensitive to changes in price and price-promotion activity so other methods (demos, give-aways) will likely be more effective in inducing variety-switching behavior; (3) category choice is highly sensitive to price and price-promotion, but is inelastic with respect to advertising so category-switching from bananas and grapes is more likely to occur as a result of relative price changes than advertising activity; (4) at current levels, apple advertising is just sufficient to offset rival banana advertising and additional advertising expenditure will be most efficiently targeted to lower income, older, and less educated demographic groups within larger urban areas.

The Research Problem: A Change in Marketing Strategy

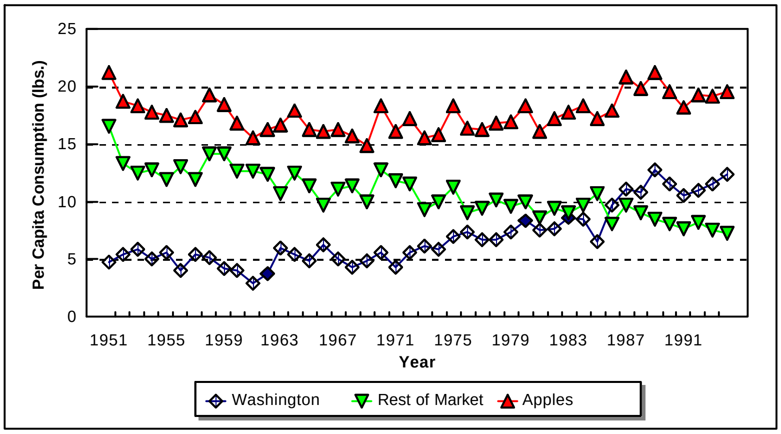
Washington apple growers recognize the need to refocus their marketing strategy. While past marketing efforts have been successful in increasing Washington growers' share of the U.S. and export apple markets (figure 2), the size of both of these markets, particularly the export market, has emerged as a key constraint in marketing Washington apples. Faced with potential record apple production in 1998 and beyond, apple marketers realize that "share of stomach" is a more appropriate goal and category expansion a likely strategy.[1] While the Asian financial crisis and Mexican protectionism are two major factors limiting growth of the export market, rising U.S. consumption of Chilean grapes, Latin American bananas, tropical fruits from Mexico and U.S. summer fruits all represent challenges to any attempt at building the demand for apples as a category (figure 1). Consequently, apple marketers now recognize the need to acquire a deeper understanding of the microeconomics of households' fruit choice behavior. Recent marketing research highlights many dimensions of this problem that have not been addressed for any agricultural commodity.

Figure 1 Apple Share of Fruit Category



First, researchers argue that consumers make category purchase (ie. type of fresh fruit) decisions for different reasons than brand (or apple variety) choice. While the former may be determined by such things as family size or inventory level, the latter is more likely to reflect tastes or loyalties. Second, these tastes or loyalties are likely to exhibit considerable heterogeneity between households. Existing research also shows that ignoring demographic differences among buyers causes statistical models to underestimate the effect of marketing variables on the probability of buying a given category (purchase incidence), brand choice, and purchase quantity. Third, marketing researchers are sensitive to the fact that manufacturers of a product (growers) and retailers have fundamentally different interests in how consumers respond to product promotion. Whereas growers are more likely to be interested in understanding what causes consumers choice of a

Figure 2 Washington Share of U.S. Apple Market



[1] Production in 1996 reached a record 85 million boxes, while surveys of planted acreage indicate production in the year 2000 of over 115 million boxes (*The Packer*).

particular brand or variety, retailers are more interested in category sales. Promotion programs are likely to attract retailer participation and grower support if they can promise both brand switching as well as accelerate category purchases. Fourth, this research also shows that promotion and advertising are fundamentally different in that promotion is designed to influence current *behavior*, while advertising is intended to change consumer *attitudes*. Therefore, each is expected to have a different effect on the timing of category and brand sales - whereas promotion has an immediate effect, advertising's impact may not be realized for some time. Consequently, any model of consumers' purchase behavior must be able to differentiate between the effects of price-discounts, advertising, and differences among households' fruit preferences.

Although all types of promotion expenditure together consume almost as much of the WAC's annual marketing budget as advertising, the short-term attractiveness of price-promotions in particular may be misleading. Several authors argue, and demonstrate empirically, that frequent sales promotion programs, such as coupons, have two potentially negative effects on future sales of the promoted product. First, frequent sales promotions can result in an erosion of brand loyalty as consumers can feel that they are buying the product only because of the promotion and not because of a preference for it. Second, promotions can increase consumers' price sensitivity as they develop an expectation that the product will be promoted again in the future. Others argue that the net effect of promotion is positive as consumers' preferences are reinforced through repeat purchases and greater exposure to the product. Promotion can also cause consumers to substitute between stores if the mix of promoted products differs within a market. Further, if promotion merely accelerates purchases of loyal apple customers, then it may indeed cannibalize future sales and not build long term incremental volume within the fresh fruit category. For all of these reasons, therefore, it is important to account for several indicators of consumers' dynamic purchase behavior: their loyalty to a particular brand or variety, their average rate of consumption, and the amount of the product they hold in inventory, when estimating the effectiveness of price-promotions in generating incremental sales volume. While no single study or database is amenable to analyzing each of these issues, this study addresses those that are most central to Washington apple growers' current needs.

Objectives

Therefore, the objectives of the proposed research are:

(1) to determine the effects of prices, price promotions, and buyer loyalty on consumers' choice among apple varieties, given that they have already made the decision to buy apples as a category;

(2) to determine the independent effect of these marketing variables, in addition to generic or non-variety specific advertising, on the likelihood that households will buy apples, as opposed to other types of fruit on a single shopping trip;

(3) to determine the effect of marketing variables and demographics (or household heterogeneity) on the quantity purchased on each shopping trip;

(4) to compare consumption rates among market segments defined on demographic grounds;

(5) to define market segments also on the basis of households' sensitivity to changes in price,

promotion, and advertising;

(6) to draw implications for the effectiveness of grower-funded apple marketing programs through the Washington Apple Commission (WAC).

This report will address these objectives using a household-scanner database collected by the A.C. Nielsen company for the last two quarters of 1997. These data include purchase quantities and prices paid for all fruits on all shopping trips taken over this period, from all possible outlets. These data also include a full description of each household in terms of their income, age of household head, education of household head, age distribution of children, household size, ethnicity, and place of residence. Panel respondents are drawn from six urban markets including Atlanta, Baltimore/Washington D.C., Chicago, Los Angeles, San Antonio, and New York. Focusing on these markets allows the study to determine the effect of market-specific WAC marketing expenditures. Data on these expenditures, and for all other fruits in these markets, are from Competitive Media Reporting, Inc. A more complete description of this database is included in Appendix A. For purposes of this report, however, these data are used in two ways: to describe market segments based on demographic characteristics of each household, and to estimate econometric models of apple variety, fruit category, and purchase quantity response in order to measure the response in consumers' purchase behavior with respect to prices, price-promotional activity, and media advertising. The elasticities from this estimation phase are then used to define market segments where members of each segment are similar in their response to each marketing variable - either very responsive, not responsive, or moderately responsive. These segments are then described according to their demographic characteristics. The report concludes by drawing implications for marketing-strategy by the Washington Apple Commission marketers.

Demographic Segmentation

Traditional market survey research is used to delineate groups within the overall market that are either more likely to buy a particular product, or, when they do visit the store, how much they purchase on each occasion. This section presents summary results derived by calculating average purchase quantities per store visit for the entire sample for each apple variety, bananas, grapes, and soft fruit. Soft fruit, for current purposes, consists of nectarines, peaches, and plums. These average quantities are calculated for each class within each demographic segment of the AC Nielsen panel. The segments considered here consist of households of similar income, family size, urban market, race, age, education, and measures of loyalty. Two measures of loyalty describe whether a household is, first a loyal, or heavy, apple buyer and second, a loyal banana buyer. Although loyalty is difficult to define in concrete terms, it is defined here using each household's own purchase history. Namely, if a household makes more than 50% of their fruit purchases from within the apple category, then they are deemed heavy buyers. Similarly, households with greater than 50% of their fruit consumption in bananas are defined as banana loyal. Research has shown that these loyalty measures produce similar results whether a 50%, 60%, or 70% share is used.

In order to test whether the difference between the fruit consumption of any class and the overall average consumption from all classes is due to simple randomness or represents a true difference in consumption, statistical tests compare the class and the overall means. In practical terms, if the results show a mean to differ from the mean of that class, we can be 95% confident that this does indeed represent something other than statistical noise. The results from each comparison are found in the tables to follow.

Income Group

Table 1 shows the difference in fruit purchase volumes (average pounds per store visit) by income class. This table reveals results typical of most demographic variables - no clear pattern emerges across the set of apple varieties and other fruits, but each nonetheless provides some valuable information on how households of differing incomes buy fruit. While only one of the income classes differ from the sample average purchase amount for Red Delicious apples (0.22 lbs. per visit), both high income and low income groups purchase significantly less Golden Delicious than the two middle income groups. Similarly, upper-middle income households purchase almost twice as many Granny Smith apples compared to lower income groups. This pattern is also apparent in specialty apple consumption - upper income households purchase roughly double the amount of Fujis, Galas, Jonagolds, and Braeburns. Banana purchases, however, do not exhibit the same level of income sensitivity as, again, only one income class consumes bananas at a rate different from the sample average 1.57 lbs. per visit. Purchases of grapes and soft fruit also appear to differ little by income group, with the sample average level of 0.20 lbs. of grapes and 0.45 lbs. of soft fruit per visit differing little across groups. The implication to be drawn from this summary table is relatively clear - apple consumption rises with income to a greater degree than competing fruits, suggesting that continued strength in personal disposable income should favor apple consumption over these other products. Such differences in income may help to explain differences in apple consumption by market.

[table 1 here]

Markets

A test of this hypothesis is possible by comparing average purchase rates from sample households in six major U.S. markets. Perhaps the most apparent feature of the data revealed in Table 2 is the considerable heterogeneity in purchase amounts between markets. Few markets are indeed "average." With respect to Reds, Los Angeles, Baltimore/D.C., and San Antonio consumers buy significantly more than the sample average, while those in Chicago and Atlanta buy significantly less. Golden Delicious apples, on the other hand, are preferred by those in L.A. and Baltimore, but not by consumers in Chicago or San Antonio. New York consumers show a strong preference for Granny Smiths relative to consumers in other markets, consuming almost double the amount bought per trip in Chicago or Baltimore. Perhaps reflecting the greater dietary diversity typical of West Coast markets, consumers in L.A. purchase almost double the amount of specialty apples per shopping trip as those in other markets. These consumers, however, purchase only an average amount of bananas per trip, while households in Baltimore and San Antonio buy significantly greater than average. Consumers in Chicago buy almost three times the amount of grapes per shopping trip as do consumers in L.A., while N.Y. and Baltimore are also significantly below the national average. Although not consuming grapes, households in N.Y. purchase soft fruit at a rate over 50% greater than average, while shoppers in Atlanta, Baltimore, and San Antonio purchase significantly less than average. Several implications may be drawn from these results, but the most clear are the window of opportunity for both specialty and traditional varieties in L.A. and the preference for Red Delicious in Baltimore and San Antonio. These results also support the market-specific promotional strategy currently adopted by the Washington Apple Commission. Knowledge of how consumption differs among other demographic characteristics is critical in designing Efficient Consumer Response (ECR) programs for Washington apples.

[table 2 here]

Household Size

Analyzing fruit purchases by household size provides an example of how this information can be used. Table 3 shows that for all types of apples, households consisting of either four, five, or six members purchase significantly more apples per trip that do either smaller or larger households. While the former result is to be expected, the latter suggests that per-member apple consumption rates are far higher in medium-sized households compared to larger ones. This, in turn suggests that as household size rises, apple purchases rise, reach a plateau, and then fall with further increases in household members. A similar pattern is apparent also in banana, grape, and soft fruit purchases. While medium-sized households tend to purchase more of all fruits than do those in smaller households, the largest two household-size groups purchase only an average amount of fruit per trip. Market researchers also often believe that purchasing behavior differs significantly by age group.

[table 3 here]

Age and Education

These data provide limited support for this belief. Although the average Red Delicious consumption rate of three of the youngest age groups is greater than the sample mean, table 4 shows that such heavy consumption also characterizes older buyers as well. This heterogeneity extends to other varieties, and to other fruits. Whereas the youngest group purchases less Golden Delicious apples than average, the next-youngest consumes significantly more than average - a pattern that reverses itself with the next oldest age group. Given the general trend towards an aging population, perhaps the most relevant result in this table is the behavior of buyers in the bottom three age groups. While buyers in these groups exhibit a distinct aversion to Granny Smith apples, they appear to buy considerably more specialty apples than average. This bodes well for Fuji, Gala, Braeburn, and Jonagold growers. Surprisingly, the oldest age groups also purchase less bananas and grapes on a typical shopping trip, but more soft fruit. Older consumers' reputation for buying bananas is clearly formed around those in their forties and early fifties rather than among the group of senior citizens. The lost consumption from these groups during this time period (QIII and QIV of 1997) is clearly picked up by soft fruits such as nectarines, plums, and peaches. This result suggests that a stronger seasonal effort to promote apples may be successful in these groups as they search to diversify relatively heavy fruit-purchase patterns. Capitalizing on trends towards older consumers may prove valuable as the population ages, just as focusing on more educated groups may prove lucrative as consumers graduate from College at higher and higher rates in the future.

[table 4 here]

Such trends, however, seem to favor some apple varieties over others, but clearly favor apples in general over other fruits. Table 5 shows the average purchase rates by education-group in the six-market sample. Specifically, the heaviest Red Delicious apple buyers tend to be those with at least a high school education, although consumers with postgraduate degrees appear to consume less than the sample average. This pattern is also generally true for other apple varieties, although those in the highest education class buy significantly more specialty apple varieties compared to the sample mean. Such behavior reflects their greater willingness to experiment with new products and to vary the content of their diets. Apparently, this demand for variety does not include bananas or soft fruit as more educated consumers tend to purchase less of these apple-alternatives. Clearly, this is a finding that bodes well for apple sales in the future as education levels rise and growers respond to the demand for new varieties by breeding and planting apples with characteristics that consumers demand. Consumer preferences, however, are likely to change over time as the ethnicity and racial makeup of the market continue to evolve.

[table 5 here]

Race and Children

Table 6 shows how such trends are likely to affect the demand for fruit. Considering first the choice between apple varieties, the "other" racial group, largely Hispanic, shows a distinct preference for apples other than Red Delicious, favoring both Golden Delicious and Granny Smith apples. Blacks share this preference for Goldens, but consume significantly less Granny Smith and other apple varieties compared to the sample average. Perhaps not surprisingly, oriental buyers prefer specialty apples, including Fujis and others favored in East Asian export markets. Given projections for Hispanic population growth in the U.S., the market opportunity for green apples in general will strengthen into the next century. Hispanic consumers also tend to buy significantly more bananas than other groups, but are not heavy grape buyers. African Americans, on the other hand, tend to buy more grapes and soft fruit than others - significantly more than white consumers, but are only average consumers of bananas. These results suggest opportunities to build demand for particular apple varieties among specific racial groups, but confirm the strength of the apple market among white buyers. A final demographic trend that will shape fruit demand in the future, and one that is inextricably linked to changes in the racial composition of society, is the age-structure of households, or the existence and age a family's children.

[table 6 here]

Specifically, markets with a concentration of Hispanic consumers and other immigrant families tend to have a greater percentage of large families with many young children living at home. Table 7 shows that this trend is particularly favorable for Red Delicious demand since households with children less than 12 years of age tend to consume a far greater quantity of apples than do other households. These type of households also tend to be relatively heavy Golden Delicious and Granny Smith buyers, but do not tend to buy specialty apples. Households with teenagers only (13 - 17 yrs.) appear to prefer Granny Smith and specialty apples, while consuming far less Golden Delicious apples than others. With respect to other fruit consumption, the results are considerably diverse. Families with young children tend to buy more than the average amount, as do families with both adolescents and young children. These families also tend to buy more grapes than average, but are not heavy buyers of soft fruit. If fruit consuming habits are formed at an early age, the strength of bananas among young consumers represents a strategic threat facing WAC marketers. Although not an exogenous, or pre-determined demographic trait, it is also valuable to compare fruit consumption across buyer-loyalties - how much do loyal apple buyers purchase on each shopping trip as opposed to loyal banana buyers?

[table 7 here]

Loyalty

As stated above, loyalty in this context is defined as buying a majority of their fruit from within a single category. Although there are many other definitions of loyalty in the literature, this definition has been shown to be highly correlated with other, more sophisticated variable definitions. For this analysis, two such indices are developed: one indicating loyal apple buyers, consisting of 16.0% of the entire sample, and loyal banana buyers, comprising 35.8% of the sample. Within each segment, we expect to see higher consumption of the chosen fruit, but it is also of value to gauge the magnitude of the "loyalty bump" as well as how this behavior effects the demand for particular apple varieties and other fruits. For all varieties, the summary statistics in table 8 show that loyal apple buyers tend to purchase three times the amount of apples that non-apple loyal buyers do on a per-trip basis. However, these consumers purchase roughly 30% less bananas per trip than non-loyal apple consumers and half as much grapes and soft fruit. These latter results suggest that buyers do have a relatively fixed fruit-budget when they shop and allocation of this budget is a key determinant of the "stomach share" of each type of fruit. Among banana-loyal buyers, table 8 shows that, not surprisingly, the average apple varieties amounts are roughly one-third of the non-banana-loyal group. Further the differences in grape and soft fruit consumption between segments is far more dramatic than in the apple-loyal case. Banana buyers typically purchase only a quarter to a third of the alternative fruits bought by non-loyal buyers.

[table 8 here]

Clearly, there are advantages to attracting consumers and ensuring that they remain loyal apple buyers. However, beyond their average purchase amounts, it is also likely that loyal and non-loyal buyers differ in their sensitivities to key marketing variables. While the summary statistics above emphasize how apple consumers can be segmented along demographic or socio-economic lines, or demographic segmentation, the remainder of this report shows how consumers are segmented along behavioral lines, or through response segmentation. In fact, many researchers now define market segments in terms of groups of consumers that are similar in either their responsiveness to price changes, promotional activity, or mass advertising. Being able to target consumers in these segments promises to significantly increase the efficiency of an overall marketing program and the effectiveness of ECR or category management programs. These issues are explored in the contexts of category choice, and purchase quantity decisions, while variety and category choice are also allowed to vary by the degree of variety or product loyalty, respectively, shown by each household.

Response Segmentation

On each visit to the produce section, a consumer's decision making process can be thought of as consisting of three separate decisions in a tree-like structure. First, a consumer must decide what type of fruit to buy from among categories defined narrowly as bananas, apples, soft fruit, or grapes. Within each of these categories, consumers have the choice of several different varieties or brands - each of which shares important features in common with the rest of the category, but also having characteristics that significantly differentiate them from other varieties. In packaged goods, this choice is called "brand choice," but in produce is more accurately called "variety choice." Finally, once the type of product is selected, consumers must then decide how much to purchase. While this choice is likely to be driven by such things as income, family size, existing inventory, or a household's number of children, variety and category decisions are more likely to be dependent upon prices, promotional programs, or advertising. Therefore, the current research uses statistical models of each decision stage (described in Appendix B) to estimate fruit buyer's responsiveness to key marketing variables. Once these response parameters are estimated, it is possible to explain differences between "responsive" and "non-responsive" consumers resulting from differences in their socioeconomic or demographic backgrounds. By incorporating demographic information only after estimating each household's response to a marketing variable, this approach essentially segments consumers on the basis of their likely response to marketing variables, rather than simply by who they are. This section will present and discuss the response parameters from each model and describe how these results can be used to segment the sample of consumers along behavioral, as opposed to demographic or characteristic, lines.

Variety Choice

Although all three decisions are taken simultaneously, it is convenient to begin the discussion at the bottom of the decision tree, or how consumers make their choice of fruit variety. As interest focuses on apples for this report, only choices between apple varieties will be considered and not the choice among grape varieties, type of soft fruit, or brands of bananas. As explained in the appendix, the choice at this stage is discrete, or yes/no among four different apple varieties - Red Delicious, Golden Delicious, Granny Smith, and other apples. The other apple choice is dominated by Fujis, Galas, Braeburns, and Jonagolds, so this choice is termed "specialty apples" as these varieties share more characteristics in common with one another than with the other apple varieties. Because consumers face a discrete decision among many alternatives, the models described in the appendix are often called "discrete choice" or "multinomial choice" models. With these models, the estimated response parameters describe how the utility, or value, that a consumer derives from a particular variety is influenced by each of several explanatory variables.[2]

Consistent with brand choice models in the marketing literature, at this variety choice stage, the set of explanatory variables includes apple prices, whether or not the chosen apple is on promotion, two measures of variety-loyalty, and an interaction term designed to capture how price sensitivity changes with the degree of loyalty. The first loyalty measure is similar to the one described above. If, over the sample period, a consumer buys more than 50% of his or her apples from the same variety then the consumer is termed "variety loyal" (LOYAL2 in table 9a). Rather than consider a consumer's entire purchase history, the second measure considers only the most recent shopping trip upon which apples were bought. If the consumer bought the same variety of apple twice in succession, then he or she is also defined as being loyal (LOYAL1 in table 9a). In this model, loyalty not only affects the probability of a consumer choosing a particular variety on a given occasion, but also may affect his or her responsiveness to price changes. With this information, marketers may be able to target price promotions only towards those for whom it would be profitable and not those who need no inducement to consume a particular variety. The entire set of variety choice parameters are presented in table 9a.

[table 9a in here]

These estimates show the marginal value, or incremental value to a consumer who chooses a particular variety of a $1.00 change in price, or a change from loyal to non-loyal, or similar one unit change in an explanatory variable. For example, table 9a shows that a $0.10 increase in the retail price of Red Delicious apples causes a 1.6% reduction in the value a typical consumer derives from buying Reds on a

[2] The effect of each explanatory variable on choice probability is simply this marginal utility weighted by the probability of making a particular choice. In the variety model, this probability is conditional on the probability of selecting from within the apple category. In this report, we discuss choice elasticities in addition to marginal utilities because an elasticity is inherently more intuitive and, thereby, managerially relevant. The appendix makes the logic of a conditional choice more clear.

single shopping trip. With respect to the LOYAL1 parameter, if a consumer buys Red Delicious apples on one trip, he or she receives 121% more value from buying Reds again on the next trip, and so is more likely to buy them again. Similarly, consumers who typically purchase a majority of their apples as Reds derive 269% more value from buying Reds than those who are not "Red buyers." The next parameter shows the difference between a loyal consumer's sensitivity to price and a non-loyal consumer's response to price changes. As expected, loyal consumers are less sensitive to price changes in their variety choice decision than non-loyals. The logic behind this result is clear - loyal consumers, by definition, have a preference for Red Delicious apples so a relatively large price change is required for them to switch to a less-preferred variety. Examining the DEAL and DEAL*LOYAL2 interaction variables provides corroborating evidence of this result. While consumers receive 41% more value from buying Reds when they are on deal as opposed to when they are not, shoppers' sensitivity to price promotions does not differ between loyal and non-loyal segments. This result is important because it implies that price promotions do not induce brand or variety-switching behavior when the market is segmented into loyal and non-loyal groups. Finally, this model also shows that choice probabilities do not vary significantly by market. Except for this result, the Red Delicious variety choice estimates are broadly consistent with those found for the other varieties.

In fact, the price sensitivity of Golden Delicious buyers is very close to that shown above (-0.175 vs -0.161). This is to be expected as they are both mature products with relatively well known characteristics and price points. Variety loyalty, however, is a much more important determinant of Gold choice behavior. Specifically, if a household purchased Golds on a given shopping trip, they receive 82% more utility from doing so again. Similarly, if a household is a heavy Gold buyer (> 50% category share), then they derive almost 20% more value from buying Golds than a household that is not loyal to any one variety. On the other hand, contrary to the Red case, loyal and non-loyal buyers do not differ in their responsiveness to price changes. This insensitivity appears again in their response to price promotions - neither the marginal utility from buying Golds, nor the reaction to deals between loyal segments appears to be a significant determinant of Gold choice probability. Nor are price promotions likely to induce variety-switching behavior among Granny Smith buyers. Price promotions do not have a significant effect on choice, even when this effect is allowed to differ between loyal and non-loyal segments. Granny buyers are, however, much less sensitive to changes in price than either of the two previous cases. This suggests that habits or loyalty are likely to be correspondingly more important influences on demand. This is indeed true for both the "last purchase" definition and "category share" definition of loyalty used here. This insensitivity to promotion and price suggests that price promotions on Grannies are likely to be ineffective as consumers tend to buy them more for their distinctive characteristics than for their economy.

As in the Golden Delicious case, most markets have a higher average choice probability than the San Antonio control market. Only consumers in Baltimore/D.C. have a lower average value from choosing Granny Smiths than shoppers in San Antonio. Compared to each of the above varieties, specialty apples are likely to exhibit choice characteristics most similar to Granny Smiths, given the apparent importance of taste and loyalty in choosing outside of the two traditional varieties.

This is particularly true with respect to buyers' sensitivity to changes in price. Specialty apple buyers are nearly as unresponsive to changes in price as are Granny buyers, but even more loyal. In fact, by the last purchase definition of loyalty, previous buyers of specialty varieties find fully 96% more value in buying one of these apples again. Unlike Granny Smiths, however, specialty apple buyers' price sensitivity does not vary between loyal and non-loyal buyers. Nor do specialty buyers respond to price promotions, whether loyal or non-loyal shoppers. Interestingly, buyers in L.A. place far greater marginal value on specialty varieties than typical shoppers elsewhere, while the difference between buyers in Baltimore/D.C.

and those elsewhere is similarly high, albeit statistically insignificant in this case. This result suggests that consumers in these two markets are relatively more willing to try new varieties, and so may be more responsive to promotions and mass advertising directed to more new varieties and methods of distribution. Converting these response parameters to "choice elasticities" shows the effect of each marketing variable on the probability that a particular consumer will choose each variety.

These elasticities, which are shown in table 9b, show the percentage change in the probability of buying a particular variety for a 1% change in the marketing variable of interest. For example, a 1% change in Red Delicious price reduces the probability that a typical consumer will buy Reds by 0.13%. All varieties are very price-inelastic in choice, meaning that price reductions cannot be expected to induce significant brand-switching. Applying the elasticity interpretation to each of the marketing variables confirms many of the marginal utility effects cited above. Specifically, in each case variety choice is most sensitive to brand loyalty. This simply means that apple choice is subject to considerable inertia and habitual purchase behavior as consumers tend to stay with a variety they like. Such variety-loyal consumers differ in their sensitivity to price from non-loyal buyers. In fact, the PRICE*LOYAL2 row in table 9b suggests that loyal shoppers have a near zero price elasticity for each variety. Not surprisingly, therefore, promotional deals have very little impact on variety choice - a 1% change in the probability that a loyal consumer faces apples on deal often only increases the probability of a choice, given that apples are bought, by 0.03 to 0.06%. This effect is hardly economically significant. While variety choice is relatively insensitive to all marketing variables, the same is not likely to be true for the choice of fruit, or category choice. The next section specifically analyzes the effect of advertising on the probability of apple category choice from among other fruit categories of bananas, grapes, and soft fruit.

[table 9b here]

Category Choice

At the category level, fruit buyers again face a discrete choice from among apples, bananas, grapes, and soft fruit. Although other fruits are, of course, often chosen these groups were the most frequently purchased product groups in the HomeScan dataset.[3] To implement the category choice model, it is necessary to keep the specification as simple as possible so that the most important effects remain discernable from the clutter of a large number of economic and socioeconomic variables. As in the previous model, the parameter estimates at this stage describe the effect of changes in each marketing variable on the marginal value of consuming from each category (table 10a). This model also includes three other factors that are likely to influence a household's likelihood of buying from a particular category on a given shopping trip: (1) household consumption rate; (2) current inventory, and (3) category value from the variety choice stage.

[table 10a here]

While the category value term is required in order to "nest" the variety choice and purchase incidence decisions, thereby ensuring the category estimates are consistent, the others represent behaviors that are

[3] Other non-citrus fruit categories, broadly defined as melons, berries, or tropical fruit, were represented by less than 1.5% of all purchase occasions in the panel dataset. This response rate was deemed to low to achieve any reliable parameter estimates so these categories were excluded from the analysis.

likely to be unique to each household. From table 10a, it is clear that these variables are indeed important determinants of the decision to purchase each type of fruit. In each case, the faster a household's consumption rate, the greater the marginal utility of consuming more. On the other hand, the more inventory a household possesses, the lower is the marginal value of the opportunity to buy within a given category. Both of these parameter estimates are of the expected sign and are highly significant. Although these are important influences, they are nonetheless beyond the control of the marketing manager. Consequently, the remaining discussion of this section focuses on the impact of marketing variables on category choice, or incidence elasticities.

In this model, incidence elasticities show the percentage change in the likelihood of buying within a category for a given percentage change in a particular marketing variable. Again, allowing the response to marketing variables to vary by loyalty shows how heavy apple buyers are likely to be influenced in their category choice - behavior that is likely to be significantly different from non-loyal or occasional buyers.

These results are shown in table 10b. Unlike the variety choice case, category choices are very sensitive to changes in price, ranging from -2.188 for grapes to -6.082 for bananas among buyers that are not loyal to either apples or bananas. This suggests that a 1% reduction in the price of bananas increases the probability that a consumer will bananas instead of apples, grapes, or soft fruit by over 6%. As expected, if consumers are loyal buyers of either apples or bananas, their category-switching behavior is less sensitive to changes in price. However, the magnitude of the elasticity reduction is very small - from -3.213 to -3.079 for loyal apple buyers - suggesting that lower prices are a powerful tool in generating category volume and can overcome much of the apparent resistance to change existing fruit buying patterns. The deal elasticities in table 10b support this argument. Increasing the probability that a household faces apples on promotion by 1% increases the probability that they will buy apples by about 3.25%. Not only does this suggest that fruit choice is sensitive to promotional deals, but the impact of promotion differs little between loyalty segments as well. Apple-loyal consumers are only marginally more likely to buy apples again if offered a deal than are non-loyal or even banana-loyal buyers. Each of the other fruits exhibits a similar result - buyers are uniformly sensitive to price promotions and will easily change the type of fruit they buy in response. Given the amount spent by the WAC on both price-promotions and advertising, it remains to be seen whether advertising has a similar impact on category-switching behaviors.

[table 10b here]

Although apple buyers do respond to mass advertising, its effect on the fruit-choice decision is not nearly as strong as the price-promotion effect. Specifically, a 1% increase in advertising expenditure in a given market will increase the probability a consumer buys apples by only 0.3%.[4] Perhaps equally as important as the direct effect of advertising on apple incidence probabilities, apple advertising takes fruit-market share from banana sales with an elasticity of 0.27. Combining these two results, a 1% increase in apple advertising can be expected to produce a 0.57% swing in the market share differential between apples and bananas, if everything else is held constant. Apple advertising over the sample period did not likely narrow

[4] Advertising expenditures are allocated on a monthly basis to the city/market as defined by Competitive Media Reporting. These markets tend to correspond closely to the AC Nielsen markets. To determine the return to promotion from this elasticity, data on aggregate quantities sold per market, retail prices, and grower costs must be known.

this gap, however, because the share effects attributable to banana advertising are nearly symmetrical. Because banana advertisers spend considerably more than apple advertisers in our sample markets, the quantity effects from banana advertising are likely to be far greater than the quantity effects resulting from much lower apple advertising spending levels. This suggests that current levels of apple advertising expenditure are required for defensive purposes alone, and are not generating apple category growth at the expense of bananas. Grape advertising also tends to reduce the probability that a consumer chooses apples on a given store visit, but soft fruit advertising tends to be complementary. This is likely due to the fact that Washington tree fruit growers advertise relatively heavily, emphasizing the positive attributes of Washington in general, thus conveying a strong generic message that benefits apples as well as tree fruit. If apple marketers were able to define market segments that respond particularly well to promotion or advertising, however, it may be possible to improve the efficiency of current expenditure levels in generating fruit market share from banana sellers.

Response Segmentation: Category Choice

Such information is obtainable by conducting a response segmentation analysis. By allowing each of the response elasticities (price, promotion, and advertising) to vary by household, consumers can then be grouped according to "high response," "medium response," and "low response" to each of the marketing variables. Characterizing members of each of these groups by their income, race, family size and other demographic variables will create market segments that are more managerially relevant than simple demographic segmentation alone. Such response segmentation can help to guide apple marketers towards segments defined on a behavioral rather than descriptive basis, allowing them to target marketing efforts to where they are likely to be most successful.

Focusing on the apple category, the results of this analysis are shown in table 10c. In constructing segments for these elasticities, we assume that high, medium, and low response groups can be defined from the distribution of elasticities over all households as described in the appendix. In terms of the elasticity of apple purchase probability with respect to changes in price, there appears to be considerable heterogeneity between each of the segments. However, both the low and high elasticity groups appear to be more like each other than the largest (medium) response group. Specifically, both low and high response groups have relatively higher incomes than expected for the medium response group. Consistent with this result, both the low and high response groups tend to be more educated, and are younger than the rest. High response households also tend to be disproportionately Black, and are slightly smaller than the average household. Price response also differs significantly by market. Interestingly, both high and low response households appear to be over-represented in Chicago, whereas there is also a concentration of high response households in Atlanta, but not New York. While the reasons for these differences are not immediately clear, this information can potentially be used to price-to-market in each case. Pricing-to-market, or price-discrimination by its less palatable name, means charging a higher price in the market with less elastic demand. Opportunities for pricing-to-market, however, may be limited due to the disproportionate number of price-responsive households. If the choice elasticity were normally distributed (bell-curve distribution) over the sample households, we would expect 2.5% of all households in the most responsive segment. However, table 10c shows that 11.5% of households are in this group - far more than we would expect. This result is dramatically different from the advertising response elasticity case, where over 75% of the sample falls in the low-response category.

[table 10 c in here]

Although the probability that most households will buy apples as opposed to another fruit on any given shopping trip is inelastic, or relatively insensitive, to advertising exposure in that market, this analysis reveals some very sharp distinctions between groups. Most apparent is the geographic differences in responsiveness - all of the high response group is located in either Chicago or LA. The implication of this result is clear - if consumers in these markets are relatively more responsive to advertising than those in other segments, then advertising expenditure could be profitably reallocated to these markets. Besides this glaring difference, households in each segment differ in more subtle ways as well. In particular, more responsive households tend to have significantly higher incomes than those in the least responsive segment. Households categorized as advertising-responsive also tend to be slightly larger than the medium response group (2.86 versus 2.70), but tend to be older and more likely to be white than the typical household in a lower response group. In terms of their education, however, this difference in age does not carry the usual corollary that the high response group is more educated as the time spent in school is roughly equal between each segment. Comparisons to the two-segment price promotion market analysis can be made to see if this pattern applies to consumers' responsiveness to deals as well.

Overall, the mean deal-elasticity is very high, indicating that price-discounts in general are likely to be an effective tool in increasing apple category purchase probability. Exploiting differences in this elasticity between segments, however, can improve the efficiency, or return per dollar, of these promotions. In characterizing these segments, deal-responsive households tend to be broadly similar to those that respond well to advertising. However, some important distinctions exist. Whereas highly advertising-responsive households tend to be more predominantly white than less responsive households, Blacks represent a disproportionately large share of the deal-responsive households (9.2%). Similar to the previous case, deal sensitive households tend to be older and have larger families than the other segment, but the difference in education here is more significant. Perhaps not surprisingly, this group also tends to have slightly lower incomes compared to households that are relatively insensitive to price-promotions. With lower incomes and larger families, these household are more likely to find it economically viable to search out and take advantage of temporary price reductions for a product that they buy regularly. In terms of specific markets, a promotion-responsive household is more likely to be found in Chicago, but rather less likely in either New York or San Antonio. Taking into account the deal and advertising results together suggests that buyers in Chicago are responsive to both promotions and advertising. Because of these similarities, and others like them, there is clearly the possibility of mounting joint programs on a market-specific basis in order to generate a greater sales-increment than would come from using one marketing tool alone.

Summary of Category Purchase Results

Combining the results from each of the tables presented in this section provides some useful guides to designing marketing programs that may help increase the probability that a given household will buy apples on each shopping trip. Overall, purchase probability tends to be very elastic with respect to apple prices, but relatively insensitive to the use of advertising. Households are nearly as responsive to the use of price-promotions as they are to general price levels, suggesting that purchase probabilities can be held relatively constant through increasing prices, but offering price promotions more often. Retailers will likely be interested in this result. Further, differences between households' consumption rates and inventory levels are significant determinants of their apple purchase probability, as expected. Also consistent with prior expectations is our finding that loyal apple buyers are less price sensitive than those who do not regularly buy apples. Breaking these response elasticities down by segment reveals that price-responsive households tend to be younger, more educated, and have higher incomes than those with average response rates. Sample members from Chicago and Atlanta appear to be more price sensitive than in other markets as well, suggesting that price discrimination may be effective between regional apple markets. Advertising appears to be particularly effective among older, high income households with large families. Advertising's effectiveness is also very market-specific as all of the most responsive households are located in either Chicago or Los Angeles. Chicago households also appear to be more responsive to price-promotion than average. Beyond this similarity with the advertising-responsive profile, deal-sensitive households also tend to be older and are larger than less responsive consumers, suggesting that advertising and promotion could likely to be used together to generate synergistic results among a targeted segment of consumers sharing these traits. However, total expected purchase amounts are determined not by choice probability alone, but by the total quantity purchased weighted by the probability that the consumer will buy at all on a given purchase occasion. The next section analyzes the conditional quantity-purchase decision.

Purchase Quantity

The final component of the complete model of apple sales concerns the amount purchased on each visit, given the choice of a particular type of fruit. Conditional on the probability of choosing each category, the quantity purchased is determined according to the economic model developed in the appendix. Consistent with economic theory, this model assumes households purchase fruit in order to maximize utility, but in this case they often arrive at corner solutions - or where the best plan on a purchase occasion involves zero purchases of some types of fruit. The method used here accounts for these corner solutions to produce unbiased, or statistically accurate parameter estimates.

As in the models of variety and category choice, the parameter estimates of primary interest are demand elasticities with respect to price, the use of price-promotions, and the amount of advertising expenditure in the buyer's market. Unlike the other models, however, these elasticities show the percentage change in quantity for a change in each of the explanatory variables, rather than a percentage change in the probability of a purchase. Because the quantity purchased is conditional on the probability that a household bought apples, for example, on a given day, the relevant quantities are *expected* or *average* values over a series of purchase occasions for each household and not the amount every household buys on each shopping trip. With this in mind, the quantity model elasticities provide many insights into household purchase behavior, but they are given deeper relevance by conducting a response segmentation analysis similar to the exercise conducted for the category model above . The results of this analysis follow a brief discussion of the quantity model elasticities.

By including the prices for all fruits in each fruit-demand equation, this study estimates both the own- and cross- price elasticities of demand for all four fruits. However, only the behavior of apple buyers is of interest here, so the discussion focuses on these households alone. Conditional on the purchase of apples at the category level, therefore, table 11a provides all price-response elasticities in addition to the own- and cross-advertising and promotion responses.[5] These elasticities are also used to define quantity response segments similar to those used in the category-response model above, namely, they define a "high response," "medium response," and "low response" segment for each marketing variable. Table 11a, however, provides the mean elasticity over all segments.

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[5] Although determining the return on investment for advertising is not the objective of this study, these elasticities can easily be combined with sales-quantity and advertising expenditure data to obtain an estimate of the gross return to advertising.

[table 11a here]

These mean elasticities are each statistically significant and offer considerable insight into the apple-buying behavior of households in the six major Nielsen markets. First, the demand for apples on a shopping trip basis is inelastic (-0.611), meaning that buyers reduce the quantity they purchase in response to a price increase on a given shopping trip less than proportionate to the rise in price. Clearly, if the percentage reduction in quantity purchased is less than percentage rise in price, then total sales revenue on that day will rise. If maximizing retail apple revenue is an objective, therefore, apple prices should be increased until this elasticity is equal to 1.0. Notice, however, that sales of each of the other fruits rise when apple prices fall. This is a case of complementarity, and is a common result in the published research on fruit demand. Simply, this means that consumers likely buy fruit with a relatively fixed fruit-budget in mind. If the price of one good rises and the quantity purchased is reduced very little, then the consumer must necessarily reduce her purchases of all other fruits to compensate. This complementary relationship is also true with respect to the effect of changes in banana prices on apple sales. The fact that bananas are responsible for such a large proportion of the fruit budget makes the explanation for this complementarity offered above even more plausible. With respect to grapes and soft fruit, however, apples are weak substitutes. Given that the sample period includes many weeks where new supplies of each of these goods overlaps with the new apple harvest, this substitute relationship is to be expected.

Most of the advertising elasticities are also consistent with our prior beliefs. Namely, apple advertising causes per-shopping trip apple sales to rise. Specifically, a 10% rise in apple advertising can be expected to produce a 0.34% increase in sales.[6] Although this response may seem trivial, when applied to the total level of apple sales on an annual basis and for the whole country, this 0.34% amounts to millions of dollars of additional apple revenue. As expected, banana advertising has a negative impact on apple sales, nearly offsetting apple advertising for equal percentage changes in each. In this respect, current levels of apple advertising are necessary for defensive purposes alone and are not likely to be responsible for much overall apple-category growth. Among the other fruit categories, soft fruit advertising also reduces apple demand, but the scale of advertising for these fruits likely means that the overall impact is quite small. On the other hand, grape advertising is significant in many markets and is complementary to apple sales. This result, also seemingly paradoxical, is found quite often and results from advertising's ability to increase traffic through the produce section, where buyers of advertised products are likely to buy apples as well. Price promotion also has this effect, but, as is clear from the elasticity shown in table 11a, the ability to increase volume through price reductions is limited. Recognizing that apple buyers are a heterogeneous group and are not likely affected by these marketing variables in a similar way, segmenting households into groups with similar response patterns and describing membership in those groups by their demographic traits is a useful exercise.

Response Segmentation: Purchase Quantity

Similar to the category level response analysis, table 11b shows the membership of each response segment differs by age, income, household size, education, market, and race. The insight provided by this analysis

[6] This is the average advertising elasticity across all six markets. Prior specifications that allow advertising response to vary by market showed that advertising has approximately the same effect in each market, so they can be aggregated for current purposes. In the segmentation procedure to follow, however, this does not say that advertising response must be the same for all markets and for *all* segments. We test for this formally.

will again allow the category manager to target promotions, mount advertising campaigns, and help the retailer set prices in order to exploit their particular market profile with maximum efficiency. Because of the large number of demographic variables considered, this table provides comparisons between segments using only those factors deemed the most important. For example, table 11b shows that households that are relatively price responsive to changes in price tend to have higher incomes than less responsive households. The implication of this result is counterintuitive - if lower income segments are defined geographically, sales revenue can be increased by charging a higher price in these markets. Price responsive households also tend to be larger and have a higher level of education than average or low response households. Both of these findings suggest that consumers with a knowledge, awareness, and concern (given the likely higher number of children in large households) for nutrition tend to compare prices more carefully than others. Price sensitive household heads also tend to be slightly younger, and less likely to be Black than the typical consumer. Because younger consumers tend to have fewer food-buying habits and their buying patterns are less entrenched than others, the finding that they are more price-responsive is not surprising. Lower price elasticity among Blacks can, at least partly, be explained by their residence choices. Living disproportionately in inner-city areas, these consumers are likely to have less opportunity to compare fresh produce prices among grocery stores. On the other hand, the New York market appears to contain a disproportionate share of price-responsive families, perhaps reflecting a more competitive retail grocery market than elsewhere. These results are also broadly consistent with the deal, or price promotion response elasticity segments.

[table 11b here]

Although many studies do not account for price-promotions independent from the price paid by the consumer, it is critical to determine whether such one-time changes have a different impact from simply adopting an "everyday low price" strategy. As the table of elasticities (table 11a) shows, however, both price and promotion have separately significant effects on purchase quantity. Therefore, it is possible that price and promotion sensitive segments may differ in composition. Similar to price responsiveness, table 11b shows that more deal responsive households tend to have higher incomes - higher even than the price-responsive ones. These consumers are also considerably younger, and slightly better educated than members of the other segments. In this respect, we would expect households that have the knowledge and opportunity to price compare to be more likely to take advantage of special deals. Responsive households also tend to be slightly larger than in the other groups, perhaps reflecting a greater need to economize on food purchases, in spite of their higher average incomes. Geographically, households in larger cities - NY and LA in particular - are more likely to take advantage of price promotions than others. This result again reflects both a greater opportunity to source fresh produce from a greater variety of outlets, and perhaps access to more information on deals through newspapers, radio, or outdoor advertising. Race, however, does not appear to be a significant determinant of the response to price promotion as African Americans in the high-response segment tend to be only slightly under-represented compared to the whole sample. Households also differ in their response to all forms of media advertising.

Aggregating television, radio, newspaper, billboard, and other media on a per-market basis, this analysis assumes households react differently to advertising not because of variations in the quality of each advertisement, but because of factors unique to their household. Albeit a strong assumption, it is necessary to able to form some conclusion as to the variation in advertising's effectiveness among different demographic groups. Defining effectiveness here narrowly as a relatively high response elasticity, table 11b again describes each response segment by its typical demographic. This table presents a profile of an advertising-responsive household as one that is smaller than average, has less income, its head is considerably older, and the shopper has less education than is typical. This description accords well with the theory of advertising as applied to experience goods, such as apples, as opposed to search goods, such as cars or clothing (Nelson). If the good is not one whose characteristics are well known, where these characteristics only must be communicated to potential buyers (search good), but whose characteristics must be experienced first-hand, then the effectiveness of advertising depends upon its ability to persuade buyers to initiate a purchase rather than to inform. Such persuasion is likely to be the case with respect to the type of household described here because the other type of household (younger, well educated, higher income) are likely to experience products freely of their own accord without the need for advertising. The responsive segment also tends to be disproportionately located in New York and San Antonio, compared each of their full-sample shares. Similar to the price and promotion response segments, the response to advertising appears to vary little between races with African Americans' share of this segment only 0.5% greater than their full-sample share. This result is, in turn, consistent with the geographic and income profile of this segment. Drawing all these results together, this analysis creates a much more detailed assessment of the effectiveness of advertising and promotion than is currently available.

Summary of Quantity Response Results

Treating the fruit market as a single aggregate, the overall elasticity estimates of this section imply that apple sales can indeed be effectively increased using any of the three marketing tools outlined here. However, we also show that current advertising levels appear to be just enough to offset the competitive effects of banana advertising, while the response of sales to price promotion is quite weak. While not necessarily desirable from the industry's perspective, the greater price elasticity of apples compared to other types of fruit means that marketing large apple crops in the future, and the rise in "stomach share" that this implies, may be a simple matter of allowing market prices to fall. This scenario can be avoided by focusing marketing efforts to where they are likely to be most effective, thereby increasing the efficiency of marketing expenditure. The response-segmentation analysis suggests that this may be achieved by targeting advertising to markets, or using ECR methods, to consumers, that fit the profile outlined here - lower income, smaller households with decision makers who are slightly older and less educated than average. In contrast, everyday-low-price or occasional price-promotion strategies are likely to be most effective among entirely different demographics - high income, predominantly white, younger, well educated households in major metropolitan areas such as New York and Los Angeles.

Conclusions and Implications

This analysis investigates the apple variety choice, category purchase probability, and purchase quantity decisions of households in a sample of over 5,200 households in six major U.S. metropolitan markets. By estimating the responsiveness of each decision with respect to apple prices, price promotions, and media advertising, this analysis determines the effectiveness of each in increasing apple market share. Grouping the sample into segments that are relatively homogeneous in their response to each of these variables provides a demographic profile of the types of consumer that are likely to be most responsive to each marketing tool. It is hoped that this type of information will allow the WAC to further increase the efficiency with which their marketing budget is allocated among markets and tools.

Segmenting apple markets by demographic characteristics alone reveals some significant differences in consumption patterns between types of household. Specifically, these findings show that households in high income market segments tend to purchase double the amount of specialty apple varieties (Fuji, Gala, Braeburn, Jonagold, etc.) than do lower income groups. Among the six sample markets considered here, consumers in Los Angeles are most likely to buy specialty apples, while those in Baltimore and San Antonio are both heavy consumers of Red Delicious apples. Households in these latter cities also tend to be heavy buyers of bananas, the primary rival to apple consumption. Perhaps surprisingly, medium-sized households tend to consume more apples than either smaller households or larger households. Age is also an important factor in that households with older heads tend to consume more of specialty apple varieties than younger families. Further, older consumers appear to substitute soft fruit for grapes and bananas during the summer fruit season, but are less likely to substitute away from apples. Trends towards more educated consumers bodes well for apple category growth as consumers with more education tend to consume greater amounts of specialty apple varieties and lesser amounts of bananas and soft fruit. Similar trends with respect to the ethnic composition of the population also argue for greater specialty-apple consumption in the future as Hispanic and Asian consumers prefer non-Red Delicious apple varieties. These groups also consume more bananas and grapes than White consumers, while African Americans prefer soft fruit to bananas. Among all these groups, however, product-loyalty is perhaps the most significant determinant of demand.

In fact, apple-loyal buyers tend to consume three times the amount of apples as non-loyal buyers, while they consume 30% less bananas and half as much grapes and soft fruit. Statistical models that consider all demographic and marketing effects simultaneously treat apple consumers' choice of variety as depending upon prices, promotional activity, two measures of variety-loyalty, and a combination of price and loyalty. Estimates of the this model show that consumers' of all varieties are unlikely to switch varieties due to changes in price. Moreover, the variety-switching elasticity drops to nearly zero when loyal buyers are modeled separate from non-loyal buyers. This result implies that variety-loyal consumers virtually cannot be induced to change preferences due to changes in price. Loyalty to a fruit-type, however, seems to be less binding at the category level.

Economic models at the category level determine the factors that influence the probability that a consumer buys each type of fruit on a given shopping trip. Such category choice is determined by prices, promotion, consumption rates, inventory, product-loyalty, and advertising. Estimates of this model show that product choice is highly sensitive to changes in price and the use of price-promotions for both loyal and non-loyal consumers. While results from the variety choice model show that price changes cannot induce variety switching, the opposite is true at the category level as banana buyers are more sensitive to price, and therefore more likely to switch, than apple buyers. Further, apple and banana advertising have nearly offsetting rivalrous effects on the probability of buying within their respective categories. This result suggests that current levels of apple advertising are not likely sufficient to generate net movement of consumers out of bananas and into apples. Segmenting consumers by their response elasticities may provide clues as to how the effectiveness of each marketing tool may be improved.

Specifically, consumers who are relatively price-sensitive in category choice tend to have higher incomes, are younger, and are better educated than non-responsive consumers. Such price-sensitive consumers are also more likely to be African American and to live in Chicago. On the other hand, advertising-responsive consumers tend to have higher incomes, larger families, are slightly older and more likely to be white than non-responsive. These findings at the category level are not necessarily consistent with those that drive purchase quantities.

In fact, a consumer's behavior in purchasing apples differs significantly from their response to marketing variables for other fruit. Specifically, when taking the amount of each purchase into account, apple buyers are more price-elastic than are consumers of other fruits but, somewhat paradoxically, are less likely to increase purchases in response to a price-promotion. This result is consistent with the importance of product-loyalty cited earlier. If a large proportion of consumers buy apples out of habit and loyalty, then they are likely to accelerate purchases in time due to a one-time price decrease, but are not likely to increase their total volume over time. Apple consumers are, however, relatively insensitive to changes in the amount of apple advertising. On average, a 10% increase in advertising expenditure increases household purchase quantity by some 0.34% across all sample markets, although this elasticity varies considerably by household.

Much of this variability can be explained by demographic factors unique to each household. In particular, households that are relatively price-responsive tend to have higher incomes, larger families, and are younger and better educated than the largest response-segment. These consumers are more likely to be white and to live in N.Y. than non-price responsive households. This pattern is similar to those who respond strongly to price-promotions, only the age and education differences are much more pronounced in this case. This example also illustrates the importance of taking into account the relative size of each segment. In this case, only 4% of the sample belong to the responsive segment, while over 94% have responses that lie in the vicinity of zero. Clearly, in order to take advantage of this information, promotional programs would have to be targeted to specific geographic and demographic groups. This caveat applies also in interpreting the advertising response results. Advertising has its greatest impact on those households with lower income, smaller families, and those who have older and less-educated heads. Further, advertising was most effective during this sample period in New York and San Antonio than elsewhere. Again, however, this segment represents only 4.3% of the sample so the incremental response obtained by targeting this group must be sufficient to justify the added cost of reaching them.

In terms of potential WAC marketing strategies, the implications that follow from these results are many. First, growth-segments (young consumers, more educated, Hispanic, LA) tend to favor specialty apple varieties over traditional ones, suggesting that these segments be targeted in future promotions for these varieties and that new varieties (eg. Pink Lady) be test marketed with these groups. Second, consumers' choice of variety is largely determined by loyalties and are insensitive to changes in price and price-promotion activity. Consequently, other methods (demos, give-aways) will likely be more effective in inducing variety-switching behavior. Third, category choice is highly sensitive to price and price-promotion, but is inelastic with respect to advertising so category-switching from bananas and grapes is more likely to occur as a result of relative price changes than advertising activity. Further, this result assumes that stockpiling and average consumption rates are held constant, so increasing the probability of purchase on each shopping occasion is *not* likely to suggest that price-discounts cause significant cannibalization from future sales.

Finally, at current levels, apple advertising is just sufficient to offset rival banana advertising on a percentage-response basis. Given that banana advertising is much greater than apple advertising, however, this means that banana advertisers are gaining volume over apple sellers due to the size of their marketing programs alone. If the goal of the WAC is to increase fruit share at the expense of bananas, this result implies that overall apple promotion will have to grow to the scale of the banana program. Irrespective of the amount of expenditure, additional advertising will be most efficiently targeted to lower income, older, and less educated demographic groups within larger urban areas. Because these responsive segments are only a small part of the total market, however, future programs may be targeted to high-response segment-expansion in addition to consumption expansion. Such activities could include using these responsive segments as reference groups or idea leaders in media advertising campaigns.

Appendix A: Data and Methods

AC Nielsen's HomeScan Perishables Service provides the household panel transactions data for this study. The entire sample consists of 177,000 shopping trips taken by 12,000 households from July to December of 1997. To estimate the variety choice, purchase incidence and quantity models, however, several refinements to this sample were required. Because the entire sample consists of over 275 distinct UPC codes, to limit the number of different products to a manageable number the study focuses on non-citrus fruits individually representing at least 2% of the recorded transactions. Further, each type of fruit is represented by at least eight UPC codes in the AC Nielsen data. Excluding organics and specialty products accounting for less than 1% of sales reduced the number of UPCs to four per type of fruit. Nectarines, plums, peaches, and pears are then combined into one aggregate called soft fruit, leaving four major fruit categories: apples, bananas, grapes, and soft fruit. These products represent almost 99,000 of the total transactions reported.

Additional deletions are required in order to incorporate several key explanatory variables. First, media advertising expenditures (Competitive Media Reporting, Inc.) are available for six major markets (Atlanta, Chicago, Baltimore/D.C., Los Angeles, New York, and San Antonio), so only households in these markets were retained in the final data set. Second, previous research demonstrates that a household's consumption rate and inventory of a non-durable good category is a significant determinant of the probability that it will buy a product within that category on any shopping occasion. A household's consumption rate is estimated by dividing the quantity purchased (subsequent to the first purchase in the sample period) by the number of days intervening between two purchases. This rate is averaged for each household on the assumption that consumption rates are relatively stable over a short (six month) time period. Using this estimate, an inventory measure for each purchase date is estimated by adding the quantity bought on the previous shopping date to inventory at that time, and then subtracting the consumption rate multiplied by the length of time between the two purchase dates (Bucklin and Gupta):

$$INV_t^h = INV_{t-1}^h + Q_{t-1}^h - CR \cdot I_{t-1,t}, \qquad \textbf{(1)}$$

where INV_t is the inventory amount in period t, Q_t is the amount purchased at t, CR is the constant consumption rate, and $I_{t-1,t}$ In order to construct estimates of both of these variables, it is necessary to have at least six purchase observations for each household, or one purchase per month. While excluding households that purchase less frequently than this may induce some bias, these households are not likely to be fruit buyers of any type, so can be treated as anomalous for statistical purposes and of little interest to apple marketers for practical purposes. With this exclusion, the final data set consists of 38,207 purchase observations. Of these, the vast majority (21,335) involve bananas, while the next most frequently purchased item is Red Delicious apples with some 5,823 purchases. With the sample so defined, each estimated model includes variables specific to its particular purpose.

For the brand choice model, the key variables include price, deal, two measures of loyalty, and interaction terms between price and loyalty and deal and loyalty. The price vector used throughout this analysis is corrected for likely variations in apple quality between households using Cox and Wohlgenant's adjustment procedure. This method regresses observed apple prices on a series of demographic and socioeconomic variables that are likely to reflect differences in the quality of product these households are likely to purchase, and then adds the equation residuals back to the estimated constant term. This provides a series of prices exhibiting considerable variation between households, where, in theory, none of this variation is due to differences in apple quality purchased by different households. The "deal" variable is simply a binary variable indicating wether or not the product was purchased on a price-promotion. Although the data include detailed codes on each type of deal, few types are repeated often enough to represent separate consideration. Nor do any represent influences on a household's variety choice probability that are likely to be truly distinct from any other type of deal.

Heterogeneity between households is captured at this level by including two measures of variety-loyalty. The first is a binary variable that is 1 when a household buys the same variety on two successive shopping trips. Bucklin and Gupta refer to this variable as the "last purchase" definition of loyalty. The second is similar to one used often in the literature that defines a consumer as loyal if he or she purchases a majority of his or her apples from the same variety (i.e. > 50% household share). Estimates with alternative definitions of the threshold share have been shown to vary little within a reasonable range of the chosen value (i.e. +/- 20%). Finally, the variety choice model assumes that choice probabilities will differ between households in each of the six markets. As discussed in the text, this assumption is supported only in a few markets. While this model includes variables thought to affect the relatively desirability of different varieties, the category choice (purchase incidence) model includes variables intended to capture demand for the broader product-class.

Hence, the motivation driving choice at this level is as much from need as from preference. Factors such as household size, presence of children, household consumption rate, inventory on hand, income, and other variables reflect pressures that determine when a household buys a type of product rather than what form of that product is bought. Each of these behavioral or demographic variables is defined elsewhere in this appendix, but the category model also includes one variable that is unique to the nested multinomial logit approach. Including the log of the denominator of the choice probabilities from the variety choice model as an explanatory variable in the category model is the means by which the two levels are "nested." McFadden (1981) shows that this variable represents the expected maximum utility attainable from the brand choice decision. As such, this variable reflects the total value to each household of all apple-category purchases, so is often referred to as "category value" or the "inclusive value" variable. One key advantage of this approach is that category value varies by household, thus explaining some of the heterogeneity among household category choices not already explained by demographic factors.

Appendix B: Model of Promotion and Consumer Choice

This study uses a procedure for estimating a model of purchase incidence, category volume and brand choice, while allowing for inherent brand preferences over households, brand loyalty, advertising and promotion, and inventory or stockpiling behavior. This approach provides elasticities of brand choice with respect to apple variety prices, variety loyalty, and promotional deals. In the second and third stages of the model, this approach also provides elasticities of category choice and category volume, respectively, with respect to each of the marketing and behavioral variables, thus achieving all of the objectives of the proposed research. Whereas Chintagunta estimates a semi-parametric variant of this model, this research proposes a parametric alternative similar to the approach taken by Bucklin and Lattin, Dillon and Gupta, Gupta, and many others.

Conceptually, this approach uses McFadden's random utility assumption as applied to household's choice of between branded consumer products by Guadagni and Little. This model maintains that a buyer chooses discrete alternative *i* only if it provides the highest level of utility from among all choices. This utility is, in turn, assumed to be determined by characteristics of the choice (including store, promotion, advertising) or of the buyer (including loyalty, inventory, family size, age, etc.). With this assumption, the three purchase decisions (category choice, brand choice, purchase quantity) are assumed to comprise two interrelated problems. In the first, the unconditional probability of buying a particular variety *i* by household *h* at time *t* is given by:

$$P_t^h(i) = P_t^h(i|C)\, P_t^h(C), \qquad \textbf{(2)}$$

where $P_t^h(C)$ is the probability of buying in category *C* (apples, bananas, grapes, or soft fruit) on a given shopping trip, or the purchase incidence and $P_t^h(i|C)$ is the probability of purchasing apple variety *i* (Reds, Golds, Grannies, or a specialty variety) conditional on the choice of category *C*. The conditional variety or brand purchase depends upon the utility derived by household *h* according to a multinomial logit process:

$$P_t^h(i|C) = \frac{\exp(U_{it}^h)}{\sum_k \exp(U_{kt}^h)}, \qquad \textbf{(3)}$$

where $U_{it}^h = u_i + \beta \boldsymbol{X_{it}^h}$, u_i represents a household-specific preference parameter, and X_{it}^h consists of a set of household and brand-specific variables, including promotion, loyalty, and price (Bucklin and Gupta). Bucklin and Lattin demonstrate one of many possible methods of operationalizing both inventory and loyalty indexes. These are described in Appendix A above. Similarly, the binary category purchase decision (yes/no) is modeled in terms of a nested logit specification as:

$$P_t^h(C) = \frac{\exp(V_t^h)}{1 + \exp(V_t^h)}, \qquad \textbf{(4)}$$

where $V_t^h = {}_o + \ \boldsymbol{Y_t^h}$, and $\boldsymbol{Y_t^h}$ again consists of a set of household and category specific variables, including category value: $CV_t^h = \ln[\sum_k \exp(U_{kt}^h)]$, which serves to nest the brand and category decisions (Bucklin and Lattin), inventory and consumption rate. Including these household-specific variables also provides a valuable function in allowing the response parameters to vary by household - a feature that makes the response segmentation exercise possible.

The second problem, of category volume, assumes that consumers maximize a well-behaved utility function defined as: $u = u(\ (\boldsymbol{X},\ )\boldsymbol{Q}, z)$, where $\boldsymbol{Q}$ is a vector representing the discrete variety choice decision taken on each store-visit, *z* is the expenditure on a composite "other good" that is not of direct interest, and is an index of variety quality attributes that is influenced by variety and household specific factors, $\boldsymbol{X}$, and a random component, .. Utility is further assumed to rise in each of these quality attributes. The variable ${}_{it}(\boldsymbol{X_{it}^h},\ )$ is also interpreted as a "variety preference index" that captures any perceived quality-enhancements created through marketing brand *i* (Hanemann; Chintagunta). Indirect utility functions derived from direct forms such as *u* above include the preference index as a price-scaling factor, reflecting the fact that utility falls in *p*, but rises in perceived quality. Hanemann shows that method can be used to generate a wide variety of indirect utility functions that are consistent with the discrete/continuous choice decision. With each of these specifications, it must be true, however, that maximizing indirect utility subject to a budget constraint results in the positive consumption of only one variety and a corner solution with respect to the others. Hanemann provides several examples that lead to estimable binary demand functions.

For current purposes, we define an indirect utility function similar to Chintagunta that can be written as:

$$v\left(\frac{p_{it}^{h}}{\;_{it}^{h}}, y_{it}^{h}\right) = \left(y_{it}^{h} + \;_{1}\frac{p_{it}^{h}}{\;_{it}^{h}} + \;_{2}\right)\left(\frac{p_{it}^{h}}{\;_{it}^{h}}\right)^{-}, \qquad \textbf{(5)}$$

where y_{it}^{h} is the quantity of brand i purchased by household h, and $\;_{1}$, $\;_{2}$, are parameters to be estimated. Assuming the quality index is an exponential function of the variety and household specific quality perception variables described earlier, it can then be written:

$$\;_{ij} = \exp(\;_{ij} + \sum_{k} X_{ijk}\beta_{k} + \;_{ij}) = \exp(\mu_{ij} + \;_{ij}), \qquad \textbf{(6)}$$

for household i, variety j, and quality trait k. Further assuming that the errors in (6) are iid extreme-value distributed, the conditional demand function is found by applying Roy's Theorem to (5) to produce:

$$E[q_{ij}(p_{ij}, y_{ij})] = (\;/p_{ij})(y_{ij} + \;_{1}p_{ij} + \;_{2}) - \;_{1}(1 - \;)[\sum_{k} \exp(\mu_{ik} - \ln p_{ij})]^{-1}, \qquad \textbf{(7)}$$

which is simply a bivariate LES model, estimable with non-linear least squares (Hanemann) using the two-step procedure suggested by Chintagunta.[7] Although the parameter $\;_{1}$ captures the effect of marketing variables on the demand for variety j, other factors thought to be independent of the quality perceptions of j, and yet important to its demand may be included in the parameter $\;_{2}$. We use this fact to incorporate the effects of advertising, promotional deals and competing goods prices on the quantity-demand for product j. By including the price-corrected logit index value in the quantity model, all price, advertising, and promotion elasticities vary by household. Such heterogeneity among the response elasticities permits the response segmentation that is key to our analysis of the apple market.

Appendix C: Method of Response Segmentation

Many studies emphasize the importance of constructing market segments that group consumers with similar responses to marketing variables. The reason is clear - if managers allocate promotional materials using ECR methods, or design advertising programs to specific markets, these expenditures will generate

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[7] In this two-step procedure, the first step consists of the conditional logit / nested logit model of brand choice and purchase incidence. Specifying μ_{ij} in this model to be identical to the deterministic components of the random utility specifications in these models allows for each step of the analysis to be fully nested in the previous step. This also ensures that the two-step procedure yields consistent estimates, although Heckman shows that they are not fully efficient.

incremental sales more efficiently if they are targeted towards those consumers who are most likely to respond. Traditional segmentation methods, along demographic traits alone, assume that similar demographic groups respond to marketing variables homogeneously. There is little reason to believe that this assumption holds uniformly, or even at all. There are many ways to group consumers by their response to marketing variables. While Bucklin and Gupta; Bucklin and Lattin; Kamakura and Russel; and Bucklin, Gupta, and Han all use probabilistic mixture models to estimate segment sizes, and then a Bayesian updating procedure to assign households to particular segments, this method is an unnecessarily complicated way of achieving a fundamentally simple task. Because of this complexity, these studies are also often limited to segmenting the market in only a limited number of ways. For example, Bucklin and Gupta consider both brand choice and purchase incidence response segmentation, but are only able to segment households by their response to price. By adopting a more straightforward method, this study segments apple consumers in their purchase incidence (category choice) and purchase quantity elasticities with respect to price, promotion, and advertising.

In each case, the analysis begins by estimating a single-segment model of purchase incidence, or purchase quantity in which the response parameters are allowed to vary by household. These parameters are used, in turn, to calculate household-varying response elasticities. Assuming these elasticities are normally distributed among the consumers who buy apples, each of the price, promotion, and advertising elasticities are divided into segments of low, medium, and high responsiveness. These groups are defined according to how many standard deviations each household lies from the mean response. The “high” group, for example, has a mean response elasticity two standard deviations above the mean of the entire sample, the “medium” group comprises all observations one standard deviation above to one standard deviation below the mean, and the “low” group comprises all those below this level. Using the empirical rule and extending the high and low groups to contain all extreme observations, this means that there are approximately 68% of the observations in the medium group, and 16% each in the high and low groups. Because of the law of large numbers, the assumption of normality is likely to be a close approximation to the true distribution of elasticities. Once these segments are defined, the mean of each response elasticity and demographic variable are calculated for each segment. Testing the hypothesis that the elasticity or factor either the low or high response group is equal to the medium response group indicates whether there is a statistically significant reason to segment the market along the lines of the particular variable. For example, if it is found that consumers who respond well to advertising tend to have higher educations compared to the medium response group, advertising expenditures should be targeted towards those sub-markets or consumers with more-than-average education. Completing this analysis for all three response parameters and demographics provides a very clear picture of how marketing expenditures should be allocated optimally across consumer groups.

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Table 1. Fruit Consumption by Income Class: AC Nielsen HomeScan Database, Average Pounds per Shopping Trip

Income (,000)	Number	Reds	Golds	Granny Smiths	Others	Bananas	Grapes	Soft Fruit
< 15	889	0.24	0.10	0.08	0.08*	1.81*	0.25*	0.59*
15.1 - 30	4755	0.20	0.05*	0.07*	0.10	1.59	0.17*	0.42
30.1 - 45	8903	0.21	0.09*	0.07*	0.17	1.52	0.20	0.46*
45.1- 60	8311	0.22	0.11*	0.10	0.19*	1.58	0.20	0.45
60.1 -100	11489	0.23	0.09*	0.12*	0.17	1.58	0.21	0.43
>100.1	3860	0.24*	0.07*	0.10	0.17	1.51	0.20	0.46*
Total/Avg	38207	0.22	0.09	0.09	0.16	1.57	0.20	0.45

[1] A single asterisk indicates that the class-mean is significantly different from the overall mean at a 5% level of significance.

Table 2. Fruit Consumption by Market: AC Nielsen HomeScan Database, Average Pounds per Shopping Trip

Market[1]	Number	Reds	Golds	Granny Smiths	Other Apples	Bananas	Grapes	Soft Fruit
Chicago	5723	0.15*	0.07*	0.08*	0.13*	1.53*	0.32*	0.46
L.A.	6676	0.26*	0.10*	0.10	0.26*	1.60	0.12*	0.45
N.Y.	5137	0.23	0.08	0.15*	0.15	1.17*	0.15*	0.72*
Atlanta	7121	0.15*	0.09	0.09	0.17	1.58	0.22*	0.32*
Balt./DC	7538	0.25*	0.11*	0.07*	0.13*	1.66*	0.17*	0.40*
San Ant.	6012	0.28*	0.06*	0.09	0.13*	1.78*	0.23*	0.41*
Total/Avg	38207	0.22	0.09	0.09	0.16	1.57	0.20	0.45

[1] A single asterisk indicates that the class-mean is significantly different from the overall mean at a 5% level of significance.

Table 3. Fruit Consumption by Household Size: AC Nielsen HomeScan Database, Average Pounds per Shopping Trip

Size[1]	Number	Red	Gold	Granny Smith	Others	Banana	Grape	Soft Fruit
1	5872	0.15*	0.05*	0.07*	0.13*	1.28*	0.16*	0.40*
2	15127	0.18*	0.08*	0.07*	0.16	1.53*	0.18*	0.43
3	6613	0.23	0.08	0.10	0.15*	1.62*	0.19	0.44
4	6492	0.28*	0.12*	0.12*	0.19*	1.71*	0.24*	0.50*
5	2832	0.35*	0.14*	0.14*	0.21*	1.74*	0.24*	0.46
6	828	0.27	0.15*	0.14*	0.14	1.86*	0.29*	0.48
7	309	0.18	0.10	0.14	0.28	2.11*	0.33*	0.98*
8	101	0.32	0.10	0.30*	0.19	2.41*	0.25	0.41
9	33	0.47	0.01*	0.05	0.00	1.87	0.71	0.33
Total	38207	0.22	0.09	0.09	0.16	1.57	0.20	0.45

[1] A single asterisk indicates that the class-mean is significantly different from the overall mean at a 5% level of significance.

Table 4. Fruit Consumption by Age of Household Head: AC Nielsen HomeScan Database, Average Pounds per Shopping Trip

Age	Number	Reds	Goldens	Granny Smiths	Others	Bananas	Grapes	Soft Fruit
< 25	108	0.17	0.03*	0.12	0.16	1.57	0.14	0.64
26 - 29	1329	0.22*	0.11*	0.16*	0.17	1.43*	0.20*	0.35*
30 - 34	3549	0.25*	0.10	0.10*	0.13*	1.60*	0.17*	0.43*
35 - 39	4364	0.28*	0.11	0.13*	0.16*	1.62	0.23*	0.45
40 - 44	4555	0.26	0.12	0.09*	0.16	1.64	0.22	0.46
45 - 49	4229	0.22*	0.09*	0.14*	0.15	1.54*	0.20	0.45
50 - 54	4552	0.25*	0.06*	0.11*	0.21*	1.62*	0.20	0.42*
55 -64	7091	0.16*	0.07*	0.06*	0.15*	1.59*	0.21	0.43
65 +	8430	0.17	0.07	0.05	0.17	1.47	0.17*	0.49*
Total	38207	0.22	0.09	0.09	0.16	1.57	0.20	0.45

[1] A single asterisk indicates that the class-mean is significantly different from the overall mean at a 5% level of significance.

Table 5. Fruit Consumption by Education Level of Household Head: AC Nielsen HomeScan Database, Average Pounds per Shopping Trip

Educ.[1]	Number	Reds	Golds	Granny Smiths	Others	Banana	Grape	Soft Fruit
0 - 8	58	0.07	0.09	0.00	0.04*	1.60	0.12	0.37
Some HS	427	0.18	0.11	0.01	0.18*	1.67	0.20*	0.63*
Grad HS	5151	0.20*	0.08*	0.06*	0.13*	1.69	0.19	0.49*
Some Coll.	10639	0.23	0.09	0.08*	0.16*	1.59*	0.20*	0.44*
Grad Coll.	12318	0.23*	0.09*	0.12*	0.17	1.57	0.20	0.44
Post Grad.	9614	0.21*	0.08*	0.10*	0.19*	1.47*	0.21	0.43
Total	38207	0.22	0.09	0.09	0.16	1.57	0.20	0.45

[1] A single asterisk indicates that the class-mean is significantly different from the overall mean at a 5% level of significance.

Table 6. Fruit Consumption by Race: AC Nielsen HomeScan Database, Average Pounds per Shopping Trip

Race	Number	Reds	Goldens	Granny Smiths	Others	Bananas	Grapes	Soft Fruit
White	33367	0.22	0.08*	0.10	0.16	1.56	0.19*	0.44
Black	2654	0.21	0.13*	0.06*	0.13	1.54	0.28*	0.50*
Oriental	793	0.26	0.09*	0.06	0.30	1.56	0.27	0.52
Other	1393	0.18*	0.13*	0.07	0.18*	1.80*	0.23*	0.58
Total	38207	0.22	0.09	0.09	0.16	1.57	0.20	0.45

[1] A single asterisk indicates that the class-mean is significantly different from the overall mean at a 5% level of significance.

Table 7. Fruit Consumption by Degree of Purchase Loyalty: AC Nielson HomeScan Database, Average Pounds per Shopping Trip

Apple Loyal[1]	Number	Reds	Golds	Granny Smiths	Other Apples	Bananas	Grapes	Soft Fruit
0	32077	0.15*	0.06*	0.06*	0.11*	1.64*	0.22*	0.49*
1	6131	0.60*	0.21*	0.25*	0.46*	1.17*	0.10*	0.25*
Total	38208	0.22	0.09	0.09	0.16	1.57	0.20	0.45

Banana Loyal	Number	Reds	Golds	Granny Smiths	Other Apples	Bananas	Grapes	Soft Fruit
0	24547	0.29*	0.12*	0.12*	0.22*	1.29*	0.27*	0.60*
1	13661	0.08*	0.03*	0.04*	0.06*	2.06*	0.06*	0.18*
Total	38208	0.22	0.09	0.09	0.16	1.57	0.20	0.45

[1] In this table, 0 indicates non-loyal, while 1 indicates loyal household. A single asterisk indicates significantly different from the entire sample mean at a 5% level.

Table 8. Fruit Consumption by Age and Presence of Children: AC Nielsen HomeScan Database, Average Pounds per Shopping Trip

Age	Number	Reds	Golds	Granny Smiths	Other Apples	Banana	Grape	Soft Fruit
< 6 yrs.[1]	3415	0.25*	0.10	0.10	0.16	1.65*	0.21	4.14*
6 - 12	2370	0.27*	0.14*	0.11	0.17	1.55	0.22	5.65*
13 - 17	2649	0.26*	0.07	0.15*	0.19*	1.68*	0.22	4.67
0 - 12	2715	0.39*	0.16*	0.13*	0.16	1.88*	0.27*	4.75
0 - 17	233	0.27	0.17*	0.15	0.13	1.61	0.37*	5.09
6 - 17	2165	0.27	0.12*	0.13*	0.22*	1.70*	0.23	4.20
0 - 17	15	0.00*	0.00	0.10	0.43	2.78	0.13	0.00
None<18	24645	0.18	0.07	0.07*	0.16	1.50	0.18*	4.38
Total	38207	0.22	0.09	0.09	0.16	1.57	0.20	0.45

[1] A single asterisk indicates that the class-mean is significantly different from the overall mean at a 5% level of significance.

Table 9a. Apple Variety Choice Parameters: Six U.S. Markets

	Variety			
Variable	**Reds**	**Golds**	**Granny Smiths**	**Specialties**
Constant	1.386* (6.589)	0.179 (0.754)	**0.542*** **(4.632)**	0.973* (4.613)
Price	-0.161* (-2.417)	-0.175* (-2.005)	-0.531 (-1.074)	-0.088 (-1.707)
Loyal 1	1.212* (4.934)	0.818* (3.244)	0.832* (3.308)	0.965* (3.889)
Loyal 2	2.691* (11.934)	1.952* (8.870)	2.087* (10.077)	2.148* (10.078)
Price*Loyal 2	0.390* (3.498)	0.095 (0.841)	0.227* (2.422)	0.054 (0.591)
Deal	0.414 (1.585)	-0.057 (-0.203)	0.038 (0.135)	0.231 (0.867)
Deal*Loyal 2	0.209 (0.439)	0.561 (1.148)	0.488 (0.990)	0.472 (0.976)
Chicago	-0.466 (-1.616)	0.614* (2.017)	0.044 (0.147)	-0.112 (-0.386)
L.A.	-0.039 (-0.151)	0.718* (2.570)	0.255 (0.934)	0.711* (2.691)
N.Y.	-0.055 (-0.195)	0.769* (2.603)	0.768* (2.681)	0.094 (0.332)
Balt./D.C.	-0.078 (-0.280)	0.117* (3.991)	0.475 (1.644)	0.476 (1.693)
Atlanta	-0.292 (-1.202)	0.733* (2.836)	-0.341 (-1.311)	-0.215 (-0.867)

$= 2(LLF_u - LLF_r) = 926.178$

Table 9b. Apple Variety Choice Elasticities: Six U.S. Markets

	Variety			
Variable:	**Reds**	**Golds**	**Granny Smiths**	**Specialties**
Price	-0.130	-0.063	-0.032	-0.054
Loyal 1	0.903	0.273	0.464	0.542
Loyal 2	2.219	0.743	1.298	1.331
Price*Loyal 2	0.029	0.025	0.009	0.024
Deal	0.104	-0.006	0.007	0.043
Deal*Loyal 2	0.036	0.039	0.061	0.059

Table 10a. Category Choice Parameters: Apples, Bananas, Grapes, and Soft Fruit

	Fruit Category							
Variable:	**Apples**		**Bananas**		**Grapes**		**Soft Fruit**	
Constant	53.217	(26.813)	56.627	(28.497)	50.567	(25.541)	52.635	(26.480)
Price	-4.517	(-8.648)	-8.552	(-16.296)	-3.077	(-5.908)	-4.149	(-7.956)
Deal	15.895	(20.690)	15.394	(20.051)	16.516	(21.521)	16.128	(20.995)
Consume Rate	5.786	(21.309)	3.813	(11.869)	5.795	(21.229)	5.773	(21.099)
Inventory	-0.005	(-13.652)	-0.004	(-10.777)	-0.005	(-12.637)	-0.004	(-11.205)
Apple-Loyal	6.345	(8.687)	-6.781	(-9.309)	-8.569	(-11.467)	-8.259	(-11.102)
Price*A-Loyal	1.031	(1.153)	0.069	(0.076)	0.909	(1.009)	0.849	(0.939)
Deal*A-Loyal	4.695	(6.472)	4.413	(6.075)	4.636	(6.281)	4.638	(6.361)
Banana-Loyal	1.239	(3.055)	1.506	(3.757)	1.412	(3.462)	0.973	(2.401)
Price*B-Loyal	1.775	(5.043)	3.200	(8.967)	0.917	(2.584)	1.568	(4.486)
Deal*B-Loyal	-3.675	(-7.294)	-3.931	(-7.949)	-3.945	(-7.706)	-3.824	(-7.671)
Category Value	0.078	(23.552)	0.075	(22.687)	0.075	(22.661)	0.075	(22.597)
Apple Advert.	0.099	(9.462)	-0.013	(-16.155)	-0.018	(-20.875)	-0.054	(-34.291)
Banana Advert.	-0.012	(-15.226)	0.009	(8.793)	-0.172	(-19.591)	-0.0127	(-12.051)
Grape Advert.	-0.191	(-21.704)	-0.183	(-20.834)	0.098	(9.216)	-0.166	(-18.919)
Soft Advert.	1.011	(18.079)	1.040	(18.713)	1.087	(19.386)	1.227	(22.069)

$= 2(LLF_u - LLF_r) = 24{,}787.1$

Table 10b. Category Choice Elasticities with Respect to Marketing Variables by Loyal and Non-Loyal Market Segments

		Fruit Category			
Elasticity:	**Segment:**	**Apples**	**Bananas**	**Grapes**	**Soft Fruit**
Price	**Non-Loyal**	-3.213	-6.082	-2.188	-2.951
Price	**A-Loyal**	-3.079	-5.994	-2.011	-2.842
Price	**B-Loyal**	-2.841	-5.347	-1.996	-2.828
Deal	**Non-Loyal**	3.258	3.275	3.352	3.048
Deal	**A-Loyal**	3.382	3.392	3.475	3.171
Deal	**B-Loyal**	3.024	3.015	3.100	2.804
Apple Ad.	**All**	0.304	-0.321	-0.475	-1.354
Banana Ad.	**All**	-0.270	0.248	-0.269	0.347
Grape Ad.	**All**	-1.502	-1.437	1.359	-1.311
Soft Ad.	**All**	0.626	0.644	0.673	0.759

Note: All elasticities are significantly different from zero at 5% level.

Table 10c. Apple Category Choice: Response Segmentation by Demographic Variable

		Response Elasticity Level		
	Demographic:	**Low (below 1.383)**	**Medium (1.383 to 5.042)**	**High (above 5.042)**
Price Response Elasticity	**Income**	$66,732.00	$58,457.00	$61,548.00
	Market	27.3 % in CH 12.2% in AT 16.4% in LA	12.8% in CH 18.5% in AT 17.9% in LA	24.1% in CH 22.8% in AT 14.4% in NY, LA
	HHSize	2.777 hd.	2.732 hd.	2.692 hd.
	Race	86.8% W 6.5% AA 3.3% AS	87.6% W 6.8% AA 1.9% AS	86.0% W 7.9% AA 2.7% AS
	Age	45.2 yrs.	46.7 yrs.	45.6 yrs.
	Education	15.7 yrs.	15.3 yrs.	15.8 yrs.
	Segment Size	2.6%	82.5%	11.5%
		Low (below 6.344)	**Medium**[1]	**High (above 6.344)**
Deal Response Elasticity	**Income**	**$59,924.00**	N.A.	**$56,852.00**
	Market	**10.7% in CH** **14.2% in NY** **17.6% in SA**	N.A.	**32.0% in CH** **10.2% in NY** **8.3% in SA**
	HHSize	**2.723 hd.**	N.A.	**2.760 hd.**
	Race	**87.9% W** **6.4% AA** **2.0% AS**	N.A.	**85.0% W** **9.2% AA** **2.3% AS**
	Age	**46.3 yrs.**	N.A.	**46.9 yrs.**
	Education	**15.4 yrs.**	N.A.	**15.2 yrs.**
	Segment Size	**80.1%**	N.A	**19.9%**
		Low (below 0.304)	**Medium (0.304 to 0.986)**	**High (above 0.986)**
Advertising Response Elasticity	**Income**	$58.831.00	$60,333.00	$61,400.00
	Market	10.8% in CH 12.1% in LA 18.3% in BA	13.4% in CH 17.0% in LA 45.0% in BA	45.7% in CH 54.3% in LA

HHSize	2.717 hd.	2.701 hd.	2.860 hd.
Race	87.1% W 7.1% AA 2.1% AS	87.9% W 7.9% AA 1.7% AS	88.1% W 5.1% AA 2.7% AS
Age	46.4 yrs.	46.4 yrs.	47.2 yrs.
Education	15.4 yrs.	15.3 yrs.	15.4 yrs.
Segment Size	75.9%	13.0%	11.1%

[1] The “deal” variable is binary (0 or 1), therefore, the elasticity assumes one of two values for each household.

Table 11a. Fruit Purchase Quantity Response Elasticities: Discrete Choice Linear Expenditure System, NLS Estimates

	Fruit Category[1]			
Variable:	**Apple**	**Banana**	**Grape**	**Soft Fruit**
Apple Price	-0.611	-0.078	-0.016	-0.019
Banana Price	-0.038	-0.212	0.004	-0.006
Grape Price	0.315	0.036	-0.304	-0.055
Soft Fruit Price	0.045	-0.123	-0.055	-0.241
Apple Advertising	0.034	0.015	0.012	-0.019
Banana Advertising	-0.031	0.143	-0.003	0.002
Grape Advertising	0.012	0.005	0.026	0.054
Soft Fruit Advertising	-0.091	-0.001	-0.063	0.209
Price Promotion	0.002	0.020	0.064	0.014

[1] The estimates in this table were found using four independent LES demand equations, where alternative product prices enter as environmental variables in Hanemann's $_1$ variable. In each case, the sample consists of only those households consuming the indicated category. All elasticities are significantly different from zero at a 5% level of significance.

Table 11b. Apple Purchase Quantity: Response Segment Membership by Demographic Factor

		Response Segment:		
	Demographic:	**Low[1] (below 0.404)**	**Medium (0.818 to 0.404)**	**High (above 0.818)**
Own Price Response Elasticity	**Income**	$58,517.00	$62,341.00	$62,558.00
	Market	16.1% in NY 19.9% in BA	21.6% in NY	25.8% in NY
	HHSize	2.67 hd.	2.92 hd.	3.29 hd.
	Race	87.4% W 7.1% AA 1.9% AS	87.2% W 6.8% AA 2.3% AS	87.6% W 5.6% AA 3.1% AS
	Age	46.88 yrs.	45.03 yrs.	45.08 yrs.
	Education	15.27 yrs.	15.51 yrs.	15.56 yrs.
	Segment Size	79.1%	17.1%	3.8%
		Low (below -0.002)	**Medium (-0.002 to 0.005)**	**High (above 0.005)**
Deal Response Elasticity	**Income**	$49,269.00	$59,146.00	$63,156.00
	Market	53.8% in NY 3.1% in LA 4.6% in AT	19.9% in BA 13.2% in LA 18.8% in AT	22.8% in NY 19.4% in LA
	HHSize	2.065 hd.	2.726 hd.	2.842 hd.
	Race	93.8% WH 2.1% AA 1.2% AS	87.3% WH 7.0% AA 2.0% AS	86.9% WH 6.5% AA 2.9% AS
	Age	51.35 yrs.	46.58 yrs.	43.03 yrs.
	Education	14.62 yrs.	15.31 yrs.	15.79 yrs.
	Segment Size	1.7%	94.3%	4.0%
		Low (below 0.034)	**Medium (0.034 to 0.068)**	**High (above 0.068)**
~~Advertising~~ Response Elasticity	**Income**	$59,297.00	$61,053.00	$56,055.00

Market	16.7% in NY 19.6% in BA 15.6% in SA	20.0% in NY 21.4% in BA	27.5% in NY 18.8% in SA
HHSize	2.728 hd.	2.878 hd.	2.486 hd.
Race	87.6% WH 6.8% AA 2.0% AS	84.6% WH 8.3% AA 2.5% AS	86.1% WH 7.5% AA 2.4% AS
Age	46.51 yrs.	45.48 yrs.	47.56 yrs.
Education	15.31 yrs.	15.49 yrs.	15.28 yrs.
Segment Size	88.1%	7.6%	4.3%

[1] Price response elasticities are in absolute values. Values in cells indicate the change in probability of belonging to a segment with respect to a single-unit change of the demographic variable. N.D. indicates that there is no change in the probability of membership due to this demographic factor. WH indicates white; AA indicates African American, and AS indicates Asian. Racial percentages do not add up to 100% due to an omitted "other" category. Markets are NY = New York; CH = Chicago; BA = Baltimore / D.C.; LA = Los Angeles; SA = San Antonio; AT = Atlanta.