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Abstract: A structural latent variable model of apple variety demand is used to analyze the effect of variety specific newspaper advertisement characteristics on variety attraction (preferences), and in turn on variety demand. The influence of advertisement size, the use of color and the Washington apple logo were analyzed. The estimated variety attraction variable is important in explaining demand. Model specifications which exclude this variable tend to understate demand elasticities. Advertisement size has a positive impact on Granny Smith, Fuji, and Gala sales. Red Delicious sales are positively influenced by color ads, but negatively affected by ads with the Washington apple logo.

Keywords: Apple demand, newspaper advertisements, structural latent variable model

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The leaders of farm commodity associations are under increased pressure to demonstrate the effectiveness of promotion expenditures. Marketing managers in these associations are demanding measures on the effectiveness of alternative media, like magazines, newspapers, radio, television, direct mail, in-store demos, and outdoor formats (billboards and bus banners), so that they can evaluate past allocation decisions and plan for the future. In response to these demands, there is a growing literature on media choice decisions by generic commodity promotion organizations (see Kinnucan and Thomas).

Decisions on media type, though, are just the beginning for marketing practitioners, as decisions on advertisement design and format must also be made. These decisions can influence the effectiveness of the advertisement and, ultimately, the return to total promotion expenditures. Returns on promotion investment depend not only on media choices, but also on the features of each choice that can influence its effectiveness or “productivity.” Analysis of the effectiveness of the design elements of an advertisement in a given media may be particularly important for some commodity associations, as institutional relations with retailers or merchandisers may limit direct decisions on media choice.

Among the media types, newspaper advertisements take the leading position, accounting for 23.2 percent of all the advertising messages delivered (Coen). In terms of generic promotion expenditures, newspapers play an especially important role. A recent study reported that the Pear Bureau spent more on “ad buys [newspaper advertisements] than any other promotion type” (Erikson, et al). Analysis of Washington Apple Commission financial reports indicates that expenditures on newspaper advertisements account for as much as 20 percent of the Commission's entire operating budget. For some commodity associations, newspaper advertisements may play an even larger role in promotion, as the fixed costs of mounting a radio or television advertisement may be prohibitive, thereby forcing them to rely exclusively on newspapers. In spite of its importance in advertising in general, little is known about the economic returns associated with newspaper advertisements, nor, more specifically, on the influence of newspaper advertisement design characteristics.

In developing newspaper advertisements, retailers must make decisions on the space allocated to featured items, the use of color, illustrations or logos, and the textual information provided. Each of these characteristics is likely to have unique measurable effects on consumer response and brand attraction. Indeed, given that the cost of advertisements vary with these characteristic choices, the market suggests they may have differentiable effects on consumers, as valued by advertisers. Their effects, which are ultimately revealed through purchase behavior, are manifested through consumer tastes or preferences, which are not observable. Preferences for specific brands, in turn, reflect an attraction to that brand or variety. In cases where preferences are linked to specific brands, they may be described as a "brand attraction."

The objective of this paper is to determine the impact of alternative newspaper advertisement design characteristics on consumer demand for apple varieties. A latent-variable demand-system model, which can be interpreted as a variant on a multiple-indicator and multiple-cause model (MIMIC), is developed for seven apple varieties. Whereas Joreskog and Goldberger (1975) develop the MIMIC model for one latent variable, this study considers several -- one for each apple variety. Essentially, MIMIC models use the covariance structure among a set of “indicator” variables and the direct relationships with a set of “cause” variables to identify the unobservable, latent variable (preferences or brand attraction). In this context, apple varieties are treated as brands. Like brands of any consumer product, apple varieties share a common association with apples in general, but each has unique characteristics (sweetness, texture, etc.) that serve to differentiate it from other varieties. This study links demand for apple varieties to variety specific advertisements through a latent measure of brand or variety attraction.

In doing so, the analysis provides commodity associations and retailers with new information on the impact of alternative newspaper advertisement design characteristics on consumer preferences or brand attraction. Commodity associations can use this information in their negotiations with retailers on the requirements or recommendations for newspaper advertisements. Retailers, too, directly benefit from the analysis, as these design characteristics impact their costs and revenues.

In the next section, this paper develops arguments on how advertisement characteristics may influence consumer preferences. This is followed by the development of the empirical model and a brief discussion of the data. Then, the empirical results are presented, followed by a discussion of the implications.

Print Advertisement Characteristics

For grocery retailers, decisions on advertising space allocation are of great importance. Traditionally, it has been accepted that large advertisements are better better attention-getters than small ones. Research has shown that indeed advertisement size is positively related to the ability of consumers to recall information from an advertisement (Homer). Beyond being able to recall an advertisement, consumers have also been shown to form perceptions on brand quality based on advertisement size. However, the relationship between brand perceptions and advertisement size traces out on an inverted-u shaped curve. Increasing advertisement size is positively related to favorable brand or product perceptions up to a certain point and then begins to decline, as consumers begin to believe that the advertisement is more manipulative than informative (Kirmani; Homer). Other studies on the effects of yellow page advertisements revealed that relative size is more important than absolute size (Kelly and Hoel). However, this finding is likely specific to this media, where firms offering similar products or services are grouped together. Other studies have suggested that readers, through a process of selective exposure, are more likely to screen out large print advertisements (Feldman and Halterman). This research suggests that several small advertisements may be more effective than a single large advertisement. This screening process, though, has also been shown to be influenced by whether the reader is predisposed towards being a prospect for the advertised product or product category (Silk and Geiger).

Although color does generally affect the cost of printed advertisements, little is known of its effect on consumer behavior. In one study on yellow page advertisements, color was shown to not significantly affect the readers' evaluation of the advertisements (Kelly and Hoel). However, given the unique characteristics of this media, it is unclear whether this result applies to newspaper and other print advertisements.

Research on the effectiveness of illustrations provides support for the old saying that a "picture is worth a thousand words." Important among the findings in this area of research is that readers are more likely to remember advertisements that contain pictures or illustrations (Starch).

Further, consumers are more likely to recall brand names when the advertisement contains a picture (Leong, Ang, and Tham). It is unclear, though, whether the findings on illustrations carryover to graphical representations of company logos or brand names.

While these findings offer some insight into how advertisement characteristics affect consumer perceptions, no study to date has attempted to incorporate advertisement characteristics in a model of product sales. Indeed, all previous studies were conducted in experimental settings using test subjects and questionnaires on perceptions. This underscores the need to link consumer perceptions, as it influences preferences (brand attraction), to consumption behavior using appropriate empirical methods, as discussed in the next section.

A Structural Latent Variable Model of Brand Attraction

Brand attraction can be thought of as analogous to the unobservable tastes and preferences commonly modeled in aggregate demand studies (Eales and Unnevehr; Chavas; Gao, Wailes, and Cramer). Research on aggregate product shares typically consider tastes and preferences as accounting for some of the observed variation in demand that is not already explained by variation in own- and related-good prices and category expenditure within a system of demand equations. This unexplained variation, therefore, constitutes one indicator of brand attraction - the ability of a brand to generate sales irrespective of price or expenditure effects. Retailers, on the other hand, are aware of perhaps a more practical measure of brand performance, namely, the gross margin of a product relative to the others in its category. Both of these indicators are rarely available in aggregate demand data.

Measures of such performance, however, are most readily available through aggregate (store-level) scanner data, which provide high-frequency category share and gross margin information on a store-level. As retailers and their suppliers implement category management or efficient consumer response programs, the high-quality data that form the backbone of these programs is ideal for store-level demand analysis. Data on sales volume and prices for fresh produce are provided on a product, or even variety-specific basis. These data, when combined with other market or consumer information, are well adapted to the estimation of latent-variable demand-system models.

Empirical models of the latent effect of brand attraction, or equivalent concepts such as knowledge, goodwill, or tastes and preferences, typically include proxy variables in an attempt to measure what is inherently unobservable. For example, promotion expenditure is often used as a proxy for “goodwill” (Chang and Kinnucan), while demographic variables are often used to proxy heterogeneity among household preferences (Park and Capps). Although this approach offers advantages of directness and simplicity in estimation, there are two reasons to expect biased and inconsistent parameter estimates to result. First, proxy variables are erroneous measures of the true latent variables upon which demand is thought to depend. Using promotion spending expenditure to proxy brand attraction introduces potentially significant measurement error and, hence, inconsistency. Second, latent variables such as brand attraction are likely to be endogenous. Thus, simultaneity bias will be introduced when proxies for latent variables are introduced into models estimated by OLS or similar limited-information frameworks, which fail to account for this endogeneity. Beyond these sources of bias, introducing a single proxy variable may provide misleading results simply because there are many possible proxies for any latent variable, each leading to a different estimate of the true effect. Consequently, measuring brand attraction, and the effect of advertisement characteristics on brand attraction, requires an approach that explicitly considers the latency of this variable. Within the general class of structural latent variable models, the multiple-indicator, multiple-cause (MIMIC) model (Joreskog and Goldberger ; Anderson; Bollen) is becoming more prevalent in the marketing and demand-analysis literature (Gao and Shonkwiler).

This approach relies on covariance relationships between observable endogenous "indicators" of latent variables and exogenous observable "causes" to identify latent variable values that are otherwise unobservable. Formally, MIMIC models consist of two sets of equations: (1) measurement equations that describe the relationships between indicator variables and latent constructs, and (2) causal or structural equations that show how these latent variables are determined by observable, exogenous economic variables. While measurement equations are used to scale and identify the latent constructs, causal equations provide the parametric estimates that are of key interest to researchers. Formally, structural equations specify relationships between the set of latent variables ($\boldsymbol{\eta}$), their causes ($\boldsymbol{z}$), and a random error term ( ):

$$\boldsymbol{\eta} = \quad \boldsymbol{\eta} + \quad \boldsymbol{z} + \quad , \tag{1}$$

where and are parameter vectors showing the marginal effects of the latent variables on each other and the cause variables on the latent variables, respectively. Measurement equations, on the other hand, show how each indicator variable ($\boldsymbol{y}$) is related to the latent variables, a vector of exogenous factors ($\boldsymbol{x}$), and a vector of random measurement-errors (Joreskog and Goldberger; Bollen; and Anderson):

$$\boldsymbol{y} = \quad {}_y\eta + \quad \boldsymbol{x} + \quad . \qquad \textbf{(2)}$$

In this set of equations, the components of $\quad_{y}$ are also known as factor loading coefficients. Further, the error terms of (1) and (2) are uncorrelated with each other, have zero means, and have covariance matrices given by and , respectively. These covariance matrices are central to the estimation method.

Whereas ordinary least squares regression finds parameter estimates by minimizing the sum of squared deviations between the fitted and observed values of ***y***, the fact that some of the dependent variables in a MIMIC model are unobserved makes this impossible (Gao and Shonkwiler; Bollen). Therefore, estimates of the model parameters are found instead by minimizing the difference between the sample covariance matrix of observed variables (**S**) and a fitted covariance matrix (( )) for a parameter vector, . Bollen provides details on the decomposition of ( ) into its component moment matrices of ***y*** and ***x***. The difference between these two matrices is expressed in terms of a general class of loss functions (Browne 1994):

$$F(\;, \boldsymbol{S}) = (\boldsymbol{s} - \;)' \quad ^{-\mathbf{1}}(\boldsymbol{s} - \;), \qquad \textbf{(3)}$$

where ***s***, and are vectors of the non-redundant elements of their corresponding symmetric matrices, and is a positive-definite weighting matrix. Assuming the observed variables are multivariate normal, Ivaldi, et al. explain that minimizing the specific form of *F*:

$$F(\;, \boldsymbol{S}) = \log| \quad | - tr(\boldsymbol{S} \quad ^{-\mathbf{1}}) - \log|S| - n, \qquad \textbf{(4)}$$

is equivalent to maximum likelihood, where n is the number of observations. Through this estimation procedure, an estimate of the latent variables ($\boldsymbol{\eta}$)can be developed. The influence of this variable on the indicator variables $\boldsymbol{y}$ is measured by $\;_y$ in the measurement equation and factors influencing the latent variable are evaluated in the structural equations. In practice the estimated latent variables can be thought of as index values. The specific form of the measurement and structural equations are explained in greater detail below.

In the current example, there are six latent variables. Defining apple varieties as brands, these latent variables measure the "brand attraction" of each of six apple varieties: Red Delicious, Golden Delicious, Granny Smith, Gala, Fuji, and McIntosh. The measurement model consists of two sets of indicator equations, the first serve to identify the latent variable, while the second are included to scale or determine the value of each latent variable. In the first set, the indicator variables are defined as residuals from each equation of a Linear Approximate Almost Ideal Demand System (LAIDS). Deaton and Muellbauer derive the AIDS model from a price independent generalized logarithmic (PIGLOG) expenditure function:

$$\ln e(\boldsymbol{u},\ \boldsymbol{p}) = (1 - u)\ln a(\boldsymbol{p}) + u\ln b(\boldsymbol{p}), \qquad \textbf{(5)}$$

where in this case:

$$\begin{aligned} \ln a(\boldsymbol{p}) = {}_0 &+ \sum_i {}_i \ln p_i + (1/2)\sum_i \sum_j {}_{ij} \ln p_i \ln p_j \\ &+ \sum_i {}_i \ln B_i + (1/2)\sum_i \sum_j {}_{ij} \ln B_i \ln B_j + \sum_i {}_{i,w} \ln B_i \ln p_i \end{aligned} \qquad \textbf{(6)}$$

and:

$$\ln b(\boldsymbol{p}) \;=\; \ln a(\boldsymbol{p}) \;+\; {}_{0} \;\; {}_{i} p_{i}^{\;\;i}, \qquad \textbf{(7)}$$

for a vector of prices ***p*** and utility level *u*. Applying Shephard's Lemma to the expenditure function that results from substituting (6) and (7) into (5) provides a system of Hicksian, or utility-dependent, share equations:

$$w_i \;=\; {}_{i} \;+\; \sum_{j} \;{}_{ij}\ln p_i \;+\; {}_{i,w}\ln B_i \;+\; {}_{i}u \;\; {}_{0} \;\; {}_{i}p_i^{\;\;i} \;+\; {}_{i,w}. \qquad \textbf{(8)}$$

Inverting the expenditure function to solve for utility as a function of prices and expenditure and substituting the result into (8) leads to the share equations written in Marshallian form:

$$w_i \;=\; {}_{i} \;+\; \sum_{j} \;{}_{ij}\ln p_i \;+\; {}_{i,w}\ln B_i \;+\; {}_{i}\ln(X/P) \;+\; {}_{i,w}, \qquad \textbf{(9)}$$

where w_i, is the share of variety i, p_i is the price of variety i, X is the total amount of apple expenditure, B_i is the latent attraction to brand or variety i, and ln P is a Stone price index for the apple category such that: $\ln P \;=\; \sum_i w_i \ln p_i$. These equations form the basis for the first set of indicator equations.

While these equations are written in share-dependent form, it is the variation in variety-share that is not explained by prices and expenditure that helps determine the latent variable values. The indicators are, therefore, not expenditure shares, but rather demand shares with price and expenditure effects "filtered" out (Gao and Shonkwiler; Gertler 1988). It is this interpretation that underlies the analogy to unobservable tastes or preferences referred to above. Further, defining indicator variables in terms of a demand system also serves a secondary purpose by providing estimates of all price, expenditure and latent variable elasticities. Green and Alston (1990) provide elasticity expressions consistent with an LAIDS model, so they are not repeated here. Just as this set of indicator equations can be derived from a formal model of consumer optimization, the second set are consistent with Gardner's (1975) model of competitive margin behavior — an application of which is provided by Wohlgenant and Mullen (1989).

Specifically, their relative price spread model (RPS) maintains that, in a competitive market, the retail-farm price spread will be more than simply a markup over costs. Rather, margins are determined by retail demand, farm supply, and the demand for marketing services. Including each of these in a simple empirical margin model leads to:

$$m_i \;=\; {}_1 p_i^{\,r} \;+\; {}_2 p_i^{\,r} q_i \;+\; {}_{i,m} B_i \;+\; {}_{i,m}, \qquad \textbf{(10)}$$

where m_i is the retail-farm margin of variety i, p_i^r is its retail price, q_i is the quantity sold, and $\epsilon_{i,m}$ is a vector of independent, identically distributed errors. Marketing cost was not included in this application, as these data were not available and are not expected to vary widely over a sample period of only 13 weeks. However, retail margins may also be influenced by brand attraction, which is introduced in the RPS model. For each brand, ${}_{i,m}$ is normalized to 1.0 in order to scale and identify the latent brand attraction variable. Using the margin equations to scale the latent variables means that brand attraction is measured in the same units as margins, or dollars per pound. Conveniently, therefore, each B_i represents the dollar value of marketing activities used to attract buyers to variety i. As such, each equation of the structural model can be interpreted as a price-dependent Lancaster-Ladd input demand equation wherein each input (advertisement) is differentiated by its mix of creative characteristics: size, use of color, or presences of a logo or illustration.

To see this, consider the problem faced by a commodity promotion association that does not grow or process commodities, but only markets growers' output through one media.[1] In Ladd's notation, marketers choose the scope and frequency of print advertisements (v_{jh}) for product h, while sales of the commodity depend directly upon the impact desired from each advertisement (x_{ih}) according to the production technology:

$$q_h = F_h[x_{1h}(v_{1h}, v_{2h}, \dots v_{mh}), x_{2h}(v_{1h}, v_{2h}, \dots v_{mh}), \dots, x_{nh}(v_{1h}, v_{2h}, \dots v_{mh})], \qquad \textbf{(11)}$$

where x_{ih} consists of features designed to achieve product identification (logo, illustration), sensory impact (color, illustration), or product information (size, logo). In this way, each advertisement can be interpreted as a fixed bundle of characteristics, where the marketer chooses not the characteristics, but the particular bundle. Each advertisement, in turn, contributes some proportion of the total amount of product identification, impact, or information that is desired. This is consistent with the way in which advertisements are purchased. Given this sales relationship, an association responsible for marketing several products, such as varieties of apples, chooses v_{jh} in order to maximize the profit from each product:

$${}_h = p_h F_h - \sum_{j=1}^{n} r_j v_{jh},$$

where r_j is the price of advertisement j and p_h is the price of product h. The first-order conditions for a solution to this problem require the price of each advertisement to equal its marginal value product, which, in this case, is the sum of the marginal value products of each advertisement characteristic:

$$r_{jh} = p_h \sum_i \left(\frac{\partial F_h}{\partial x_{ih}} \right) \left(\frac{\partial x_{ih}}{\partial v_{jh}} \right) . \qquad \textbf{(13)}$$

Further, the marginal cost of promoting each variety, or brand, must also equal the value of brand attraction: $r_{jh} = B_h$. Therefore, (13) implies that brand attraction can be expressed as a linear function of the marginal value product of each advertisement characteristic multiplied by the contribution of each advertisement to the total effect that these creative elements are designed to achieve.

In terms of the empirical MIMIC model, advertisement characteristics are, therefore, the causal variables in this system. Using the logic developed in (13), the structural model becomes:

$$B_h = {}_{10}L_h + {}_{11}L_h^2 + {}_2G_h + {}_3C_h + {}_4I_h + {}_h , \qquad \textbf{(14)}$$

where L_h is the number of lines per advertisement, G_h is a variable indicating the proportion of advertisement lines that were associated with the "Washington Apple" logo, C_h is the proportion of advertisement lines that were in color, I_h is the proportion of advertisement lines that were supplemented with an illustration, and ${}_h$ is a vector of independent and identically distributed errors. Including both the number of lines and lines squared permits a test of the theoretical effects of advertisement size outlined by Kirmani. Kirmani believes that larger advertisements will have a greater impact on consumers due, in part, to the signal they provide that management is confident in the product and is willing to invest large amounts in assuring its future success.

However, excessive advertising may provide a signal that the product has deficiencies which must be addressed through manipulating consumers' attitudes through highly visual means. Note that this structural model is a simplification of the more general expression above as the brand attraction variable for one brand does not enter the causal equation for another.[2] Nevertheless, estimates of the simpler version are useful to apple marketers as they show the marginal effects on brand attraction of individual advertisement characteristics.

For illustrative purposes, the model given by equations (9), (10), and (14) is depicted in figure 1 in the form of a path diagram. Path diagrams are commonly used in the structural latent variable literature to describe linkages among observable and unobservable variables and their indicators and causes. Figure 1 simplifies the structure described above by considering only a two-latent -variable case. Starting at the top, this diagram demonstrates the linkages that exists between the causal variables, line size, logo, color and illustrations (L_i,, G_i,, C_i,, and I_i,) and the latent, brand attraction variables (B_h), which are also influenced by a random error term, $_i$. The relationship between the brand attraction variables and the indicator equations (the share equations in the demand system and the retailer's margin equations) can then be traced out. In the diagram, the brand share and margin variables are denoted by w_i^* and m_i^* to indicate that they are adjusted for price and expenditure effects (Gao, Wailes, and Cramer). The curved, two-headed arrows connecting the disturbance terms in the share equations and the margin equations show the covariance assumptions that are necessary to identify each of the latent brand attraction variables. In fact, some popular software packages (Amos, for example) use graphical interfaces similar to that shown in figure 1 to enable users to estimate models in path diagram form.

In order to incorporate the parametric restrictions implied by homogeneity and symmetry of the LAIDS system, this study explicitly specifies the set of causal and indicator equations and estimates the entire system simultaneously. Estimates of this system are obtained using weekly data for the period January through March 1997 on sales of several apple varieties by major grocery chains in six markets: Buffalo, Los Angeles, Atlanta, Newark, Dallas, and Chicago. These data were compiled by Bishop Consulting and were provided to the researchers by the Washington Apple Commission. The Commission also supplied the researchers with weekly data on advertisement characteristics compiled by Leemis Market Research.

The "ad lines" measure reported by Leemis is a measure specific to this firm, though it is proportional to other measures of advertisement space. As an example, the average advertisement for Golden Delicious apples in the sample had approximately 34 ad lines. This is equal to a space two and one-sixteenth inches wide and two inches high and is equivalent to the standard advertising unit 24A. Since a chain may run more than one advertisement per week for an apple variety, the sum total of lines per week were calculated for each market and variety. Further, these advertisements could vary in their other design characteristics, so measures on the space associated with them were weighted by their ad lines, giving rise to the proportional measures of space associated with each advertisement characteristic.

Since the varietal shares sum to one, the expenditure share equation for "other apples" was dropped to avoid singularity of the covariance matrix. The entire model given by (9), (10), and (14) was estimated simultaneously in AMOS 3.6. The estimation results are presented in the next section.

Empirical Results

Prior to estimating the model it was necessary to aggregate the weekly store data for each market (chain) and variety across the alternative apple package forms (bulk, 3 pound bags, 5 pound bags, etc.) and apple sizes (small, large). In order to develop consistent prices, quality-adjusted prices were developed in the manner suggested by Cox and Wohlgenant.[3] All quantities were reported in pounds, so total weekly varietal sales are simply the sum across package forms and sizes. Using these quantity-aggregates, all quality-adjusted prices are expressed as weighted averages. To ensure that the estimates are consistent with restrictions implied by consumer utility maximization, symmetry and homogeneity constraints are imposed on the LAIDS system.

Table 1 presents the estimated own-price and cross-price conditional demand elasticities, including an elasticity measuring the affect of the brand attraction on demand. All the own-price elasticities, except for the McIntosh variety, were found to be significantly different from zero and generally quite elastic. Interestingly, the two varieties that are the most price-elastic (Granny Smith and Gala) tend to be regarded as “specialty” varieties and, therefore, the most likely to be bought on impulse or in addition to the usual variety choice. In fact, the own-price elasticities appear to be significantly higher than obtained elsewhere with data over different time periods and markets (Richards and Patterson). However, more consistent with other studies of fresh fruit demand (Lee, Brown and Seale), the cross-price elasticities presented in table 1 suggest that many variety-pairs tend to be gross complements. This is particularly true in pairing varieties with Red Delicious apples. In this case, consumers may be induced to buy within the apple category due to a favorable price or an effective promotion on their “usual” variety, but then buy other varieties as well once in the produce aisle. Expenditure elasticity estimates also show a pattern, albeit weakly, differentiating mature from specialty varieties. The more mature varieties, like Red and Golden Delicious, Granny Smith, and perhaps Fuji, have expenditure elasticities that suggest they are necessities, while newer or less common varieties have expenditure elasticities suggesting they are luxury goods. Specifically, whereas the expenditure elasticity for Red Delicious apples is 0.769 (a necessity), estimates for the Gala and McIntosh varieties are 1.123 and 1.740 (luxuries), respectively. Again, these expenditure elasticities tend to be higher than commonly found in the literature. While the difference in price and expenditure elasticities may indeed be due to different samples, they may also be due to bias due to differences in model specification. In fact, the primary argument for using a structural latent variable model approach is to correct for biases caused by using inappropriate proxy variable methods.

Specifying and estimating a LAIDS model of apple-variety demand without latent brand-attraction variables, but with advertisement characteristics entered directly as proxy variables, provides an assessment of the extent of the proxy-variable bias (Gao and Shonkwiler). Following the same model structure as the LAIDS used in the measurement model above, absent the latent brand attraction variables, table 2 shows the price and expenditure elasticity estimates that result. Comparing the own-price elasticities of demand shows that many varieties (all except Fujis) appear to be less elastic in demand when brand attraction is not included. This suggests that estimation methods that ignore the effect of brand preference tend to understate own-price elasticities. Such understatements are perhaps to be expected because the usual estimation methods do not consider differences in brand loyalty. Brand loyalty, the result of brand attraction, causes consumers to become less price sensitive, so a failure to explicitly account for loyalty causes this effect to be built into estimates of the price-response parameters. More importantly, this result implies that apple consumers should be segmented into groups of loyal and non-loyal behavior if the appropriate micro-level data are available (Allenby and Lenk). Note also that no cross-price elasticities are significant in the proxy-variable model. This result is also not surprising because a failure to account for the effect of brand specific preferences causes the remaining brand-specific variables (own price and group expenditure) to play a more important role in explaining share variability. Paying more attention to brand loyalty in farm products appears to be a promising avenue for future research, both in avoiding bias and estimating variety-specific buyer behavior.

Central to the analysis is the impact brand attraction has on variety-demand. For all cases, except for McIntosh apples, brand attraction has a positive influence on brand demand. In these cases, though, the estimated elasticity is less than one, suggesting that a one percent increase in brand attraction (or preference towards a specific variety) is associated with less than one percent change in demand. In determining the optimal amount of marketing expenditure designed to achieve brand attraction, however, the Dorfman-Steiner condition suggests that it is the relative elasticity that matters. Even for the most price-elastic varieties, this condition implies a ratio of marketing expenditure to sales far higher than current practice (Galas: 7.2% suggested versus 1.9% actual for all Washington apples).[4] Consequently, this analysis suggests that greater efforts to promote each variety, except for McIntosh, will likely return more in sales than they cost to achieve.[5] This return, however, differs by variety.

Among the positive brand attraction elasticities, the largest are for the more mature varieties, again possibly reflecting established purchase patterns or behavior. Gala apples, a relatively new variety, had the smallest positive brand attraction elasticity, suggesting that it will be more difficult for promotional efforts, which would influence varietal preference, to stimulate additional demand. Most importantly, the fact that all of the brand attraction elasticities are significantly different from zero demonstrates that the latent-variable model represents an improvement over the proxy-variable alternative. Ultimately, however, marketers need to know how to influence brand attractiveness and, thereby, product demand through control over the creative content of print advertisements.

In the sample used for this analysis, not all of the advertisement characteristic variables are unique. For example, all color advertisements are also illustrated. Thus, the illustration variable was dropped from the analysis. Similar linear dependencies exist among some of the other characteristics for different varieties, each of which is thereby eliminated from the model.

The parameter estimates from the structural equations given in (14), which show the marginal values of each characteristic in determining the brand attraction variable, are reported in table 3 for each variety. As discussed above, the coefficient on the brand attraction variable in the margin equation is normalized to one, so brand attraction is in units of cents per pound of profit. Recall also that the characteristic variables are measures of “line size” and the proportion of the advertisement space incorporating either color or the Washington Apple logo. Each parameter, therefore, provides an estimate of the marginal value of one more line of ad space, or the presence or absence of color. Note, the squared line size variable was not found to be significantly different from zero and was dropped from these equations. Comparisons of the effectiveness of each design characteristic can best be made using elasticities. This is done by first calculating each brand attraction variable using the estimated parameters and then, in turn, calculating the mean of each brand series, and, finally, each characteristic elasticity (Gao and Shonkwiler).

These elasticities are reported in table 4. Tracing the effect of the advertisement characteristics to the demand for each variety can be thought of in two stages: first, brand attraction is a function of the advertisement characteristics, and second, brand attraction affects demand. Table 4, therefore, gives both the brand-effect and demand elasticities. Focusing on only the elasticities calculated from the statistically significant parameter estimates reported in table 3, increases in line size are found to increase demand for Granny Smith and Fuji apples and, at a slightly higher p-value, Galas. These elasticities suggest that a 10% larger advertisement can be expected to produce a 9% increase in Granny Smith sales, an 8% increase in Fuji sales, and a 5% increase in Gala sales. Finding that line size has a significant negative effect on Granny and Fuji brand attraction, and yet a positive effect on demand, reflects the fact that the brand attraction series is negative for each of these varieties. Because the mean brand attraction is negative, the total demand elasticity is of opposite sign compared to the brand attraction parameter. The negative demand elasticity for McIntosh apples with respect to line size may reflect the explanation offered above for the negative brand elasticity. Simply, a brand with a poor reputation does not benefit from brand identification, but suffers.

The effect of including color and logo in Red Delicious advertisements, however, appears to dominate the size-of- effects, as line size becomes insignificant. In fact, color stimulates Red Delicious sales with a demand elasticity estimated at 2.65, whereas the appearance of a logo results in a 2.07 percent decrease in Red Delicious demand. Although these characteristics are not statistically significant determinants of either Golden Delicious or Granny Smith demand, it is nonetheless interesting to note that the point estimates are opposite from the Red Delicious case. Color is an important trait for apples, particularly for Red Delicious, Red Rome, Fuji, and Galas as growers and marketers believe that well-colored apples command a premium in the market. In fact, California growers report removing Fuji orchards simply because they are unable to obtain red coloring due to the warm California climate. Consequently, it is perhaps not surprising that color advertisements have a negative effect on the demand for two varieties of apple where color is clearly not as important -- Granny Smiths and Golden Delicious. This result, combined with the line size elasticities, underscores the need for variety-specific advertisement design as opposed to advertisements that are homogeneous for each retail partner as is often now the case.

Summary and Conclusions

Media choice decisions and evaluations are receiving increased attention by commodity marketers and researchers. However, media choice is only part of the decision process, as additional decisions must be made on advertisement design in any media. Among media types, newspapers are an important source for advertisers. Yet, little is known about the economic returns to this media, much less those following from alternative design decisions. Past research has shown, though, that print advertisement design decisions can have significant impacts on consumer perceptions. When these perceptions are in response to brand specific advertisements, consumers may form preferences towards the brand, which will ultimately influence purchase decisions. These brand preferences, though, are not directly observable.

This paper develops a structural latent variable model of apple variety demand to analyze the effect of variety specific newspaper advertisement characteristics on variety (brand) attraction, and in turn on variety demand. The model consists of two sets of "indicator" equations-- varietal demand equations in the form of a Linear Approximate Almost Ideal Demand System and a relative price spread model. The model also contains a set of “causal” equations, which link the newspaper advertisement characteristics to the latent brand attraction variable through a Lancaster-Ladd-type input demand model. In addition to providing evidence on the effect of brand attraction on apple variety demand and the factors influencing this brand attraction, the model provides other apple demand parameter estimates of interest.

The model was estimated using weekly data on varietal sales and advertisement characteristics over the period January through March 1997. Six markets and six apple varieties were included in the sample. The influence of advertisement size, the use of color, and the presence of the Washington Apple logo were analyzed.

Nearly all the variety attraction variables have positive and significant effects on the demand for each variety. Brand attraction elasticities tend to be largest in magnitude for mature apple varieties, reflecting strong patterns of brand or variety loyalty. To the extent that promotion efforts can influence brand attraction, mature varieties are more responsive to variety-specific marketing efforts. However, the mature varieties tended to exhibit lower expenditure elasticities. It was also found that when variety attraction is incorporated in the model, own-price elasticities appear to be more elastic than those estimated with a more typical proxy variable model, suggesting that these models tend to understate demand elasticities.

In analyzing the influence of the advertisement characteristics on variety demand, some key findings arose. Advertisement size has a significant, positive impact the sales of Granny Smith, Fuji, and Gale apples. The use of color has a strong, positive effect on Red Delicious demand, but a negative, albeit statistically insignificant, effect on the “green varieties.” Perhaps more surprising, the presence of the Washington Apple logo reduces Red Delicious demand.

This paper has demonstrated that structural latent variable models can be useful in evaluating media characteristics, which may affect consumer preferences towards specific brands. One area of future work relates to how the incorporation of these brand specific latent variables in demand models affects demand parameter estimates, including those relating to promotion variables.

Endnotes

1. Although most commodity commissions use a mix of broadcast and print media, this assumption is valid for small commissions that cannot afford the more capital-intensive media such as television or radio.   Generalizations that include choice of media increase the complexity of the model without altering the qualitative conclusions.

2. While including all brands in each cause equation improved their fit, excessive multicollinearity among the brand attraction variables caused each latent variable and ad characteristic variable to become statistically insignificant at a 5% level.

3. The premiums and discounts associated with the alternative package forms and apple sizes were consistent with observations in the market and with previous studies on apples. The results from these estimated models are available from the authors.

4. Recall, the Dorfman-Steiner result shows that profit maximizing advertising to sales ratio equals the ratio of the advertising elasticity to the demand elasticity.

5. The negative brand elasticity for McIntosh apples reflects the fact that not all brands are worthy of development. If consumers develop a negative impression of a brand or variety, reinforcing previous experience can only deter any inclination they may have to buy the variety in the future.

Figure 1. Path Diagram of A Latent-Variable Demand Model for Apples Incorporating Advertisement Characteristics.

Table 1. Estimated Elasticities and Model Parameters from Latent Variable LAIDS / MIMIC Model.

Equation	Price Elasticities							Expend. Elasticity	Brand Attraction Elasticity
	Red	Golden	Granny	Fuji	Gala	McIntosh	Other		
Red Delicious	-1.844** (-7.683)	-0.153** (-10.802)	-1.322** (-3.019)	-0.199** (-5.776)	0.015 (0.036)	0.354 (1.472)	0.458** (2.552)	0.769** (320.060)	0.951** (459.079)
Golden Delicious	-1.601** (-2.005)	-1.038** (-21.827)	0.091 (0.070)	0.378** (3.641)	1.345 (0.958)	0.252 (0.323)	-0.480 (-0.811)	1.073** (122.582)	0.917** (70.132)
Granny Smith	0.598 (1.576)	0.102** (4.540)	-3.267** (-4.617)	0.245** (4.622)	1.510** (2.224)	-0.294 (-0.787)	-0.644* (-1.980)	0.781** (194.403)	0.925** (568.698)
Fuji	-3.853** (-3.371)	0.061 (0.867)	4.163** (2.130)	-1.882** (-10.494)	-1.944 (-0.937)	-1.261 (-1.102)	-1.822** (-2.098)	0.809** (72.159)	0.809** (2.004)
Gala	-2.131** (-3.899)	0.198** (5.791)	-0.329 (-0.357)	-0.160** (-2.171)	-7.272** (-6.042)	-0.531 (-0.970)	-0.427 (-1.040)	1.123** (205.358)	0.532** (8.747)
McIntosh	1.765 (1.190)	0.286** (3.336)	-0.363 (-0.148)	0.419** (2.127)	-1.812 (-0.687)	-2.090 (-0.950)	-1.122 (-1.003)	1.740** (99.480)	-3.043** (-5.465)

t-statistics are given in parentheses. A double asterisk (**) denotes significance at the 5% level, while a single asterisk (*) denotes significance at the 10% level.

Table 2. Estimated Elasticities and Model Parameters from Proxy Variable LAIDS Model.

	Price Elasticities							
Equation	**Red**	**Golden**	**Granny**	**Fuji**	**Gala**	**McIntosh**	**Other**	**Expend. Elasticity**
Red Delicious	-1.637** (-3.991)	-0.126 (-1.265)	-0.201 (-0.724)	-0.031 (-0.199)	0.072 (0.303)	0.379 (1.489)	3.319** (4.432)	0.910** (18.102)
Golden Delicious	-0.408 (-1.367)	-0.909** (-5.222)	0.123 (0.459)	0.224 (1.216)	0.166 (0.837)	-0.029 (-0.120)	-0.066 (-0.306)	1.032** (14.315)
Granny Smith	-0.322 (-0.701)	0.083 (0.559)	-1.535** (-2.787)	0.236 (1.073)	0.469 (1.451)	-0.102 (-0.264)	3.204** (2.794)	0.880** (12.723)
Fuji	-0.093 (-0.196)	0.240 (1.284)	0.430 (1.057)	-1.987** (-5.158)	0.126 (0.433)	0.202 (0.568)	0.059 (0.184)	0.906** (8.270)
Gala	0.226 (0.267)	0.199 (0.848)	0.981 (1.416)	0.137 (0.405)	-3.453** (-3.342)	0.740 (1.047)	-0.239 (-0.291)	1.006** (9.741)
McIntosh	0.964 (1.398)	-0.034 (-0.157)	-0.207 (-0.327)	0.161 (0.506)	0.559 (1.032)	-1.881** (-2.176)	-1.376* (-1.789)	1.113** (11.246)

t-statistics are given in parentheses. A double asterisk (**) denotes significance at the 5% level, while a single asterisk (*) denotes significance at the 10% level.

Table 3. Structural Equation Parameters -- Brand Attraction Model.

Equation	Line Size	Color	Logo
Red Delicious	-0.024 (-1.104)	-11.040** (-2.216)	9.993* (1.903)
Golden Delicious	0.003 (0.318)	0.366 (0.080)	-2.329 (-0.473)
Granny Smith	-0.114** (-2.424)	0.052 (0.033)	.
Fuji	-0.007** (-2.099)	.	.
Gala	0.054 (1.649)	.	.
McIntosh	0.002 (1.425)	.	.

t-statistics are given in parentheses. A double asterisk (**) denotes significance at the 5% level, while a single asterisk (*) denotes significance at the 10% level.

Table 4. Advertisement Characteristic Elasticities.

	Brand Attraction Elasticities			**Demand Elasticities**		
	Line Size	**Color**	**Logo**	**Line Size**	**Color**	**Logo**
Red Del.	0.389	2.784	-2.173	0.370	2.648	-2.067
Golden Del.	-0.167	-0.228	1.395	-0.153	-0.209	1.279
Granny	1.007	-0.008	.	0.931	-0.007	.
Fuji	1.000	.	.	0.809	.	.
Gala	1.000	.	.	0.532	.	.
McIntosh	1.000	.	.	-3.043	.	.

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