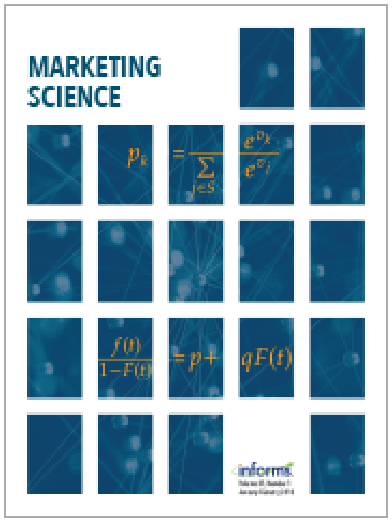

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A Model for Trade-Up and Change in Considered Brands

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A common theme in marketing literature is the acquisition and retention of customers as they trade up from inexpensive introductory offerings to those of higher quality. We develop a nonhomothetic choice model to accommodate effects of advertising, professional recommendation, and other factors that facilitate the description and management of trade-up. Our model allows advertising to affect the relative superiority or inferiority of products. This allows for a wide variety of trade-up patterns beyond those obtained from a standard random utility formulation of the logit model. Our nonhomothetic model allows for advertising to affect more than just brand intercepts (perceived quality), but also the rate at which consumers are willing to trade up to higher-quality brands. Advertising effects are measured using a randomized treatment and evaluated by considering their direct implications for firm pricing and profits.

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1. Introduction

A wide array of products of differing quality and price are offered in many product categories. Examples include automotive and electronic products, and what might appear to be narrowly defined categories such as razor blades, where a variety of price points and qualities are displayed, including inexpensive disposables and multiblade shaving systems. In marketing research, it is common to narrow consideration to a set of products that are highly substitutable rather than to model an entire category. In part, this is due to the limitations of commonly used models that assume a very high degree of substitutability. Economic demand models based on a linear utility have the undesirable property that as expenditure in the category increases, the products chosen will not change but merely the quantities. Consumers attain higher utility levels by simply consuming more of the same brand rather than "trading up" to a higher-quality brand.

In our model, consumers plan an expenditure level for both the products in the category as well as the outside option. This expenditure allocation is not directly observed but can be influenced by consumer demographics such as income, or by marketing actions such as advertising. In addition, price-induced "income effects" play a role in brand choice in our model but not in standard linear utility models. Most important, our model captures the effect of marketing mix variables on the willingness of consumers to "trade up" to higher-quality brands and provides a modeling framework for broad categories of nonhomogenous products.

An alternative approach to dealing with extended product categories is to treat purchases as arising from multiple categories (Mehta 2007). Multiple-category purchase often assumes linear utility within category, with across-category dependencies induced through correlated error terms or correlated model parameters (see, e.g., Ainslie and Rossi 1998, Seetharaman et al. 2005). Such an approach is problematic for studying trade-up because across-category demand is treated descriptively, without the ability to structurally model income effects and the effects of price changes. Recent research has documented that price thresholds and asymmetries exist in extended product categories, where expensive brands respond differently to price than cheaper brands (Pauwels et al. 2007). Such findings point to the need for structural models for understanding consumer behavior in extended product categories.

Our data come from an over-the-counter healthcare category, where the manufacturer uses pricing and advertising to manage a diverse product line. Given that higher-quality products have higher margins, it is important to consider the effect of marketing actions on the decision of consumers to trade up and allocate higher expenditure to the product category. We take a structural approach to this problem. That is, we postulate a specific utility model that allows for expenditure allocation and effects on trade-up and derive the associated demand system. An alternative, informal approach would be to take a standard choice model and add terms and additional regressors to achieve flexibility. Our view is that a structural approach will be more useful for analysis of marketing actions and provide a parsimonious and interpretable specification (see, e.g., Chintagunta et al. 2006 for a discussion of the advantages of a structural model of demand).

Our model is based on the nonhomothetic utility function of Allenby and Rossi (1991) extended to accommodate the effects of advertising and professional recommendation, the presence of an outside good, and product attributes. The nonhomothetic function retains the property of linear indifference curves (underlying the random utility formulation of logit and probit models), ensuring corner solutions while allowing marginal utilities to change as overall expenditure increases. Indifference curves fan out in the positive orthant, with their rates of rotation related to consumer tendency to trade up to higher-quality offerings if their budget allows. Our model separates the effects of baseline preferences, trade-up, and changes in the considered set of brands as budgetary allotments increase.

Our nonhomothetic model provides a new manner in which advertising may affect demand. In standard utility specifications, advertising is usually entered as a demand shifter (Pedrick and Zufryden 1991, Horsky et al. 2006) or in influencing consideration set formation (Zhang 2006). In our nonhomothetic model, advertising can have an effect on the marginal willingness to pay for the quality attribute. That is, advertising can accentuate the motive for trading up from lower-quality to higher-quality brands.

We apply our model to a nationally representative sample of consumers using a virtual shopping experiment that portrays actual retail shelf layouts. Respondents engage in choice tasks prior to and after viewing advertisements for some of the higher-quality offerings. The advertising treatment was administered in a randomized experiment, making it possible to measure advertising effects without concern for selection bias or endogeneity. The prepost measurement of demand under different prices, and background information provided by the respondents, provides sufficient information to estimate both pricing and advertising effects.

In addition to describing the way in which advertising effects affect the relative superiority (desirability for trade-up) of some goods, we consider the magnitude of advertising effects via an equilibrium pricing simulation. As advertising shifts the structure of demand, competing firms will adopt different optimal pricing policies. We solve for optimal pricing with and without advertising exposure to assess the economic magnitude and implications of advertising effects.

The results provide a description of consumer behavior useful for effectively targeting marketing expenditures for trade-up. We find that perceptions of quality differences among choice alternatives to be most pronounced among young high-income respondents. As respondents become older, their aspiration brands appear to lose their appeal, as the perceived quality differences among brands is less pronounced. Our results contribute to the marketing discipline's understanding of factors associated with trade-up. We also investigate the management of trade-up through the use of profession endorsements and media advertising.

The remainder of this paper is organized as follows. Section 2 presents the nonhomothetic choice model for trade-up and contrasts its properties to standard discrete-choice models. The data and choice experiment are described in §3, and §4 presents estimation results. Section 5 then investigates use of the model for understanding and managing consumer trade-up. Concluding remarks are offered in §6.

2. A Trade-Up Model

We start from the proposition that consumers make an expenditure allocation to the product category and an outside "good" or option. This expenditure allocation is determined, in part, by utility afforded by various products in the category. Once a household has made an expenditure allocation for the category, then demand for products whose prices exceed this allocation is zero. Thus we term the expenditure allocation *affordability*. Our specification has a standard intercept or *baseline* utility as well as parameters, which govern the relative inferiority or *superiority* of products. Some products can be viewed as relatively superior in the sense that as attainable category utility increases, the marginal utilities of these products increases faster than other products. This allows for a structural implementation of the phenomenon of trade-up to higher-quality brands.

To formulate a structural model, we must postulate a utility function for purchases within the category and the outside alternative. We assume that respondents are maximizing their utility across items in the product category, represented by the vector x, and an outside good, z, subject to a budget constraint:

$$\max\ \ln u(x, z) = \ln u(x) + \tau \ln(z) \quad \text{s.t. } p'x + z \leq E, \quad (1)$$

where p is the vector of prices for the choice alternatives, E is the budget allotment, and the price of the outside good is assumed, without loss of generality, to be \$1.00. If the price of an item, p_i, is greater that the allotment, E, then the utility-maximizing solution must assign $x_i = 0$.

2.1. Linear Utility Models and Their Limitations

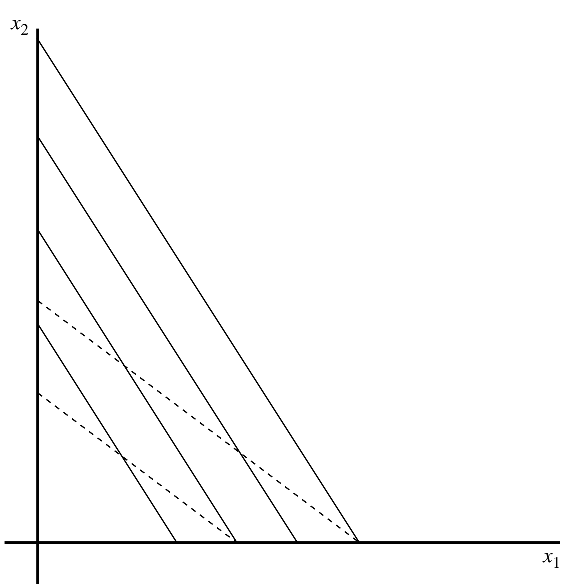
The demand problem posed by (1) is not complete without a specification of the utility function for the vector of inside goods (products in the category), $u(x)$. In many product categories, including our health-care category, consumers are observed to only purchase one product at a time. Thus, the utility maximization problem in (1) must always result in a corner solution. Consumers always purchase some of the outside good, but at most purchase one product from the category. This imposes constraints on the form of the utility function for the inside goods.

A linear utility function admits only corner solutions:

$$u(x) = \alpha' x. \tag{2}$$

Figure 1 depicts this utility function for the two-good case. The indifference curves of this utility function are simply a set of parallel lines with slope $-\alpha_1/\alpha_2$. The budget constraint is drawn in as a dotted line with slope $-p_1/p_2$. The utility maximization occurs with only consumption of good 1 (a corner solution). Note that the linear utility model in (2) has been widely used in the dynamic discrete-choice literature as the basis of the "instantaneous" or per-period utility function in situations in which consumers are choosing among a set of products over time (see, e.g., Erdem et al. 2003, Equation (1), p. 13).

Figure 1 Illustration of Homothetic Utility



Although the utility function in (2) is convenient in the sense that it results in only corner solutions, it has the very undesirable property, for our purposes, of homotheticity. A *homothetic* function is a monotone transformation of a homogenous function of degree 1. A homogenous function of degree 1 is a function of a vector-valued input for which $f(tx) = tf(x)$ for all positive scalars t and every point in the domain of $f(), x$. The implication of this property is that the slope of the indifference curves is the same along any ray through the origin. In general, this means that as we increase the expenditure allocation for the category (E), the consumer will achieve a higher level of utility simply by increasing consumption in the same proportion.

To see the implications of homotheticity for the structure of demand, we will use Roy's identity. As noted by Varian (1992), a homothetic utility function implies an indirect utility function of the form $v(p, E) = v(p)E$, where p is a vector of prices for each product in the category and E is total category expenditure. If we apply Roy's identity, we can easily see that demand is linear in E:

$$x_i(p, E) = \frac{\partial v(p, E)/\partial p_i}{\partial v(p, E)/\partial E} = \frac{\partial v(p)E/\partial p_i}{\partial v(p)E/\partial E} = \frac{(\partial v(p)/\partial p_i)E}{v(p)} = x_i(p)E. \tag{3}$$

$x_i(p, E)$ is the demand for product i when facing prices, p, and with expenditure, E. This is a very restrictive assumption as this implies that the ratio of demand for two products, i and j, is constant for any value of E:

$$\frac{x_i(p, E)}{x_j(p, E)} = \frac{x_i(p)E}{x_j(p)E} = \frac{x_i(p)}{x_j(p)}. \tag{4}$$

As E increases, we would like to allow for the possibility that consumers switch brands. That is, consumers obtain higher utility not by buying more of the same bundle of goods but by reweighting the bundle toward higher-quality products.

A linear utility function is a special case of a homothetic function that only admits corner solutions. This means that as expenditure in the category increases, a consumer will simply buy more of the same product to attain higher utility. This is depicted in Figure 1. This is clearly an unreasonable assumption. For example, if the utility function over brands of cars were linear, then a consumer who wins the lottery would continue to buy their current car (e.g., a Ford Focus) but consume more units of this product to attain higher utility. We would like to allow for the possibility that the consumer would "trade up" to higher-quality brands. In any product category in which there are large quality differences between products, the linear utility specification is not reasonable as the basis for a demand model.

Goods that have a linear indifference curve are called "perfect" substitutes in the economics literature (cf. Varian 1999, p. 38). This is viewed as an extreme case of substitution in the sense that consumers are always willing to exchange one unit of good 1, for example, with a fixed number of units of good 2 (α_2/α_1). A special case of perfect substitutes is the case of homogenous goods in which there is a slope of 1 (one-for-one exchange for utility indifference). The reason why this is called *perfect substitution* is that it really says that products are virtually the same in terms of the source of utility; it is simply the units that are slightly different. For example, we might expect this to be the case for packs of batteries of the same kind. The consumer should be indifferent between one four-pack of batteries and four single batteries. Of course, this implies an extreme degree of substitutability that is unreasonable for any group of products of different quality.

To take a health-care example, this would say that consumers would be indifferent between one electric sonic toothbrush and a certain number of manual toothbrushes. This would imply that the sonic toothbrush delivers the same sort of benefit but simply more of it. In addition, there is an assumption that there is no diminishing returns to the benefits (the marginal value of an additional unit of brushing benefits must be constant). This is clearly unreasonable for any nontrivial group of products.

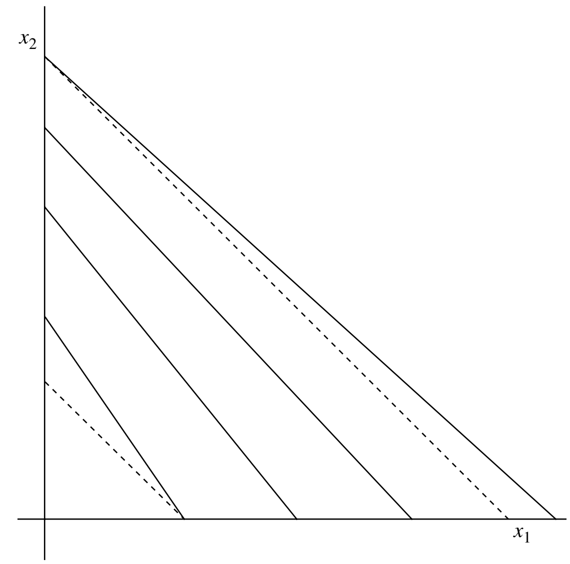
2.2. A Nonhomothetic Model for Trade-Up

Given the undesirable properties of homotheticity and perfect substitution, a linear utility function is not suitable for a structural model of demand. However, we do want to retain the property that our model only admits corner solutions with only one product demanded. If we postulate a utility function with linear, but rotating, indifference curves (shown in Figure 2), then we will retain the corner solution property without the undesirable properties of homotheticity and perfect substitution. Figure 2 depicts the situation where for low levels of expenditure (and, thus, attainable utility), product 1 is chosen, whereas for higher levels of utility and expenditure, product 2 is chosen. What happens is that as E increases, attainable utility also increases, and the slope of the indifference curves change:

$$\frac{\partial u/\partial x_2}{\partial u/\partial x_1} = f(u). \tag{5}$$

In other words, as a consumer allocates more expenditure to the category, higher utility is achieved not by simply consuming more of product 1 (as in the homothetic case) but by changing to product 2. In this sense, product 2 is a higher-quality product. As attainable utility increases, the marginal valuation of quality also increases. Although for any given level of utility the indifference curves are linear, as utility changes, the slope changes, which means that consumers are not willing to trade off product 1 for a fixed number of units of product 2. Thus, the rotating indifference curve, or nonhomothetic utility function, avoids both homotheticity and the assumption of perfect substitutes.

Figure 2 Illustration of Nonhomothetic Utility



The mathematical specification of a utility function with these properties is given by the nonhomothetic utility function of Allenby and Rossi (1991). The utility for the vector of demand, x, is defined implicitly as

$$u(x) = \sum_{k=1}^{K} \psi_k(\bar{u})\, x_k = \sum_{k=1}^{K} \exp[\alpha_k - \kappa_{k^*}\bar{u}(x, z)] x_k, \tag{6}$$

where the marginal utility of an offering, $\psi_k(\bar{u})$, is a function of attainable utility $\bar{u}$. Thus, as respondents allocate greater expenditure, attainable utility increases, and marginal utilities change. The utility function has linear indifference curves for any fixed value of $\bar{u}$.

The parameter κ affects the rate of rotation of the indifference curves. As attainable utility increases, the ratio of marginal utilities, $\psi_i(\bar{u})/\psi_j(\bar{u}) = \exp[\alpha_i - \alpha_j + \bar{u}(\kappa_j - \kappa_i)]$, is increasing in attainable utility $\bar{u}$ for $\kappa_i < \kappa_j$, implying that alternative i is superior to alternative j. Superior choice alternatives are defined as those associated with *smaller* values of κ, whereas alternatives with larger κ values are relatively inferior. The effect of price changes can be decomposed into substitution and income effects, where the income effect favors the superior good.

Thus, the model has the property that price changes of superior goods will draw disproportional share from inferior offerings.

The indifference curves, which rotate in the positive orthant, cannot intersect for Equation (6) to be a valid utility function. A necessary and sufficient condition for nonoverlapping indifference curves is for all intercepts of the indifference curves to monotonically increase as utility increases; i.e., $\partial x_i/\partial \bar{u} > 0$. This condition is assured if $\kappa > 0$, and we enforce positive κ parameters during estimation by substituting $\kappa = \exp[\kappa^*]$ and estimating κ^* unrestricted.

Baseline preferences are modeled through the intercepts (α) in Equation (6). Budgetary effects can be nullified in the model when the parameter κ is equal to zero for all alternatives. When this occurs, the utility function in (6) reverts to a standard discrete-choice model, similar to that used in standard logit and probit analysis. Equation (6), therefore, nests common homothetic utility specifications.

We use Equations (1) and (6) to study choices among a large set of alternatives, with some prices 10 times greater than others, indicating that they are not near-perfect substitutes. Since the indifference curves in the subutility function in Equation (6) are linear, the utility-maximizing solution will have just one choice alternative with nonzero demand. We can therefore engage in a direct search for the utility-maximizing solution without resorting to the use of Kuhn-Tucker conditions (see Kim et al. 2002).

The log utility associated with choosing one unit of alternative k is

$$\ln \bar{u}(x_k = 1, z_k) = \alpha_k - \kappa_k \bar{u}^k + \tau \ln(E - p_k), \tag{7}$$

where $\bar{u}^k$ is the solution to the implicit equation:

$$\ln \bar{u}^k = \alpha_k - \kappa_k \bar{u}^k + \tau \ln(E - p_k), \tag{8}$$

which is obtained using numerical methods (e.g., Newton's method). The quantity of the outside good is set equal to $z_k = E - p_k$ in (7) and (8) because the price of the outside good is \$1.00. The utility-maximizing solution corresponds to the alternative (k) that maximizes the value of log utility in Equation (7).

2.3. Likelihood Specification

The likelihood for the data is obtained by introducing an additive random error in (7). Setting $\kappa = 0$ corresponds to homothetic specifications (e.g., logit and probit models), and setting $\tau = 0$ removes the restriction that the prices of considered brands must be less than the budgetary allotment. In this latter specification ($\kappa = 0$, $\tau = 0$), the utility-maximizing solution corresponds to the Kuhn-Tucker condition, where ψ_k/p_k or $\alpha_k - \ln p_k$ is maximum, i.e., a standard discrete-choice specification.

The probability of selecting alternative k is

$$\Pr(x_k = 1) = \Pr(\alpha_k - \kappa_k \bar{u}^k + \tau \ln(E - p_x) + \varepsilon_k > \alpha_i - \kappa_i \bar{u}^i + \tau \ln(E - p_i) + \varepsilon_i \forall i \mid p_i \le E), \tag{9}$$

and assuming type I extreme value errors leads to choice probabilities of the form:

$$\Pr(x_k = 1) = \frac{\exp[\alpha_k - \kappa_k \bar{u}^k + \tau \ln(E - p_k)]}{\sum_{\{i \mid p_i \le E\}} \exp[\alpha_i - \kappa_i \bar{u}^i + \tau \ln(E - p_i)]}. \tag{10}$$

Equation (10) reflects the affordability property of trade up by assigning nonzero probability to alternatives that are within budget. Superiority is reflected in the κ parameters that govern the rates of rotation of the indifference curves. Baseline preference is reflected by α.

2.4. Relationship to Standard Choice Models

The random utility derivation of a multinomial choice model is given in McFadden (1974). The consumer is choosing between J alternatives each with utility, $\ln V_i = \alpha_i + \varepsilon_i$. The choice rule for the consumer is simply to choose the alternative with the highest utility. However, the investigator does not directly observe utility for each alternative but only some portion of this. If the consumer is facing a vector of prices for each alternative and if the consumer has sufficient budget to purchase any alternative, then the choice rule becomes

choose i if

$$\ln V_i - \ln p_i \ge \max_j \{\ln V_j - \ln p_j\}.$$

With extreme value type 1 for the error assumption, this choice rule gives a multinomial logit model (MNL) with ln(price) as a regressor:

$$\Pr(i) = \frac{\exp(\alpha_i - \tau \ln p_i)}{\sum_j \exp(\alpha_j - \tau \ln p_j)}. \tag{11}$$

Thus, the inclusion of an error term because of unobserved factors results in a choice model with nonzero demand for all choice alternatives. However, the structural origin of the MNL is a random utility model derived from a linear utility specification, $u(x) = \alpha' x$, and this specification is limited in its ability to explain income effects and asymmetric switching between low- and high-quality brands.

Our nonhomothetic utility model nests this specification but goes further in the sense that we do explicitly consider the budget constraint, not simply prices. That is, our model would not allow consumers to purchase alternatives (products) for which they do not have adequate expenditure allocation. If we set all of the κs to zero, we obtain a homothetic specification but with a budget constraint (we term this "affordability") and baseline preference parameters (αs):

$$\Pr(x_k = 1) = \frac{\exp[\alpha_k + \tau \ln(E - p_k)]}{\sum_{\{i \mid p_i \le E\}} \exp[\alpha_i + \tau \ln(E - p_i)]}. \tag{12}$$

To summarize, we can derive three random utility choice models in increasing order of flexibility and generality:

(1) A standard logit model derived from homothetic preferences—(Equation (11));

(2) A homothetic choice model but with a budget constraint—(Equation (12));

(3) A nonhomothetic choice model with a budget constraint—(Equation (10)).

We have argued that the linear utility assumption underlying the random utility interpretation of the standard logit model of choice is restrictive. At the minimum, any choice model that claims a structural interpretation should be based on nonhomothetic utility and a binding budget constraint.

Another way of understanding the differences between these models is to consider the derivatives of demand with respect to prices for each of the three models outlined above. The derivatives have the familiar structure but help clarify the role of the rotation or quality parameters (κ).

Homothetic without budget constraint (standard logit):

$$\frac{\partial \Pr(i)}{\partial p_j} = [I(i=j)\Pr(i) - \Pr(i)\Pr(j)]\left[\frac{\tau}{p_j}\right]. \tag{13}$$

Homothetic with budget constraint:

$$\frac{\partial \Pr(i)}{\partial p_j} = \begin{cases} [I(i=j)\Pr(i) - \Pr(i)\Pr(j)]\left[\dfrac{\tau}{E-p_j}\right], \\ 0 \quad \text{if } p_j > E. \end{cases} \tag{14}$$

Nonhomothetic with budget constraint:

$$\frac{\partial \Pr(i)}{\partial p_j} = \begin{cases} [I(i=j)\Pr(i) - \Pr(i)\Pr(j)]\left[\dfrac{\tau}{E-p_j}\right]\left[\dfrac{1}{1+\kappa_j u^j}\right], \\ 0 \quad \text{if } p_j > E. \end{cases} \tag{15}$$

The role of the superiority or rotation parameters, (κ), can be seen in Equation (15). Consider two brands for which $\kappa_j < \kappa_i$. In our interpretation, brand j is relatively superior to brand i. This means that as expenditure allocations increase, the purchase probability of brand j will increase relative to that of brand i as consumers value the superior goods more when attainable utility increases. The derivatives above illustrate the phenomenon of asymmetric switching. The last term in Equation (15) will be a force that can make the effect of j on i larger than the effect of i on j.

2.5. Incorporating Attribute Information and Modeling Advertising Effects

In our analysis of the data described below, we investigate various parameterizations of the model intercepts (α) and rotation (κ) parameters. A popular technique for dealing with the presence of many choice alternatives that arise in the study of trade-up is to project these model parameters onto an attribute space (cf. Lancaster 1966, Berry and Pakes 2007). We allow both the intercept (baseline utility) and rotation parameters to be a function of attributes:

$$a_h = A\tilde{\alpha}_h \quad \text{and} \quad \kappa_h^* = A\tilde{\kappa}_h^*, \tag{16}$$

where A is of dimension $a \times b$ with $a > b$. This specification constrains the estimated model intercepts (α) and/or rotation parameters (κ^*) to lie within the subspace defined by the column vectors of the attribute matrix A. The columns of A correspond to the set of product attributes. The potential advantage of this specification is a significant reduction in the number of parameters that require estimates.

Our nonhomothetic demand model offers new opportunities for incorporating advertising effects. Exposure to an ad can either change the brand intercepts or "baseline" utility parameters, α, or the quality parameters, κ. If advertising is designed to increase the perceived quality of one brand at the expense of others (a common objective of advertising), then our model can accommodate this via a decrease of the associated κ. In our application, we model advertising as changing the κ associated with a particular attribute of two of the higher-end products. Again, the nonhomothetic model will allow for a change in the strength of the trade-up utility incentive as a result of advertising. This is a fundamentally different concept that is merely a change in the brand intercept.

2.6. Reduced-Form Logit Specifications

Rather than specifying a direct utility function over products under consideration, many users of standard logit models start from the partitioning of "utility" into observed and unobserved components. In this situation, choice probabilities take the form

$$\Pr(i) = \frac{\exp(\bar{U}_i)}{\sum_j \exp(\bar{U}_j)}, \tag{17}$$

where $\bar{U}_i$ represents the observed drivers of "utility." Any arbitrary set of regressors could be included in the $\bar{U}_i$ terms. For example, there is nothing to stop the user of a logit model from putting in a log price variable, product characteristics (including intercepts), and consumer demographics.

The strict random utility derivation starts from a specification of a direct utility model (the linear utility model) and derives the form of the resulting logit model. In particular, the random utility derivation of the choice model suggests that log of price should be entered and that it should have one coefficient that is constant across choice alternatives. A purely statistically motivated model could have separate price coefficients for each alternative, avoiding the restrictive IIA property of logits.

Our view is that these approaches are nonstructural and may be useful for describing the data but cannot be used to simulate the effects of changes in the environment or marketing mix variables (for further discussion, see Chintagunta et al. 2006). The structural approach imposes a discipline on the way in which we build our model. We must start with a valid direct utility function and derive the associated demand system. This ensures that the model is interpretable and often results in models that are parsimonious but flexible. There is an alternative point of view that one could entertain many possible covariates (including demographics and marketing mix variables) and use out-of-sample validation to choose the final specification. Given that any arbitrary interaction between variables (including higher-order interactions) could be included, we believe these methods are approximations to an arbitrary, unspecified, and structural model.

The manner in which advertising is introduced into the model is a good example of the difference between a structural and reduced-form approach. In most economic models of the effects of advertising, advertising is assumed to affect the perceived quality of a product. In a logit specification, this means that advertising affects the product intercept. In our model, advertising can affect the relative superiority parameters as well. This means that advertising can affect the rate at which consumers trade up to higher-quality goods. This is absent from a standard logit specification.

In the end, our structural model suggests a particular way in which advertising can enter the probability of product choice. A nonstructural approach would be to include advertising, functions of advertising (such as polynomials in advertising), and interactions between advertising and consumer demographics and other marketing mix variables such as price. There is no doubt that, given enough interactions and other nonlinear functions of advertising, such a reduced-form model could approximate our structural model of the role of advertising. Our view is that these reduced-form approximations may have a role in uncovering interesting effects but are not very useful for evaluating advertising or building parsimonious, yet flexible, models of advertising effects.

3. Data and Statistical Specification

Data are obtained from a national survey conducted by a leading packaged goods manufacturer. The product category under study is populated by 40 nationally branded offerings and a discount house brand across three subcategories: discount, regular, and premium quality. Unfortunately, the manufacturer that commissioned the collection of these data has not allowed us to specify the product category or the brands.

Regular prices for the brands ranged from a minimum of \$0.79 and a maximum of \$219.99. Quotas were imposed on the sample so that respondents were current users in the product category, approximately 50% of the respondents were male, and there were twice as many respondents currently using one of the discount offerings as a regular or a premium offering (i.e., 50%, 25%, 25%). These quotas ensured conformity to the target population. A total of 1,323 respondents provided data for analysis.

Data were collected in three phases. The first phase involved three choice tasks in which respondents choose from among offerings arrayed on a computer screen to resemble a shelf layout in a retail setting. High-quality graphics were used to represent the actual packaging of the alternatives, with a price sticker immediately below each. Respondents could select an item, read actual product descriptions, rotate the item, obtain a close-up, and view the package back. When the respondents were done examining the items of interest to them, they proceeded to a checkout screen where their choice was recorded. For all models investigated, a no-purchase decision is included as a separate choice alternative. This is desirable in survey research when arrays of offerings are shown to respondents, and the preference for the no-purchase alternative is interpreted as reservation value needed for positive demand.

Between the first and second phases of data collection, a random sample of respondents was exposed to two television commercials that described a new product benefit available only among two of the premium offerings with a specific attribute (attribute C). Approximately 28% of the respondents were exposed to the advertisements. Video information was depicted differently in the two commercials—one showing a "lifestyle" benefit for product 40, and the other graphically explaining the specific technology incorporated in product 37. The effect of the video treatment was incorporated into the model by allowing exposure to alter the effects of the focal attribute (attribute C). This was accomplished by modifying the attribute matrix, A, for the second and third phases of the data for those respondents viewing the commercial, and this allowed us to measure the interactive effect of the commercial on the marginal utility of the attribute.

The second phase of data collection involved five pairwise choice tasks, with a no-choice option, where offerings within a respondent's currently used subcategory were displayed. Respondents who currently used discount offerings selected primarily among discounted offerings, regular users selected primarily among regular offerings, and premium users among premium offerings. Two choice options were graphically displayed on the computer screen with prices below each, and respondents were asked to make a selection of one of the two, or a no-choice option. The purpose of phase 2 data collection was to ensure that sufficient information was obtained about current respondent preferences and budget allotments.

The third phase of data collection was similar to the first phase, except that 12 choice tasks were presented to the respondent. The purpose of phase 3 data collection was to ensure that sufficient information was obtained to estimate the full structure of preferences across all products.

Evidence of the need for the proposed model is observed in a simple comparison of aggregate choice shares of discount, regular, and premium offerings. The aggregate choice shares for these groups of offerings are 0.42, 0.22, and 0.19, respectively, in the phase 1 data, with the remaining share for the no-purchase option. In phase 3 of the data, after some respondents are exposed to the television commercials, the choice shares are 0.28, 0.21, and 0.31, respectively. A homogeneous logit model would be governed by the proportionate draw property in which the gains from advertising the high-quality brands would draw shares proportionate to current market shares. The fact that the bulk of the increased demand comes from discount offerings and very little from the regular offerings is a clear violation of the IIA property. Thus, there is a clear need for a more flexible model. Our argument is that rather than using the standard homothetic logit as the base, it would be more fruitful to start from a nonhomothetic model, which can accommodate a more flexible substitution pattern and nontrivial income effects.

Respondents in the survey also provided answers to questions on their current use of the product, demographic information, and information concerning recommendations they have received about the benefits of using the premium offerings. The likelihood for each respondent h is specified by three factors related to each phase of the data:

$$\begin{aligned}\pi(Data_h \mid \alpha_h, \kappa_h, \gamma_h, \tau_h, A_{1,h}, A_{23,h}) &= \pi(Data_{h,1} \mid \alpha_h, \kappa_h, \gamma_h, \tau_h, A_{1,h}) \\ &\quad \cdot \prod_{j=2}^{3} \pi(Data_{h,j} \mid \alpha_h, \kappa_h, \gamma_h, \tau_h, A_{23,h}), \qquad (18)\end{aligned}$$

where $Data_h$ comprise the three sets of responses described above; $\{\alpha_h\}$ are baseline preference parameters; $\{\kappa_h\}$ are the trade-up parameters that govern the relative rates of rotation of indifference curves; $\{\gamma_h\}$ are the affordability parameters in logarithmic form, i.e., $\gamma = \ln E$; and $\{\tau_h\}$ are the parameters for the outside good in Equation (10). We describe the attribute matrices $\{A_{1,h}\}$ and $\{A_{23,h}\}$ further below.

The attribute matrix A consists of indicator variables for (1) the seven brands in the data set, (2) quality tiers (discount, regular, premium), and (3) three brand attributes (A, B, C) available in regular and premium offerings. A_1 is the attribute matrix for the first phase of data collection. A_{23} is the attribute matrix for the second and third phases, and includes two additional columns that indicate whether or not the respondent saw the advertisement videos with attribute C. There are two columns as one of the advertisements was targeted at product 37 and one for product 40.

For models in which the intercepts or rotation parameters were projected on characteristics, we do not estimate a full set of 40 intercepts and 40 rotation parmeters, but instead rely on the attribute matrix to populate the model as in $a_h = A\tilde{\alpha}_h$ and $\kappa_h^* = A\tilde{\kappa}_h^*$.

Heterogeneity is incorporated using a random-effect specification:

$$\pi(\tilde{\alpha}_h, \tilde{\kappa}_h^*, \gamma_h, \tau_h \mid \Delta, z_h, V_\beta) = \text{Normal}(\Delta s_h, V_\beta), \qquad (19)$$

where s_h is a vector of descriptor variables for respondent h

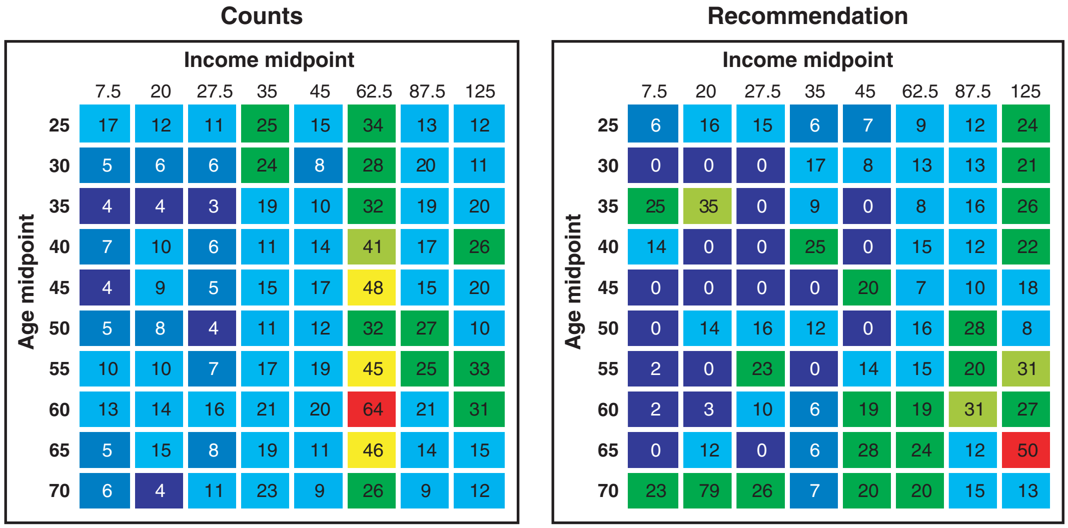
$$s_h = \big(1, \mathit{recommendation}_h, \mathit{income}_h, \mathit{age}_h, \mathit{income}_h \times \mathit{age}_h\big). \qquad (20)$$

Δ is matrix of coefficients linking the descriptor variables to each of the preference parameters. The *income*, *age*, and *income* $\times$ *age* variables are mean centered, so that the intercept can be interpreted as the mean of the random-effects distribution for respondents who have not received a recommendation. Income is divided by 100,000 and age is divided by 100, so that the resulting Δ coefficients have approximately the same scale.

Recommendation is recorded as a dummy variable, indicating whether the respondent received a professional recommendation for the premium product. This recommendation was received by the respondent some time in the past, prior to this study. Note that the recommendation is for the set of premium products rather than for specific products. The video mock ad exposure is designed, however, to promote particular high-end products, and affords us the opportunity to study an experimental manipulation of advertising exposure on choice.

Figure 3 displays the count and proportion of respondents receiving the recommendation for various age and income groups. The left side of the figure displays the sample proportion of respondents falling into each age-income group, and the right side of the figure displays the proportion within each cell that

Figure 3 **Respondent Counts and Percentage Receiving Recommendation**



received the recommendation. It appears that current practice is to make recommendations to individuals that are older and wealthier. We use higher color temperatures to indicate higher values of the variable that is displayed. That is, dark blue represents the lowest values with red corresponding to the highest value.

Note that if recommendations were made purely on the basis of our observed demographics such as income and age, we can make a causal assessment of the effect of a recommendation on demand. If, however, the professionals making the recommendation make these recommendations as a function of preference parameters, then our nonexperimental data cannot be used to evaluate the pure effect of a recommendation. That is, if professionals advise people who like premium brands anyway, then we could see an "effect" of a recommendation even if the recommendation is, in fact, completely ineffective in stimulating demand. It is our view that it is unlikely that a health-care professional making the recommendation would simply be trying to match products to preferences but, instead, is acting as an informed agent for the customer—attempting to maximize their health outcome from product consumption. However, we refrain from making statements about the effectiveness of a recommendation because of possible confounding because of endogeneity.

4. Parameter Estimates

Table 1 displays fit statistics for five variations of the model.[1] We report the log-marginal density of the model as an in-sample measure of model correctness, and hit probabilities to measure out-of-sample fit. The marginal density of the data has an implicit penalty against highly parameterized models. The ratio of marginal densities between two models forms the Bayes factors, which when multiplied by the prior odds, yields the posterior odds of one model being favored over another. Predictive fits are based on one holdout observation per respondent from the third factor of the likelihood in (18). All models include a hierarchical specification in which respondent descriptor variables can influence all model coefficients. This can be interpreted as adding a full set of interactions with "demographic" variables. Thus, all models start from a very flexible footing, and we are simply testing the value of homothetic versus nonhomothetic specifications and the restrictions imposed by a characteristics model.

The first two models presented in Table 1 are characteristics models that constrain intercepts (α) and rotation parameters (κ) to lie within the characteristics subspace. The last three models relax this restriction for the intercepts but retain it for the rotation

[1] Estimation is carried out using Bayesian Markov chain Monte Carlo (MCMC) methods. Initial conditions of the chain were varied to ensure convergence to a common posterior. A total of 40,000 iterations were executed, with the last 10,000 iterations used for parameter estimation. Details are provided in the appendix.

Table 1 **Model Fit**

Model	In-sample log-marginal density	Out-of-sample hit probability
Characteristics models		
1. Logit (15 $\tilde{\alpha}$s)	−28,174	0.652
2. Nonhomothetic logit (15 $\tilde{\alpha}$s, 15 $\tilde{\kappa}^*$s)	−25,848	0.648
Brand-specific models		
3. Logit (40 αs)	−21,899	0.688
4. Homothetic logit (40 αs, 15 $\tilde{\kappa}^*\mathrm{s} = e^{-5}$)	−21,863	0.698
5. Nonhomothetic logit (40 αs, 15 $\tilde{\kappa}^*$s)	−21,251	0.712

parameters. Models 1 and 3 are standard logit models (Equation (11)) with baseline preference and respondent price sensitivity parameters. Model 4 incorporates affordability as in Equation (12) by fixing the rotation parameters at zero. Models 2 and 5 also incorporate the effects of trade-up by estimating the rotation parameters (κ) constrained to lie within the attribute space (Equation (10)).

The fit statistics indicate that the characteristics models provide a poor fit to the data relative to models with unique intercepts. We also find that the proposed nonhomothetic model for trade-up (Equation (10)) provides better fit than the logit model (Equation (11)) and the model that only incorporates affordability (Equation (12)). Our model with nonhomothetic preferences has both a higher Bayes factor, which is based on in-sample data, and better out-of-sample fit than an extremely flexible homothetic specification. The homothetic specification without affordability (no expenditure parameters) is a very flexible logit model with full interactions of demographics with all model parameters. Our model outperforms this model on the basis of both in-sample and out-of-sample measures. We conclude then that there is ample evidence of the need for a model with trade-up and affordability in respondent choices, namely, our nonhomothetic model of choice.

Table 2 reports parameter estimates for a portion of the coefficient matrix Δ for model 5, the best-fitting model. These estimates use all available data, including the holdout observations. Reported are posterior means and standard deviations for the trade-up (κ), affordability (γ or E), and outside good (τ) parameters. Estimates of the baseline preference parameters (α) are not reported because the names of the 40 brands in the study cannot be disclosed for proprietary reasons, and therefore a detailed discussion of brand-specific coefficients is not possible.

The left side of Table 2 lists the attributes used in the analysis. There are seven brand names associated with the 40 offerings. Three attributes are associated with the quality level of the offerings (discount, regular, and premium), and three additional attributes describe specific features that are available in the regular and premium offerings only. Attribute C is the focal attribute described in the video, through which the sponsoring firm hopes to generate trade-up in the product category.

The columns in Table 2 are descriptors of the respondents in the study. Some respondents received a recommendation to buy a superior offering by an expert prior to the study. Respondent income, age, and an income by age interaction completes the description of the respondents. The remaining columns indicate, on average, how these estimates change with the presence of a recommendation, income, and age. Because

Table 2 Posterior Means for Selected Δ Parameters (Posterior Standard Deviation)

Attributes	Intercept	Rec.	Income[1]	Age[2]	Inc. × Age
Trade-up ($\tilde{\kappa}^*$):					
Brand A	−1.49	0.53	0.09	0.88	−4.52
	(0.19)	(0.21)	(0.37)	(0.79)	(3.74)
Brand B	−0.86	1.55	0.86	5.88	1.37
	(0.23)	(0.53)	(0.57)	(1.32)	(3.53)
Brand C	0.58	1.46	0.33	3.06	−4.82
	(0.13)	(0.25)	(0.42)	(0.76)	(2.67)
Brand D	−1.01	2.16	0.77	4.76	−1.24
	(0.17)	(0.39)	(0.42)	(0.98)	(3.80)
Brand E	0.33	0.62	1.96	2.12	−3.42
	(0.16)	(0.42)	(0.34)	(0.68)	(1.85)
Brand F	0.91	1.15	0.33	3.83	−5.80
	(0.19)	(0.28)	(0.33)	(1.41)	(3.97)
Brand G	0.45	−0.58	1.18	8.61	3.70
	(0.21)	(0.46)	(0.39)	(1.79)	(5.86)
Discount quality	1.51	2.66	0.02	8.10	−1.73
	(0.16)	(0.40)	(0.53)	(1.29)	(3.45)
Regular quality	−0.74	3.15	0.62	10.91	4.33
	(0.19)	(0.43)	(0.52)	(1.07)	(3.98)
Premium quality	−1.60	−0.76	−0.82	2.73	0.14
	(0.20)	(0.27)	(0.32)	(1.26)	(4.94)
Attribute A	−1.69	0.52	0.43	1.22	1.73
	(0.17)	(0.21)	(0.31)	(0.80)	(2.22)
Attribute B	−0.75	0.85	−0.63	2.80	3.45
	(0.13)	(0.25)	(0.42)	(0.92)	(2.41)
Attribute C	0.33	0.92	−0.08	4.59	8.69
	(0.30)	(0.53)	(0.59)	(2.00)	(4.79)
Video × product 37	−0.13	0.67	−1.69	−1.00	−13.49
interaction	(0.18)	(0.46)	(0.61)	(1.19)	(5.18)
Video × product 40	−0.15	−0.38	−0.75	6.14	−7.15
interaction	(0.23)	(0.31)	(0.44)	(0.68)	(3.46)
Affordability ($\gamma = \ln E$)	3.19	1.34	0.67	−0.89	−0.63
	(0.06)	(0.12)	(0.15)	(0.31)	(1.15)
Outside good ($\tau^* = \ln \tau$)	−0.15	−0.53	0.05	−0.80	−0.05
	(0.05)	(0.11)	(0.13)	(0.32)	(0.98)

[1]Income is in units of $100,000.
[2]Age is in units of 100 years.

income and age are mean centered, their coefficients should be interpreted in terms of deviations of income and age from their mean values—i.e., $61,000 and 46 years.

The coefficient estimates in the first column of Table 2 have reasonable algebraic signs and magnitudes. The trade-up coefficients (κ) are reparameterized as $\kappa^* = \ln \kappa$, with κ^* estimated without restriction. Thus, negative values of κ^* are synonymous with κ close to zero, indicating a superior offering to those with larger κ^*. We find the premium quality offerings to have the smallest estimated values of κ, followed by the regular and discount quality offerings with the largest κ. The expenditure for a hypothetical average respondent is, on average, $E = \exp(3.19) = \$24.29$, and the recommendation increases this expenditure to $E = \exp(3.19 + 1.34) = \$92.76$ for those exposed to it. The expenditure is the maximum amount that a respondent is willing to pay for an offering in the

Figure 4 Estimated Expenditure Levels by Age, Income, and Recommendation

No recommendation

Age midpoint \ Income midpoint	7.5	20	27.5	35	45	62.5	87.5	125
25	19	21	22	24	26	30	36	49
30	18	20	22	23	25	28	34	46
35	18	20	21	22	24	27	32	43
40	18	19	20	21	23	26	31	40
45	17	19	19	21	22	25	29	38
50	17	18	19	20	21	24	28	35
55	16	17	18	19	20	23	26	33
60	16	17	18	18	20	22	25	31
65	15	16	17	18	19	21	24	29
70	15	16	16	17	18	20	22	27

Recommendation

Age midpoint \ Income midpoint	7.5	20	27.5	35	45	62.5	87.5	125
25	73	81	85	91	98	113	138	187
30	71	78	83	88	95	108	131	175
35	69	76	80	84	91	103	124	164
40	67	73	77	81	87	99	118	154
45	65	71	75	79	84	95	112	144
50	64	69	72	76	81	90	106	135
55	62	67	70	73	78	86	101	127
60	60	65	68	71	75	83	96	119
65	59	63	65	68	72	79	91	111
70	57	61	63	66	69	76	86	104

category—offerings above a respondent's threshold level are excluded from the choice set.

A recommendation received for a premium offering is associated with changes in perceived superiority (κ^*), as indicated in the second column of coefficients in Table 2. Respondents receiving a recommendation view the premium quality offerings as more superior and the regular and discount quality offerings as more inferior than respondents not receiving the recommendation. In addition, brand G is seen to be viewed as more superior, whereas the other brands degrade in aggregate perceptions of quality, particularly brand D. The recommendation is associated with lower levels of perceived quality of attributes A, B, and C and higher levels of expenditure.

The relationship of recommendation, income, and age on aspects of trade-up are explored in more detail in the next section. The presence of the income-age interaction makes it difficult to obtain simple inferences from the Δ coefficients. Moreover, the Δ coefficients are the means of the random-effect distribution, and there exists substantial dispersion of individual respondent coefficients around these means. Our estimates of heterogeneity (available on request) show a great deal of variability in all fundamental preference parameters.

5. Describing and Managing Trade-Up

In this section, we examine use of the model for describing and managing trade-up. We draw inferences by computing expected values of the regression model in Equation (19). Our goal is to understand the interplay of variables under the control of marketing (recommendation, video) and those that are not (age, income), and we make use of age-income heat maps for understanding model implications. We use higher color temperatures to indicate higher values of the variable that is displayed. Dark blue represents the lowest values with red corresponding to the highest value.

5.1. Describing Trade-Up

Figure 4 displays the relationship of age, income, and professional recommendation to the budget expenditure—the maximum amount an individual is willing to pay for an offering in the category. Reported in each cell is the expected expenditure for respondents falling into each age-income group. The left portion of Figure 4 displays expected expenditures without the recommendation, and the right portion of the figure displays the expected expenditure after receiving the recommendation. Most respondents not receiving a recommendation are willing to spend about \$20, except the younger, high-income group, who are willing to spend about \$40. This corresponds to the upper threshold of prices for the regular product. Respondents who received a recommendation are willing to pay about three times this amount across all age and income levels, with an expected maximum of \$187 for the youngest, wealthiest respondents.

Regardless of whether the respondent had received a recommendation, expenditures are highest for younger, high-income respondents and lowest for older and lower-income respondents. This is interesting because it shows that willingness to pay is more related to affluence and disposable income than to the physical need that increases with age. It appears that expenditure in this category is, in part, aspirational. Whereas most respondents will pay the necessary \$60–\$80 charge for basic trade-up, younger, high-income respondents will pay two to three times that amount.

Figure 5 Estimated Trade-Up (κ^*) Parameter for Premium and Regular Quality Offerings by Age, Income, and Recommendation

Premium — No recommendation

Age midpoint \ Income midpoint	7.5	20	27.5	35	45	62.5	87.5	125
25	−1.72	−1.83	−1.89	−1.96	−2.04	−2.19	−2.40	−2.72
30	−1.59	−1.70	−1.76	−1.82	−1.91	−2.05	−2.26	−2.58
35	−1.46	−1.56	−1.63	−1.69	−1.77	−1.92	−2.12	−2.44
40	−1.33	−1.43	−1.49	−1.55	−1.64	−1.78	−1.99	−2.30
45	−1.19	−1.30	−1.36	−1.42	−1.50	−1.64	−1.85	−2.15
50	−1.06	−1.16	−1.22	−1.28	−1.37	−1.51	−1.71	−2.01
55	−0.93	−1.03	−1.09	−1.15	−1.23	−1.37	−1.57	−1.87
60	−0.80	−0.90	−0.96	−1.02	−1.10	−1.23	−1.43	−1.73
65	−0.66	−0.76	−0.82	−0.88	−0.96	−1.10	−1.30	−1.59
70	−0.53	−0.63	−0.69	−0.75	−0.82	−0.96	−1.16	−1.45

Premium — Recommendation

Age midpoint \ Income midpoint	7.5	20	27.5	35	45	62.5	87.5	125
25	−2.48	−2.59	−2.65	−2.72	−2.80	−2.95	−3.16	−3.48
30	−2.35	−2.45	−2.52	−2.58	−2.66	−2.81	−3.02	−3.34
35	−2.22	−2.32	−2.38	−2.45	−2.53	−2.68	−2.88	−3.20
40	−2.09	−2.19	−2.25	−2.31	−2.39	−2.54	−2.75	−3.05
45	−1.95	−2.06	−2.12	−2.18	−2.26	−2.40	−2.61	−2.91
50	−1.82	−1.92	−1.98	−2.04	−2.12	−2.27	−2.47	−2.77
55	−1.69	−1.79	−1.85	−1.91	−1.99	−2.13	−2.33	−2.63
60	−1.56	−1.66	−1.71	−1.77	−1.85	−1.99	−2.19	−2.49
65	−1.42	−1.52	−1.58	−1.64	−1.72	−1.86	−2.05	−2.35
70	−1.29	−1.39	−1.45	−1.51	−1.58	−1.72	−1.92	−2.21

Regular — No recommendation

Age midpoint \ Income midpoint	7.5	20	27.5	35	45	62.5	87.5	125
25	−2.88	−2.91	−2.94	−2.96	−2.99	−3.04	−3.12	−3.23
30	−2.45	−2.46	−2.46	−2.47	−2.48	−2.49	−2.51	−2.54
35	−2.02	−2.00	−1.99	−1.98	−1.97	−1.94	−1.91	−1.86
40	−1.59	−1.54	−1.52	−1.49	−1.46	−1.40	−1.31	−1.18
45	−1.16	−1.09	−1.05	−1.00	−0.95	−0.85	−0.71	−0.49
50	−0.73	−0.63	−0.57	−0.51	−0.44	−0.30	−0.10	0.19
55	−0.30	−0.18	−0.10	−0.03	0.07	0.25	0.50	0.88
60	0.13	0.28	0.37	0.46	0.59	0.80	1.10	1.56
65	0.56	0.74	0.84	0.95	1.10	1.35	1.71	2.24
70	0.99	1.19	1.32	1.44	1.61	1.89	2.31	2.93

Regular — Recommendation

Age midpoint \ Income midpoint	7.5	20	27.5	35	45	62.5	87.5	125
25	0.28	0.24	0.22	0.20	0.17	0.11	0.04	−0.07
30	0.71	0.70	0.69	0.68	0.68	0.66	0.64	0.61
35	1.14	1.15	1.16	1.17	1.19	1.21	1.24	1.29
40	1.57	1.61	1.64	1.66	1.70	1.76	1.85	1.98
45	2.00	2.07	2.11	2.15	2.21	2.31	2.45	2.66
50	2.42	2.52	2.58	2.64	2.72	2.86	3.05	3.35
55	2.85	2.98	3.05	3.13	3.23	3.40	3.65	4.03
60	3.28	3.44	3.53	3.62	3.74	3.95	4.26	4.71
65	3.71	3.89	4.00	4.11	4.25	4.50	4.86	5.40
70	4.14	4.35	4.47	4.60	4.76	5.05	5.46	6.08

Figure 5 examines the association of age, income, and recommendation to the trade-up parameters for the regular and premium quality product offerings. Recall that we reparameterized κ to ensure positive values by estimating $\kappa^* = \ln \kappa$ unrestricted, so more negative values of the estimated κ^* correspond to values of κ that are closer to zero, corresponding to offerings that are superior to offerings with positive κ^*. The top portion of Figure 5 displays the expected values of κ^* for premium offerings, and the lower portion of Figure 5 displays values for regular offerings. Focusing on the left-hand column "No recommendation," we see that the premium product is a trade-up for all consumers (i.e., $\kappa^* < 0$), especially the younger, high-income group. The regular product, by contrast, is a trade-up only for younger consumers—older consumers who have not received a recommendation, on average, do not perceive a quality distinction between the discount and regular offerings.

Respondents receiving a recommendation have increased perceived superiority of the premium product and weakened superiority for the regular product across all age and income groups. This is seen by comparing the right- to the left-hand graphs in Figure 5. Receiving a recommendation from a professional is a strong indicator of a consumer's knowledge about the

Figure 6 **Effect of Video on Trade-Up (κ^*) for Attribute C for Respondents Not Receiving a Recommendation**

No video — Product 37 (Age midpoint × Income midpoint)

Age midpoint	7.5	20	27.5	35	45	62.5	87.5	125
25	−6.17	−6.55	−6.77	−7.00	−7.30	−7.83	−8.59	−9.72
30	−5.81	−6.13	−6.32	−6.51	−6.77	−7.21	−7.85	−8.81
35	−5.46	−5.72	−5.87	−6.03	−6.23	−6.60	−7.11	−7.89
40	−5.10	−5.30	−5.42	−5.54	−5.70	−5.98	−6.38	−6.98
45	−4.74	−4.88	−4.97	−5.05	−5.17	−5.36	−5.64	−6.06
50	−4.39	−4.47	−4.52	−4.57	−4.63	−4.74	−4.91	−5.15
55	−4.03	−4.05	−4.07	−4.08	−4.10	−4.13	−4.17	−4.23
60	−3.68	−3.64	−3.62	−3.59	−3.56	−3.51	−3.43	−3.32
65	−3.32	−3.22	−3.16	−3.11	−3.03	−2.89	−2.70	−2.40
70	−2.96	−2.81	−2.71	−2.62	−2.49	−2.27	−1.96	−1.49

No video — Product 40 (Age midpoint × Income midpoint)

Age midpoint	7.5	20	27.5	35	45	62.5	87.5	125
25	−5.52	−5.98	−6.25	−6.53	−6.89	−7.53	−8.45	−9.82
30	−5.00	−5.34	−5.55	−5.76	−6.04	−6.52	−7.21	−8.25
35	−4.47	−4.71	−4.85	−4.99	−5.18	−5.51	−5.98	−6.69
40	−3.95	−4.08	−4.15	−4.23	−4.33	−4.50	−4.75	−5.13
45	−3.43	−3.44	−3.45	−3.46	−3.47	−3.49	−3.52	−3.56
50	−2.91	−2.81	−2.75	−2.69	−2.62	−2.48	−2.29	−2.00
55	−2.38	−2.18	−2.05	−1.93	−1.76	−0.46	−1.06	−0.43
60	−1.86	−1.54	−1.35	−1.16	−0.91	−1.46	0.18	1.13
65	−1.34	−0.91	−0.65	−0.39	−0.05	0.55	1.41	2.69
70	−0.81	−0.27	0.05	0.37	0.80	1.56	2.64	4.26

Video — Product 37 (Age midpoint × Income midpoint)

Age midpoint	7.5	20	27.5	35	45	62.5	87.5	125
25	−6.71	−6.94	−7.08	−7.22	−7.41	−7.73	−8.20	−8.90
30	−6.04	−6.30	−6.45	−6.61	−6.82	−7.18	−7.69	−8.46
35	−5.38	−5.66	−5.83	−6.00	−6.22	−6.62	−7.18	−8.03
40	−4.71	−5.01	−5.20	−5.38	−5.63	−6.06	−6.67	−7.60
45	−4.04	−4.37	−4.57	−4.77	−5.04	−5.50	−6.17	−7.16
50	−3.37	−3.73	−3.94	−4.16	−4.44	−4.94	−5.66	−6.73
55	−2.70	−3.09	−3.31	−3.54	−3.85	−4.38	−5.15	−6.29
60	−2.03	−2.44	−2.69	−2.93	−3.26	−3.83	−4.64	−5.86
65	−1.37	−1.80	−2.06	−2.32	−2.66	−3.27	−4.13	−5.43
70	−0.70	−1.16	−1.43	−1.70	−2.07	−2.71	−3.62	−4.99

Video — Product 40 (Age midpoint × Income midpoint)

Age midpoint	7.5	20	27.5	35	45	62.5	87.5	125
25	−7.37	−7.74	−7.95	−8.17	−8.46	−8.97	−9.69	−10.78
30	−6.35	−6.65	−6.83	−7.00	−7.24	−7.66	−8.25	−9.14
35	−5.33	−5.56	−5.70	−5.84	−6.02	−6.35	−6.81	−7.50
40	−4.31	−4.47	−4.57	−4.67	−4.80	−5.03	−5.36	−5.86
45	−3.29	−3.39	−3.45	−3.51	−3.58	−3.72	−3.92	−4.21
50	−2.27	−2.30	−2.32	−2.34	−2.36	−2.41	−2.47	−2.57
55	−1.25	−1.21	−1.19	−1.17	−1.15	−1.10	−1.03	−0.93
60	−0.23	−0.13	−0.07	−0.01	0.07	0.21	0.41	0.71
65	0.80	0.96	1.06	1.16	1.29	1.53	1.86	2.36
70	1.82	2.05	2.19	2.33	2.51	2.84	3.30	4.00

physical problem corresponding to the product category and its remedies, which tends to happen when consumers are older. We speculate that awareness of the problem forces a discontinuity in the consumer perception of quality, neutralizing the appeal of products in the \$20 range (regular products) and establishing a price premium for the superior good. This is particularly striking for younger respondents who are the primary consumers of the regular "midprice" product. Although not many of them are in the process of seeking and receiving advice, those who are make the most dramatic turnaround in perception of the value of the regular product.

Figure 6 shows the effect of the video treatment on the trade-up parameter κ^* for products 37 and 40 for respondents who have not received a recommendation. The effect for respondents who received a recommendation is similar but less pronounced. Recall that the video treatment is experimentally manipulated, with the treatment comprising two different video advertisements—one for product 37 emphasizing a new technical attribute, and one for product 40 with a lifestyle orientation. Both products are at the high end of the range of premium offerings and the highest priced of all items in the study. The κ^* values for these products are calculated using (16).

We notice the familiar pattern of highest trade-up values (i.e., smallest values of κ^*) among younger, higher-income respondents in all panels of Figure 6. However, there are interesting subtleties. The κ^* values for product 40 are banded by age more so than product 37, suggesting an age split in quality perceptions: younger consumers are more likely to trade up to product 40 but older consumers are not, regardless of income. These patterns are then accentuated by the video treatments. For product 40, κ^* intensifies within the younger age band to lower-income groups but diminishes the perceived quality for older respondents. For product 37, κ^* intensifies among older respondents in the higher-income bands. This can be seen by comparing the bottom three rows of entries corresponding to an age midpoint greater than 60 for the video versus the no-video treatment. Thus, the effects of the videos on trade-up are different for the two products. We examine the economic implications of the measured advertising effects next.

5.2. Managing Trade-Up

Typically, advertising is used to influence the perceived quality of a product offering. In most standard choice models, advertising is introduced as a demand shifter, implemented by allowing advertising exposure to increase the intercepts for the brands advertised. In a standard logit specification, an increase in the intercept results (holding all other marketing mix variables constant) in an increase in expected market share. As is well known, this increased market share is obtained from other products in proportion to the existing shares of products in the category because of the use of extreme value errors. For example, if we advertise the high-quality/high-price brands and the large-share brands are very inexpensive items, then the standard logit model would predict that advertising the high-quality brand will steal share primarily from very low-quality products. To our way of thinking, this seems to be an unreasonable restriction on behavior. We would like to allow for the possibility that advertising a high-quality brand might draw share primarily from other brands of high quality or moderate quality.

Our nonhomothetic model has parameters, which can be directly interpreted as the relative quality or superiority of products in the category. We allow for the advertising treatment (exposure to two video ads) to affect the κ parameters, which determine the relative superiority or inferiority of a brand. Thus our model is freed from the restriction of a standard logit model of proportionate draw.

In our study, there are two types of marketing communications: (1) a professional recommendation, which would apply generically to the class of premium products; and (2) exposure to two video ads for two of the high-end products. The professional recommendation was not experimentally manipulated and was included in the model as a variable describing the respondent similar to a demographic variable. The video advertisement was experimentally manipulated and was included in the model as an effect interacting with the focal attribute (attribute C) of the advertisement. We recognize that the recommendation parameter estimate cannot be interpreted as a structural parameter (the effect of recommendation) because it is confounded with the effect of who was given the recommendations. On the basis of demographic patterns, it appears that the recommendation was given primarily to those who could afford the product (see Figure 3). It may also be the case the health-care professionals who gave recommendations had access to unobserved variables, which create forms of selection bias that we cannot correct for. For this reason, we will focus on the randomized exposure to ad videos.

Figure 6 shows that the video treatment has different effects for products 37 and 40. There are interesting interactions between the effect of ad exposure and demographic variables. The perceived quality of product 40 is particularly weak among older respondents, and the video exacerbates this perception. For product 37, the video improves perceived quality among many of the wealthier respondents.

Whereas the advertising exposure does have measurable effects, the exact value of the ad exposure depends not only on the changes in estimated model coefficients but on the equilibrium behavior of firms in the category. For example, positive advertising effects should allow a manufacturer to charge a higher price for the product advertised. However, it would be naïve to simply calculate the benefits of increased demand by assuming that the competing manufacturers would hold their prices at the level set prior to the ad exposure. We should allow firms to respond to pricing changes. Price competition may reduce the ultimate benefit of advertising exposure. To allow for these competitive pricing effects, we solve for the Nash equilibrium prices and profits with and without exposure to the ad.

The ads are targeted for products 37 and 40. Expected profits are computed as the product of expected demand and contribution margin (i.e., price minus marginal cost). Marginal costs for the products are obtained through consultation with the firm participating in this study and are estimated to be 36% of regular price. The regular price of products 37 and 40 is $219.99, and therefore the per unit marginal cost is $79.20. Profits are evaluated at optimal prices, which are defined as the profit-maximizing prices.

Expected profits and optimal prices are compared using a counterfactual analysis that predicts preferences with and without the ad effects. We condition on the actual demographic distribution and recommendations received. The presence and absence of the video is obtained by allowing the attribute matrix A in Equation (16) to vary from $A = A_1$ to $A = A_{23}$ for all respondents, holding fixed all other variables.

Expected choice probabilities are estimated by integrating over the distribution of heterogeneity using the unobserved random effects and observed demographic heterogeneity in the sample:

$$E[\Pr(x_k = 1 \mid Data, p, A)] = \sum_{i=1}^{I} \int \Pr(x_{ki} = 1 \mid \Delta, V_\beta, z_i, p, A) \cdot \pi(\Delta, V_\beta \mid Data)\, d\Delta\, dV_\beta, \tag{21}$$

where p indicates the vector of regular prices, A is the attribute matrix (either A_1 or A_{23}), and I is the number of respondents. The profits for a one-product firm owning product k are given by

$$\pi_k(p_k \mid \Theta) = E[\Pr(x_k = 1 \mid price, recommendation, A, \Theta)] \cdot (p_k - c_k), \tag{22}$$

where Θ refers to the full set of common parameters.

We consider the two products (37 and 40) that are the target of the videos in our equilibrium pricing exercise. We hold the prices of the other brands constant at their current regular prices. Nash equilibrium prices are computed via simultaneous solution of the first-order conditions for both firms:

$$\frac{\partial \pi_1(p_1 \mid p_2, \Theta)}{\partial p_1} = 0, \qquad \frac{\partial \pi_2(p_2 \mid p_1, \Theta)}{\partial p_2} = 0. \tag{23}$$

Products 37 and 40 are manufactured by different firms, so we are considering single-product firm equilibrium prices. We used both solution of first-order conditions as well as alternating best response to a stationary point. Both methods give similar, if not identical, answers. Numerical solutions to (23) were not sensitive to initial values of price.

Table 3 presents equilibrium prices and profits for products 37 and 40. Product 40 has a high value to consumers who have not been exposed to the ads with higher equilibrium prices and profits than product 37. The video that is designed to promote product 37 has much more information content on the salient feature of this product, whereas the video for product 40 is more of an "image" ad that extols the lifestyle that is consistent with consumption of the product. Exposure to the ads changes the perceived superiority of product 37 relative to product 40. Both firms experience enhanced willingness to pay for their products, and equilibrium profits increase for both firms. We find that equilibrium prices show strong competitive effects, with product 40 experiencing greater competition from product 37 and lowering its equilibrium prices. Higher share allows the firm to compensate for lower margin.

Equilibrium prices without advertising exposure are higher than current prices by around 8% for product 37 and 30% for product 40. There are two possibilities that may explain this finding. First, we have only modeled competition between two of the firms at the highest end of the price and quality spectrum. These same firms also compete in the lower and moderate quality segments, and we have held constant the prices of brands in these segments. Given the well-known computational problems with multiple equilibria for multiproduct firms, we decided it was best to isolate competition to the high end. We are making a methodological point here about the need to adjust for price competition in computing pricing effects.

The second possibility is that there is unexploited value in the sense of groups of consumers who place a high value on products 37 and 40. This is a complicated issue as the expected profits are computed (see Equation (21)) by simulation methods. That is, we draw from the predictive distribution of heterogeneity in Equation (21), using more than 13,000 draws to approximate market demand with 13,000 "types" of consumers. Some care has to be taken in using this approximation. Suppose, for example, there are households with very large expenditure allocations to this product category. Then, the profit-maximizing price might well be set so high that only a small number of households purchase the product but at a very high price. To reduce the sensitivity of these calculations to outliers, we trimmed the top 5% of the draws of the expenditure parameter, $\gamma = \log(E)$.

Although ad exposure provides additional economic profits, which is not fully dissipated by competitive effects, the structure of demand changes as a result of exposure to advertising. This can be seen from the equilibrium price computations. As we increase advertising, profits rise but equilibrium prices do not always go up. The optimal price for product 40 actually declines. In our model, which we believe is a more realistic model of demand, the advertising effects the marginal value of quality, and this has effects on

Table 3 Equilibrium Prices and Profits (in $) With and Without Ad Exposure

	Equilibrium prices		Equilibrium profits (per hh)	
Treatment	Product 37	Product 40	Product 37	Product 40
No ad exposure	236.9	285.0	1.035	1.643
With ad exposure	285.0	254.3	1.660	1.820

Note. hh, household.

the structure of demand. These effects play themselves out in nontrivial ways, as illustrated in Table 3.

6. Conclusion

We demonstrate the benefit of nonhomothetic utility for studying trade-up in an extended product category, where the prices of offerings differ by more than an order of magnitude. Extended product categories include discount, regular, and premium offerings that cannot be considered close substitutes. In our application to a broad category of health-care products, the nonhomothetic model has better in-sample and out-of sample fit relative to very flexible homothetic models and standard logit specifications.

In our nonhomothetic demand specification, we are able to incorporate the effect of advertising on the marginal value of quality and, thus, the relative superiority of the advertising brand. This means that advertising can induce a stronger motive to trade-up and change the substitution patterns in the product category. In standard homothetic (logit) models, this effect is not possible. There are no trade up asymmetries in these models. Advertising can only affect the baseline utility or choice probability of a brand but not the rate at which consumers will trade up from brands with lower perceived quality. Advertising is often used to increase the perceived quality of a brand either directly or to accentuate the value to consumers of an attribute of a product. Allowing advertising to affect the relative superiority of a brand seems to be an important missing component in standard models of advertising effects.

We find large effect sizes for advertising. We also find systematic variation in expenditure levels (E) and views of superiority (κ) across income and age groups. The desire to trade up is found to be strongest among respondents who are young and wealthy. These individuals have the ability to afford the higher-priced premium offerings and have exceptionally strong views of their superiority.

Our randomized field experiment allows for the measurement of true advertising effects. The question of the impact of these measured effects on firm profits and pricing is the ultimate goal of an analysis of advertising effectiveness. To appropriately measure advertising effects on firm profits, we must also take into account competitive forces in pricing. If we allow for advertising to have a nontrivial effect on the structure of demand, we must also resolve for the industry price equilibrium to obtain an appropriate measure of the impact on profits. In our data set, we find evidence of enhanced profits from advertising as well as changes in the demand structure that result in different relative prices in an advertising simulation.

A promising avenue for future research is to jointly model the supply-side decision to make professional recommendations. These recommendations were received by respondents prior to the start of our study, and we treat them as exogenous variables in our analysis. Professional recommendations, however, are made by health-care professionals with different incentives than those of the manufacturer of the product. This means that standard models of firm profit maximization cannot be used to simultaneously model demand for the products and optimal marketing activities. Different models outside the realm of standard assumptions of firm behavior are required. Manchanda et al. (2004) provide one such approach, which is beyond the scope of this paper. Finally, we view this research as calling attention to the need for richer utility specifications appropriate for marketing problems. Structural modeling of discrete demand is currently dominated by linear utility specifications for reasons of convenience in estimation rather than because homothetic utility is realistic assumption at the consumer level.

Appendix. MCMC Estimation of Trade-Up Model

The likelihood for the proposed trade-up model is logit in form, with

$$\Pr(x_k = 1) = \frac{\exp[\alpha_k - \kappa_k \bar{u}^k + \tau \ln(E - p_k)]}{\sum_{\{i \mid p_i \le E\}} \exp[\alpha_i - \kappa_i \bar{u}^i + \tau \ln(E - p_i)]}, \tag{24}$$

where the term $\bar{u}^k$ is the value of attained utility by selected choice alternative k and spending the remainder of the budget on the outside good. The utility associated with purchasing one unit of alternative k is expressed implicitly:

$$\begin{aligned} \ln \bar{u}^k &= \alpha_k - \kappa_k \bar{u}^k + \tau \ln(E - p_k), \\ \bar{u}^k &= u(x_k = 1, z_k = E - p_k). \end{aligned} \tag{25}$$

Numerical methods (e.g., Newton's method) can be used to solve (25) for the value of $\bar{u}^k$, given the data and model parameters for each of the choice alternatives, and these values can be substituted into (24) to evaluate the choice probability. Choice alternatives with prices greater than the budget allocation have a zero probability of purchase.

We collect the parameters for respondent h into a generic vector $\theta_h' = (\tilde{\alpha}_h', \tilde{\kappa}_h', \gamma_h = \ln E_h, \tau_h^* = \ln \tau_h)$ and specify a random-effects model across respondents:

$$\pi(\theta_h \mid \Delta, s_h, V_\beta) = \text{Normal}(\Delta s_h, V_\beta), \tag{26}$$

where s_h is a vector of covariates specified in (20). The model specification is completed with the prior distributions for the hyperparameters Δ and V_β:

$$\pi(\text{vec}(\Delta) \mid V_\beta) = \text{Normal}(0, V_\beta \otimes A^{-1}), \quad A = 0.01 I_{\dim(s)} \tag{27}$$

$$\pi(V_\beta) = IW(\upsilon_0 = \dim(V_\beta) + 5, V_0 = \upsilon_0 I). \tag{28}$$

MCMC estimation proceeds by iteratively generating Monte Carlo draws from the full conditional distribution of parameters in two major steps:

Step 1. Generate θ_h, $h = 1, \ldots, H$ respondents.

A Metropolis-Hastings algorithm with a random-walk chain is used to generate draws of θ_h. Details of this algorithm can be found in Rossi et al. (2005, p. 90).

Step 2. Draws of Δ and V_β are obtained directly from the full conditional distribution of the linear model in (26)—see Rossi et al. (2005, p. 70).

Steps 1 and 2 are iterated until convergence (in distribution) of the Markov chain.

References

Ainslie, A., P. E. Rossi. 1998. Similarities in choice behavior across product categories. *Marketing Sci.* **17**(2) 91–106.

Allenby, G. M., P. E. Rossi. 1991. Quality perceptions and asymmetric switching between brands. *Marketing Sci.* **10**(3) 185–205.

Berry, S., A. Pakes. 2007. The pure characteristics demand model. *Internat. Econom. Rev.* **48**(4) 1193–1225.

Chintagunta, P., T. Erdem, P. E. Rossi, M. Wedel. 2006. Structural modeling in marketing: A review and assessment. *Marketing Sci.* **25**(6) 581–605.

Erdem, T., S. Imai, M. P. Keane. 2003. Brand and quantity choice dynamics under price uncertainty. *Quant. Marketing Econom.* **1**(1) 5–64.

Horsky, D., S. Misra, P. Nelson. 2006. Observed and unobserved preference heterogeneity in brand-choice models. *Marketing Sci.* **25**(4) 322–335.

Kim, J., G. M. Allenby, P. E. Rossi. 2002. Modeling consumer demand for variety. *Marketing Sci.* **21**(3) 229–250.

Lancaster, K. 1966. A new approach to consumer theory. *J. Political Econom.* **74**(2) 132–157.

Manchanda, P., P. Chintagunta, P. E. Rossi. 2004. Response modeling with non-random marketing mix variables. *J. Marketing Res.* **41**(4) 467–478.

McFadden, D. 1974. Conditional logit analysis of qualitative choice behavior. P. Zarembaka, ed. *Frontiers in Econometrics*. Academic Press, New York, 105–142.

Mehta, N. 2007. Investigating consumers' purchase incidence and brand choice decisions across multiple product categories: A theoretical and empirical analysis. *Marketing Sci.* **26**(2) 196–217.

Pauwels, K., S. Srinivasan, P. H. Franses. 2007. When do price thresholds matter in retail categories? *Marketing Sci.* **26**(1) 83–100.

Pedrick, J. H., F. S. Zufryden. 1991. Evaluating the impact of advertising media plans: A model of consumer purchase dynamics using single-source data. *Marketing Sci.* **10**(2) 111–130.

Rossi, P. E., G. M. Allenby, R. E. McCulloch. 2005. *Bayesian Statistics and Marketing*. John Wiley & Sons, New York.

Seetharaman, P. B., S. Chib, A. Ainslie, P. Boatwright, T. Chan, S. Gupta, N. Mehta, V. Rao, A. Strijnev. 2005. Models of multiple category choice behavior. *Marketing Lett.* **16**(3–4) 239–254.

Varian, H. 1992. *Microeconomic Analysis*, 3rd ed. W. W. Norton, New York.

Varian, H. 1999. *Intermediate Microeconomics*, 5th ed. W. W. Norton, New York.

Zhang, J. 2006. An integrated choice model incorporating alternative mechanisms for consumers' reactions to in-store display and feature advertising. *Marketing Sci.* **25**(3) 278–290.