MANAGEMENT SCIENCE
Vol. 34, No. 2, February 1988
Printed in U.S.A.

MODELING MULTIATTRIBUTE UTILITY, RISK, AND BELIEF DYNAMICS FOR NEW CONSUMER DURABLE BRAND CHOICE*

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This paper proposes a brand choice model to aid in the prelaunch management of a new consumer durable entry in an existing category. The model contributes to theory by integrating the critical phenomena of multiattribute preference, risk, and dynamics in an individual level expected utility framework. The integration is based on established theoretical constructs in utility, Bayesian decision analysis, and discrete choice theory. Measurement and estimation procedures are presented, an application is described, and the managerial relevance of this work as a planning and forecasting tool is examined.
(MARKETING; MARKETING—NEW PRODUCTS)

Introduction

New products are an important source of sales and profit for the firm (see, for example, Urban and Hauser 1980). In the market for consumer durable goods some major successes are exemplified by video cassette recorders, microwave ovens, and new autos. These new product developments typically involve large financial commitments. For example, new autos such as the Ford Tempo or Buick Electra each reflect over one billion dollars of investment. If the product fails to achieve expected sales levels large losses occur.

Forecasting the acceptance of new durable products is difficult and numerous failures have been observed (e.g. Ford's Edsel, Instant Movies by Polaroid, and RCA's videodiscs). Some of the difficulties result from the complexities that underlie the purchase of a new consumer durable. Many attributes characterize the product (e.g. in autos: miles per gallon, body style, prestige, power, durability, price, comfort, etc.) and careful positioning of the product within a market is required for success. Many of the attributes of a new product are known only approximately by the consumer. This uncertainty, as well as the inherent product variability, underlie response. Typically, consumers use media, retail salesmen, and friends as information sources to resolve uncertainty. These interpersonal communication and diffusion of innovation phenomena affect the dynamics of the product's adoption.

Forecasting the early life cycle of a new product is particularly challenging for consumer durables because they are usually not test marketed. In order to produce enough units for a test market, a production line must be established at a large fixed cost. A test market is of marginal value because the incremental cost of a national launch given a production facility is relatively low and most of the financial risk has been accepted.

In this paper we capture the phenomena of multiple product attributes, information uncertainty, risk, interpersonal communication and belief dynamics in a model to aid in prelaunch forecasting of a new consumer durable. We restrict our attention to the case of a new durable brand in an existing category (e.g. a new auto, oven, TV or audio system). This work is a component of a wider new durable product forecasting system

* Accepted by John R. Hauser; received January 28, 1985. This paper has been with the authors 16 months for 3 revisions.

0025-1909/88/3402/0167$01.25

that includes the study of category diffusion effects and of the consumer budgeting process (Hauser and Urban 1986). The dynamics of brand choice modeled here are utilized in a managerial modular customer flow model to examine the sensitivity of sales to introductory marketing strategies (Urban, Roberts and Hauser 1986).

We begin this paper with a perspective on the relevant literature. Then the overall model is developed and general measurement and estimation procedures are presented. We close with an application of the model to a new entry in the automobile market and a discussion of future research.

Perspective

One valuable line of research on consumer durables in marketing is represented by the aggregate single equation diffusion model of Bass (1969). This model forecasts category sales for a new durable product based on parameters estimated from national sales data. A minimum of six or more years of data is usually required for accurate forecasts (Heeler and Hustad 1980). The original model has been extended to include the marketing variables of advertising (Horsky and Simon 1983, Kalish 1985) and price (Robinson and Lakhani 1975, Bass 1980, Dolan and Jeuland 1981, Kalish 1985). The model has also been generalized to incorporate a number of other phenomena: multi-state populations (Midgley 1977, Dodson and Muller 1978), target market expansion (Mahajan and Peterson 1978), risk (Jeuland 1981, Kalish 1985), states of word of mouth (Mahajan et al. 1984), and distributions on individual parameters (Jeuland 1981). This literature mainly addresses the management problem of bringing a major innovation into a new market where the growth rate and size of the total product market is of primary concern.

The model proposed in this paper addresses a different problem. We are most interested in new brand innovations that fit in existing product categories where positioning is important and replacement largely determines the total market size. We attempt to mathematically model individual new product brand choice dynamics and take category sales as given. In contrast, single equation diffusion models generally focus on category sales, although recent work (e.g. Thompson and Teng 1984, Rao and Bass 1985) has extended the framework to incorporate competitive interaction and its effect on dynamics at the brand level. Our research draws its motivation from the aggregate diffusion work but utilizes a very different model formulation to represent dynamics, uncertainty, and interpersonal communication. Aggregate diffusion models primarily study how total populations change while our model examines the individual consumer purchase process and how judgments are modified over time. Some work in economics has used a similar framework. For example, Jensen (1982, 1983) and Stoneman (1981) use Bayesian updating to explain diffusion effects, however neither does so within a framework which relates preference to purchase probability using discrete choice theory.

The relationship of our model to aggregate single-equation diffusion structures can be made more clear by the following equation for an individual's adoption probability of a new branded product at any point in time.

$$P(B, C, N) = P(B)\,P(C|B)\,P(N|B, C) \quad \text{where} \tag{1}$$

$P(B, C, N)$ is the joint probability of buying in category B, considering brand N and purchasing brand N,

$P(B)$ is the probability of category purchase;

$P(C|B)$ is the probability of a customer considering a choice set containing brand N, given a category purchase; and

$P(N|B, C)$ is the probability of a customer choosing brand N, given its consideration and a purchase within the category.

In this equation $P(B)$ characterizes category sales and represents what is modeled in aggregate diffusion models. The last term is the probability of buying a brand given category purchase and consideration of the brand. It is this term that is addressed in this paper. Hauser, Roberts and Urban (1983) and Roberts (1983) discuss approaches to the dynamic modeling of $P(B)$ and $P(C|B)$ at the individual level that are consistent with the model presented in this paper.

We are striving for a brand choice diffusion model that can be implemented before any national sales history has been accrued. While some category diffusion models have been fit prelaunch (e.g. Lawton and Lawton 1979), there have been few managerial applications.

Another criterion we have established for our model is that it support the analysis of product positioning and produce forecasts for revised product designs. Product positioning requires the consideration of multiple product attributes. Early work by Lancaster (1966) in economics, Fishbein (1967) in social psychology, and numerous authors in marketing has provided a rich base for modeling multiattribute phenomena. One approach has been to link perception, preference and choice (see Shocker and Srinivasan 1979 for a review). Another has been to model the direct effect of product attributes on probability of choice with a logit formulation (McFadden 1973). A third approach is an integration of attributes and uncertainty through von Neumann-Morgenstern utility theory (Keeney and Raiffa 1976).

Recently, methods of explaining market dynamics at the individual level have been developed. This work builds on an established literature which examines the distribution of a consumer's beliefs about a brand and its attributes (Woodruff 1972) and how consumers adjust value to allow for uncertainty. A number of methods of uncertainty adjustment have been suggested; linearly subtracting a variant of the standard deviation (Pras and Summers 1978), a multilinear utility function involving expected value and perceived dispersion (Meyer 1981), and dividing by a linear function of variance (Meyer 1982). Stemming from this a number of researchers have examined the preference to purchase transformation using discrete choice theory (Meyer and Sathi 1985; and Hauser, Roberts and Urban 1983). These papers examine dynamics in value and uncertainty and study their effect on the probability of purchase. The model developed in this paper is similar to these past works but makes stronger assumptions to establish a deeper grounding in the fields of decision analysis and Bayesian updating theory. Additionally, it derives a way of relating the amount of information which will circulate about the brand to its marketplace diffusion. We also give measurement methods and results for the implementation of the dynamic brand choice model.

Model Development

In this paper we are modeling individual brand choice probability, given category purchase and consideration of the brand. We will denote it by P_N for notational simplicity. The model development starts by considering the effect of uncertainty on multiattribute preference models, using a decision analysis framework. In common with recent economics and marketing models, the transformation of preference to probability of choice is then considered. The diffusion effect is modeled by suggesting that as consumers gain more information about the brand, beliefs about mean attribute levels and uncertainty change. Bayesian updating provides the framework used to incorporate the effect of new information on a potential consumer's prior beliefs and information uncertainty. The amount of word of mouth per period circulating about the brand is related to cumulative sales, a proxy for how many owners there are early in the diffusion process. Changes in beliefs about the expected attribute levels and uncertainty in turn influence the probability of brand choice.

Multiattribute Utility, Uncertainty, and Choice

Expected Utility Function. Theoretical justification for the multiattribute modeling of consumer preference is provided in the growing literature of the Fishbein-Rosenberg class of expectancy-value models (Fishbein 1967) and the new economic theory of consumer choice advanced by Lancaster (1966). We represent the value of good j, X_j, by

$$X_j = X_j(y_{j1}, y_{j2}, \ldots, y_{jK}) = \sum_{k=1}^{K} w_k y_{jK} \tag{2}$$

where y_{jk} is the amount of attribute k in product j and w_k is the relative importance of attribute k.

In the case where the customer is certain of attribute levels, X_j is a measure of preference and is the objective criterion which a consumer is assumed to maximize. Price may be incorporated either by examining preference per dollar or by linearly discounting preference by price (see Hauser and Urban 1986 for a theoretical and empirical comparison of these methods). For expositional clarity we linearly discount preference by price. (This assumes that consumers consider value at the margin rather than globally.)

The preference function, X_j, in equation (2) assumes that the attribute levels are known with certainty. As suggested above, consumers generally make decisions with some uncertainty about the true level of attributes that they will obtain, both because of inherent product variability and imperfect information. As a result, the value X_j will be uncertain (and hence denoted by $\tilde{X}_j$). Thus it is necessary to have a method of determining how the consumer adjusts his preference to account for uncertain outcomes.

To examine this phenomenon we appeal to the expected utility tradition, based on the work of Keeney and Raiffa (1976). Bell and Raiffa (1979) show that for measurable value functions, if the consumer obeys the von Neumann-Morgenstern axioms for lotteries and if a utility function exists, the value function should show constant risk aversion with respect to the strength of preference measure. That is, the utility function should be either linear or negative exponential. There is little empirical evidence to choose between these two forms. In one of the few studies conducted, Currim and Sarin (1984) found that the exponential model gave better fits than the linear model for 40 out of 43 students evaluating job offers. Therefore, the exponential was selected to give the following form for how a consumer allows for uncertainty in his preference function, $\tilde{X}_j$:

$$U(\tilde{X}_j) = \alpha - \gamma \exp(-r\tilde{X}_j) \tag{3}$$

where $U(\tilde{X}_j)$ is the utility after allowing for the uncertainty of the value, $\tilde{X}_j$. r represents the consumer's risk aversion. r is assumed to be positive and constant. α and γ are scaling constants ($\gamma \geq 0$). Without loss of generality we set α and γ equal to 0 and 1, respectively. This preserves the required utility difference orderings. Substituting equation (2) in equation (3) with these values we obtain:

$$U(\tilde{X}_j) = -\exp(-r\tilde{X}_j) = -\exp(-r \cdot X_j(\tilde{y}_{j1}, \tilde{y}_{j2}, \ldots, \tilde{y}_{jk})) \tag{4}$$

where the tildes over the $\tilde{y}_{jk}$s indicate that the attributes are not known with certainty.

If we assume the consumer's uncertainty about the measurable value of brand j, $\tilde{X}_j$, may be characterized by a normal distribution, mean X_j and variance σ_j^2, then it is possible to calculate the expected utility that a consumer will derive from j (Keeney and Raiffa 1976):[1]

[1] Equation (5) assumes that the underlying measurable value function X has component measurable value functions $X_k = w_k y_k$ which exhibit mutual preference independence. We also require difference independence for at least one attribute.

$$E(U(\tilde{X}_j)) = -\exp\left\{-r\left(X_j - \frac{r}{2}\sigma_j^2\right)\right\} = -\exp\left\{-r\left(\Sigma w_k y_{jk} - \frac{r}{2}\sigma_j^2\right)\right\}. \tag{5}$$

Given the assumption that a consumer will choose the brand with maximum expected utility, he will choose the brand for which the expression in equation (5) is greatest. An examination of equation (5) shows that expected utility $E(U(\tilde{X}_j))$ is monotonic in $(X_j - r\sigma_j^2/2)$. We denote $X_j - (r\sigma_j^2/2)$ by χ_j and call it the risk-adjusted preference function. The consumer will choose brand j if $\chi_j > \chi_\iota$ for all $\iota \neq j$ in the consumer's consideration set, C. In multiattribute terms, this condition may be written

$$\sum_1^K w_k y_{jk} - \frac{r}{2}\sigma_j^2 > \sum_1^K w_k y_{\iota k} - \frac{r}{2}\sigma_\iota^2 \qquad \text{for all} \qquad \iota \neq j \in C. \tag{6}$$

These inequalities imply that the consumer will select the brand of maximum expected value after discounting for the variability or uncertainty associated with each brand.

Inherent Product Variability. Even if the consumer had perfect information on average quality for a specific brand and average attribute levels, he would still be subject to some risk because the quality level of individual products coming out of the factory is not the same, due to inherent production variation. For example, in autos, there is still a chance of a "lemon" even if all available information indicates the brand is of very high average quality.

To represent this "inherent product variability," we create a distribution of beliefs about what the average realization of brand j is like and model inherent variability as additive to it.

Let us denote by $\tilde{\epsilon}_j$ the inherent product variability that the consumer would realize and by $\tilde{\mu}_j$ the consumer's distribution of beliefs of what an average realization of the brand is like. We assume $\tilde{\mu}_j$ to have mean $\hat{\mu}_j$ and variance $\sigma_{\mu_j}^2$. We posit that

$$\tilde{X}_j = \tilde{\mu}_j + \tilde{\epsilon}_j. \tag{7}$$

That is, the consumer's belief about the value that he would realize is the average value for the brand plus the inherent product variability that he happened to obtain on his specific purchase.

We assume that if the consumer had perfect information, his estimate of $\tilde{\mu}_j$ would have mean μ_j and zero variance, where μ_j is the true mean value of j. The variance of the consumer's estimate of the mean, $\sigma_{\mu_j}^2$, reflects the extent to which he does not have perfect knowledge of the average quality of brand and so we call it "information uncertainty." In general, we assume that the expected value which a consumer estimates he will obtain (X_j) is equal to his estimate of the expectation of the mean level of value of brand j, $\hat{\mu}_j$, implying,

$$E(\tilde{\epsilon}_j) = 0 \qquad \text{and} \qquad X_j = \hat{\mu}_j. \tag{8}$$

The variance of $\tilde{X}_j$, σ_j^2 (the total uncertainty which a consumer expects to realize) is given by:

$$\sigma_j^2 = \sigma_{\mu_j^2} + \sigma_{\epsilon_j}^2 \tag{9}$$

assuming that cov $(\tilde{\mu}_j, \tilde{\epsilon}_j) = 0$. That is, total uncertainty equals information uncertainty plus inherent product variability.

The risk adjusted preference function is now:

$$\chi_j = X_j - \frac{r}{2}(\sigma_{\mu_j}^2 + \sigma_{\epsilon_j}^2). \tag{10}$$

Probability of Choice. Returning to the formula for expected utility, equation (5), with the decomposition of uncertainty equation (9), we have by substitution:

$$E(U(\tilde{X}_j)) = -\exp\{-r(\chi_j)\} = -\exp\left\{-r\left(X_j - \frac{r}{2}(\sigma^2_{\mu j} + \sigma^2_{\epsilon j})\right)\right\}. \tag{11}$$

The consumer will try to maximize his estimate of risk adjusted preference, χ_j. We assume that there is some additional error, $\tilde{e}_j$, associated with χ_j so that:

$$\tilde{\chi}_j = \chi_j + \tilde{e}_j. \tag{12}$$

That error arises from random individual behavior, situational factors, and measurement. If we assume further that $\tilde{e}_j$ is distributed normally, the multinomial probit model may be used to estimate the probability of choosing brand j (given its consideration, and purchase within the category). In practice, because the number of brands considered may be large, the logit approximation to the probit model may prove more tractable. Domencich and McFadden (1975) demonstrate the closeness of the double exponential and normal error distribution assumptions.

Under the logit formulation, the conditional probability of selecting brand N at any point of time becomes

$$P_N = P(N|B, C) = \frac{\exp(\beta\chi_N)}{\sum_j \exp(\beta\chi_j)} = \frac{\exp\left\{\beta\left(X_N - \frac{r}{2}\left(\sigma^2_{\mu N} + \sigma^2_{\epsilon N}\right)\right)\right\}}{\sum_j \exp\left\{\beta\left(X_j - \frac{r}{2}\left(\sigma^2_{\mu j} + \sigma^2_{\epsilon j}\right)\right)\right\}}. \tag{13}$$

Equation (13) links the preference function that reflects beliefs about mean attribute levels, information uncertainty, and inherent product variability to probability of choice for an individual. The effect of attribute perceptions on choice can be observed by substituting equation (2) in equation (13).

While the choice model could have been linked only to preference and uncertainty, the advantage of deriving a model which includes a multiattributed explanation of brand choice is that it allows for forecasts of the effects of positioning on brand share levels and gives diagnostic information as to how it can be improved by managers. Next we consider the dynamic effects of diffusion on the choice probability and its underlying components.

Changes in the Distribution of Beliefs Over Time

Given the objective function, χ_j, and its probability of choice representation equation (13), diffusion effects at the brand choice level are assumed to occur in two distinct ways. First, word of mouth communication may change estimated mean attribute levels (X_j and its components y_{jk}) with either positive or negative reviews. Second, uncertainty (σ_j^2) may be decreased by a more precise perception of the product, stemming from more information. We use Bayesian estimation theory to reflect the updating of prior information based on the receipt of word of mouth communication. The resulting posterior distribution is used to calculate a new probability of choice. The updating of beliefs is described under the following three headings: the prior beliefs of the consumer, the distribution of incoming word of mouth information, and the consumer's distribution of beliefs after receiving word of mouth. The effect of these beliefs on the risk-adjusted preference function and probability of brand choice is then specified.

Prior Beliefs of the Consumer. Before receiving word of mouth information, we assume that a consumer has a set of prior beliefs about the value of the brand and that these beliefs are normally distributed.[2] We assume that the consumer knows all of the

[2] Note that here we are modeling the effects of word of mouth communications on brand choice, conditioned on consideration of a brand and category purchase (see equation (1)). Word of mouth communication also has an effect on category purchase and brand awareness. These additional effects are considered in another paper (Urban, Roberts, and Hauser 1986).

uncertainties necessary to calculate his risk-adjusted preference for a brand, equation (10); the inherent product variability ($\sigma_{\epsilon j}^2$), his information uncertainty ($\sigma_{\mu j}^2$) and the total uncertainty associated with the brand (σ_j^2).[3]

If incoming word of mouth about the value of the brand can be assumed to come from a normal distribution, then after updating of beliefs, the posterior beliefs will still be normal.

Incoming Word of Mouth. As the consumer acquires more information about brand j, changes in estimated mean value, X_j, and uncertainty, σ_j^2, change the brand's expected utility. Implicit in the Bayesian assumption is that successive pieces of information are uncorrelated and of equal value. Slovic and Lichtenstein (1971) provide a review of the literature in which they point out the limitations in Bayesian updating to explain information integration. However, a number of other studies have found Bayesian updating a reasonable approximation (e.g., Ajzen and Fishbein 1975, and Trope and Burnstein 1975). Recently, Hagerty and Aaker (1984) have also used the concept of Bayesian updating of beliefs in marketing models.

Let us assume that during a given time period, t, a potential consumer talks to n_{jt} owners of brand j (we denote these owners by superscripts $i = 1, 2, \cdots n_{jt}$). Alternatively, we may regard the consumer acquiring n_{jt} bits of information about the brand's value from current owners, advertisements, and other information sources. For the sake of notational simplicity we will suppress the j and t subscripts of n_{jt} in the derivation that follows.

Consider owner i who provides word of mouth to the consumer. Assuming no reporting bias, his report of his durable's value, x_j^i, may be represented by:

$$x_j^i = \mu_j + \epsilon_j^i \tag{14}$$

where μ_j is the mean of the brand's true average value and ϵ_j^i is the inherent product variability which owner i realized. We assume that no product development is undertaken on brand j during the diffusion process.

The expected value and variance of owner i's WOM are given by μ_j and $\sigma_{\epsilon j}^2$ respectively. For the n owners to whom the potential consumer talks, the expected sample mean $E(\bar{x}_j)$ and sample variance ($\sigma_{\bar{x}_j}^2$) are given by μ_j and $\sigma_{\epsilon j}^2/n$ respectively.

Integration of New Information by the Consumer. Given prior beliefs at time t about the mean of brand j, ($\hat{\mu}_j(t)$), and the known level of information uncertainty associated with it, ($\sigma_{\mu j}^2(t)$), the consumer will integrate the word of mouth information he receives about the mean ($\bar{x}_j$) and the sample variability ($\sigma_{\bar{x}j}^2$) to an extent dictated by the relative strength of his prior beliefs. Since, we assume no change to the product form over time, inherent product variability, $\sigma_{\epsilon j}^2$, is known and constant and will not be updated.

DeGroot (1970, p. 168) shows that the updating formulae for the mean and the information uncertainty are given by the following expressions:

$$\hat{\mu}_j(t+1) = \frac{\tau\hat{\mu}_j(t) + n\bar{x}_j}{\tau + n} = \frac{(\tau/n)\hat{\mu}(t) + \bar{x}_j}{(\tau/n) + 1}, \tag{15}$$

$$\sigma_{\mu j}^2(t+1) = \left(\frac{\tau}{\tau + n}\right)^2 \sigma_{\mu j}^2(t) + \left(\frac{n}{\tau + n}\right)^2 \sigma_{\bar{x}_j}^2, \tag{16}$$

where τ is the relative strength of prior beliefs, also termed the equivalent prior sample size. While equation (15) indicates how expected preference will be updated, similar

[3] Roberts (1983) provides a number of generalizations to this model. They include updating formulae when variances are not known, the inclusion of heterophily, and the effect of word of mouth when owners have perceptual biases about their durables. A consequence of not allowing perceptual biases in the word of mouth from current owners (as judged by the consumer) is that all consumers eventually trend to the same valuation of the brand.

formulae could be given for the updating of beliefs about expected attribute levels and in fact the perceptual position of the new durable presented in the application was tracked as updating occurred. τ, the prior strength of beliefs, increases over time as more information is gathered (see equation (19)). n, the number of owners to whom a potential purchaser talks is also changing (equation (18)). Both relate only to brand j. Thus τ and n are implicitly subscripted by j and t.

Integration of Changing Consumer Beliefs into the Probability of Choice Function. We have advanced a method by which the consumer's beliefs about the "average" realization of brand j are updated over time (equations (15) and (16)). To relate these beliefs of the mean value of brand j ($\tilde{\mu}_j$) to what the consumer would expect to obtain if he purchased brand j, $\tilde{X}_j$, we refer to equations (8) and (9).

Substituting equations (15) and (16) in equations (8) and (9), we see how beliefs about $X_j(t)$ and $\sigma_j^2(t)$ get updated over time.

We can now obtain a probability of choice function that reflects belief dynamics by substituting the updating equations (15) and (16) in equation (13) and introducing a time subscript for the probability of purchase. We obtain equation (17):

$$P_N(t+1) = \frac{\exp\left\{\beta\left\{\frac{(\tau X_N(t) + n\bar{x}_N)}{\tau + n} - \frac{r}{2}\left[\left(\frac{\tau}{\tau+n}\right)^2 \sigma_{\mu N}^2(t) + \left(\frac{n}{\tau+n}\right)^2 \sigma_{\bar{x}_N}^2 + \sigma_{\epsilon N}^2\right]\right\}\right\}}{\sum_{\substack{j=1\\ j\neq N}}^{J} \exp\left\{\beta\left\{X_j - \frac{r}{2}\sigma_j^2\right\}\right\} + \exp\beta\left\{\frac{(\tau X_N(t) + n\bar{x}_N)}{\tau+n} - \frac{r}{2}\left[\left(\frac{\tau}{\tau+n}\right)^2 \sigma_{\mu N}^2(t) + \left(\frac{n}{\tau+n}\right)^2 \sigma_{\bar{x}_N}^2 + \sigma_{\epsilon N}^2\right]\right\}}. \quad (17)$$

This equation models the multiattribute nature of the product (recall $X_N = \sum_{k=1}^{K} w_k y_{Nk}$), mean value, information uncertainty, inherent risk, and belief updating by word of mouth communication. Note that for notational simplicity equation (17) only includes the updating of beliefs about brand N.

To relate the updated probability to changes in a brand's penetration over time, we assume that the consumer talks to a proportion, k_j of the cumulative adoptors of brand j at time t, Y_{jt}. Thus

$$n_{jt} = k_j Y_{jt} \quad (18)$$

where k_j is a constant.[4]

Next we consider the use of this general model in the prelaunch sales forecasting of a new product. We present an overall approach to measurement and estimation and then report a specific empirical application of the model to a new auto.

Measurement and Estimation

Operationalization of the model for premarket forecasting utilizes direct consumer measurement and statistical estimation. Our approach to measurement is based on exposing potential buyers in a clinic environment to successive levels of information about the new product—advertising, usage, and word of mouth communication. Measures of the impact on perception, risk, expected value and choice behavior are taken

[4] This algebraic form is based on the fact that if a consumer speaks to N members of the population of size M who are randomly selected with respect to ownership of the brand, then he will speak to an expected number of owners = $(N/M)Y_t = kY_t$.

after each information exposure. Advertising is represented by a print or T.V. ad for the new product; and word of mouth communication by a videotape of "owners" providing an evaluation of the product. The "owners" are actually actors presenting a script based on verbatims from focus group sessions made up of consumers who tested the new product. Two executions of the videotape were presented on a split sample basis to allow measurement of positive and negative word of mouth content.

We assume that advertising affects consideration, the drive simulates the effect of a test drive of the car (and thus dealer visit), and the videotape corresponds to word of mouth communication. Advertising and test drive effects can be included in the consideration and purchase incidence components of the model (see Urban, Roberts and Hauser 1986). Another variant on the design is to expose one half of the respondents to the word of mouth video before product use and one half to video after use. This would allow estimation of the interaction effects of these pieces of information in updating probability of choice.

Remeasurement may produce a demand effect bias so a test and control design is used. Similar perceptions, value, and word of mouth measures are taken for the new and control product. The control product is selected to be one which is already on the market and which is analogous to the new product. Since we are analyzing a new product in an established category such an analogy usually exists in past products in the category. For example, the existing Buick Regal is a good control for testing a new Buick Regal. The use of a control allows for adjustment for experimental biases and supplies a basis for linking clinic measures to actual sales results.

Some of the parameters needed to apply the model are measured directly, while others are based on statistical estimation procedures. We review the general procedures for estimation of the parameters in this section and the reader is referred to the next section for the specifics of the experimental design, measurement items, and estimation procedures used in our initial application.

The multiattribute levels (y_{jk}) and weights (w_k) can be measured and estimated by established procedures (Urban and Hauser 1980). Typically, many attributes would be rated (e.g. on 5-point agree/disagree or semantic differential scales) and expected value measured (e.g. by constant sum comparisons) for the existing products consumer would consider. The weights could be estimated by fitting the linear utility model to the expected values (e.g., preference regression).

Mean prior belief about the value of the new product ($\hat{\mu}_j$) is measured directly by judgments on a thermometer scale or constant sum allocations. The uncertainty, σ_j^2, could be measured by direct questions on risk (e.g., 5-point scales on "risk," "unreliability," or "uncertainty") or by soliciting a probability distribution on preference judgments.

In the application presented in this paper, inherent product variability was assumed equal to the uncertainty of the current first choice car. An examination of equation (15) shows that one updating parameter (τ/n) needs to be estimated for each individual. We can observe the prior (i.e., before word of mouth) and posterior (i.e., after word of mouth) recommendations which respondents would give to the new product using a five-point scale. This gives an approximate measure for $\hat{\mu}_j(t)$ and $\hat{\mu}_j(t+1)$. $\bar{x}_j$, the mean value of incoming information, can be measured by the respondent's rating of what recommendation the videotape represented on the 5-point scale. Given $\hat{\mu}_j(t)$, $\hat{\mu}_j(t+1)$ and $\bar{x}_j$ for each individual we can calculate a value of τ/n for each of them. We also need an estimate of the true value of $\bar{x}_j$ that would occur after using the new product, and the word of mouth variance, $\sigma_{\bar{x}}^2$. $\bar{x}_j$ may be either provided as a management input or measured by the average recommendation respondents gave the product after using it, but before seeing the videotape. With previously calculated prior and posterior information uncertainty ($\sigma_{\mu j}^2(t)$ and $\sigma_{\mu j}^2(t+1)$), the estimated updating parameters (τ/n) and inherent product variability ($\sigma^2_{\epsilon j}$), the variance of incoming information ($\sigma^2_{\bar{x}_j}$) can be calculated directly from equations (16) and (9).[5]

β and risk aversion, r, are estimated based on a logit model. The dependent variable is not, as is usual, the last brand purchased in this case. In durables, the last purchase may have been made many years ago and linking it to current preferences is speculative. Instead, we measure probability of purchase (e.g., on an 11-point scale, Juster 1966) and estimate β and r from the logit model. Note that in the model development risk affects risk-adjusted net preference, χ. However, since χ is unobserved we estimate the risk aversion parameter from the choice model (equations (13) and (17)).

The final model parameter to estimate reflects the amount of word of mouth resulting from the volume of past sales of brand j, n (or k_j using equation (18)). This enables the word of mouth which will circulate in the marketplace to be related to the amount of information contained in the videotape. k was estimated by fitting the first twelve months' sales of the *control* product with the model. A grid search is used to find the k value that along with the above estimated parameters for the control product and equation (18) best fit the actual sales history of the control brand. k represents the volume of word of mouth transfer and can be used directly for the new product or, alternatively, forecasts can be produced based on assumptions of more or less word of mouth than the control product.

In the fitting, category sales and consideration levels must be assumed ($P(B)$, $P(C|B)$ in equation (1)) to recursively calculate n. Category sales are usually available from past sales data and econometric forecasts. The consideration levels may be measured by past surveys or fit to the actual data based on an assumed pattern and a scaling parameter. Also, τ must be recursively updated. As the respondent gains more information, the strength of his prior beliefs at the beginning of each period will increase. The updating formula of τ is given by

$$\tau(t+1) = \tau(t) + n_{jt}. \tag{19}$$

The following section amplifies the measurement and estimation procedures in the context of the pre-launch forecasting of a new automobile.

Application

The model has been applied to the prelaunch planning of a new automobile to be launched in 1985 by the Buick Division of General Motors. We will call the new car the Merope. The auto industry represents an established category in which product differentiation along a number of attributes is common. The new Merope was a total redesign over its predecessor and was viewed as a new entrant in the luxury auto category. The auto was down-sized to increase fuel economy, but it was hoped it would not lose its position as a luxury car. Because of its substantial change in design and style it was expected to be affected by word of mouth communication and diffusion effects. In this section we outline the experimental design, specific measurement procedures, estimation results, and predictions of share dynamics for the new brand.

Experimental Design

A sample of 336 was interviewed in March 1983, stratified according to current ownership weighted by brand switching patterns. Sampling was done from syndicated lists of auto owners which gave details of currently held stock. Married respondents

[5] We are grateful to a reviewer for pointing out that because respondents should update their beliefs using a τ/n proportional to the ratio of the variance of sample information to the variance of prior beliefs, $\sigma^2_{\bar{x}_j}$ could be alternatively estimated by $\sigma^2_{\bar{x}_j} = \tau\sigma^2_{\mu_j}(t)/n$. The advantage of using equation (15) is that it does use reported variance changes and is thus more likely to be robust.

were asked to bring their spouse and joint responses were collected if both came. Recruitment was by telephone followed by a letter. An incentive of $25 was offered for participation. Interviews were conducted by professional interviewers and held in a hotel conference facility. A 1983 version of the Merope was used as a control treatment for one-third of the sample; the remainder drove a pre-production 1985 Merope.

In order to estimate changes in consumers' beliefs over time, respondents were given information sequentially. Respondents were first shown a concept description of the Merope (as one of a number of concepts), then given a test drive, and finally exposed to a laboratory evaluation of the car together with a videotape of "owners" reactions, as described in the previous section.

Measures of mean value, perceived attribute levels, uncertainty, and probability were taken after each exposure. Mean value was measured on an open-ended scale in which the currently most preferred model was given 100 points. The new car would be rated over 100 points if it was valued more highly than the current first choice existing car of a respondent and less than 100 otherwise. Perceptual attributes were selected on the basis of focus groups and previous auto research (see Figure 1a for attributes). The rating measure used was a 5-point scale with verbal anchors from "extremely poor" to "excellent." After the drive and videotape, in addition to perceptual attributes, respondents were asked what would be the recommendation that they would give their friends about the car on a 5-point scale (very positive to very negative). This scale was also used after the video to measure what respondents felt was the level of recommendation consumers in the video were portraying. Risk was operationalized by "Unreliability" as measured on a five-point verbally anchored scale. Probability of purchase was measured on an 11-point Juster scale (Juster 1966). For further details of these measures and stimuli, see Roberts (1983). We next report the results for the brand choice model components.

Results

The following section outlines results obtained from fitting the mean value, risk, and change in belief components of the model to post-drive data. As is typical of consumer behavior models of this type, attributes, factor perceptions, uncertainty, value, and choice are all examined separately to see what managerial implications can be drawn at each stage. The relationship between attributes and factor perceptions, factor perceptions and mean value (equation (2)), and value and risk and probability of brand choice (equation (13)) are described. These constructs are examined in a prior condition defined as after the test drive and before the word of mouth information, and a posterior condition of after the test drive and word of mouth.

After the two static pictures have been examined (before and after the word of mouth simulation), the implied updating mechanism is examined (equations (15) and (16)). Thus, prior strength of beliefs and estimates of the mean and variance of incoming word of mouth are estimated under the heading "Word of Mouth."

Finally, application of the model to the 1983 control brand allows the fit of the model to be examined and a parameter of the likely amount of word of mouth to be generated. Forecasts of the brand dynamics of the new test car are then made, giving the pre-launch estimates of its market share.

Perceptions

The Buick Division had down-sized its Merope model to increase fuel economy, but it was important that it not lose its position as a comfortable, luxurious and stylish car. The average after-drive and before word of mouth attributes (Figure 1) indicated that the 1985 Merope is comparable to the large 1983 Merope control car in "luxury and comfort" and "style and design." It is perceived as significantly better in fuel economy

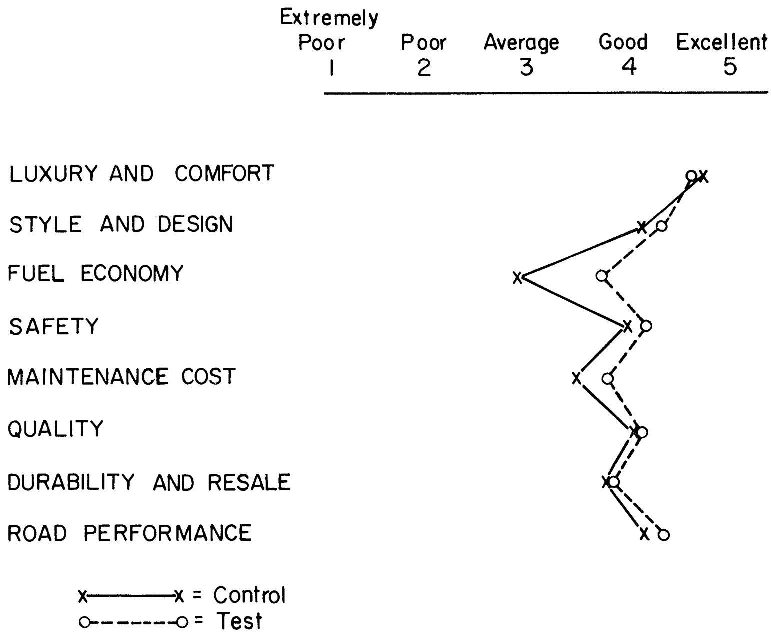

FIGURE 1. Average Attribute Evaluations for the Test.

and equal or marginally better on all other dimensions. Overall, these reflect favorable ratings.

A principal components factor analysis of the eight attributes of each consumer's three most preferred cars suggested two dimensions which may be identified from the results as "Appealing" (luxury, style, safety, performance), and "Sensible" (miles per gallon, maintenance, quality, and durability). These two dimensions accounted for 63.4% of the variance. A third dimension was not considered based on its eigenvalue, reduced interpretability, and a scree test.

A perceptual map of the market was formed, and the average perceptual position of both the 1985 Merope and the control car was plotted. Figure 2 shows the perceptions after drive and before the videotape.

Overall the new car is seen as more sensible but with less appeal than the control car. The 1985 Merope is neither as appealing as the Riviera nor as sensible as the Toyota or Honda models, but it does have a viable position in the tradeoffs of the two perceptual dimensions. Figure 1b also shows the changes for the after drive position of the 1985 and control car after word of mouth, illustrating the dynamics of attribute beliefs as more information is gathered. The videotapes had a substantial effect on perceptions in both cases with the positive treatment values being higher on both dimensions than the negative treatment.

Figure 3 shows the relative value for the test and control car and the effects of positive and negative video on value. The value points (on the thermometer scale) given to the stimuli car are divided by the total of the points given to the respondent's first three choices and the stimulus car to calculate the relative value. The new 1985 car has a higher valuation than the control after drive and after word of mouth except in the case of negative video for the new 1985 and positive video for the control car.

A linear regression model corresponding to equation (2) was estimated cross-sectionally at three stages: on currently available makes, after entry of the new brand, and after word of mouth for the new brand. Relative values were regressed on the factor scores

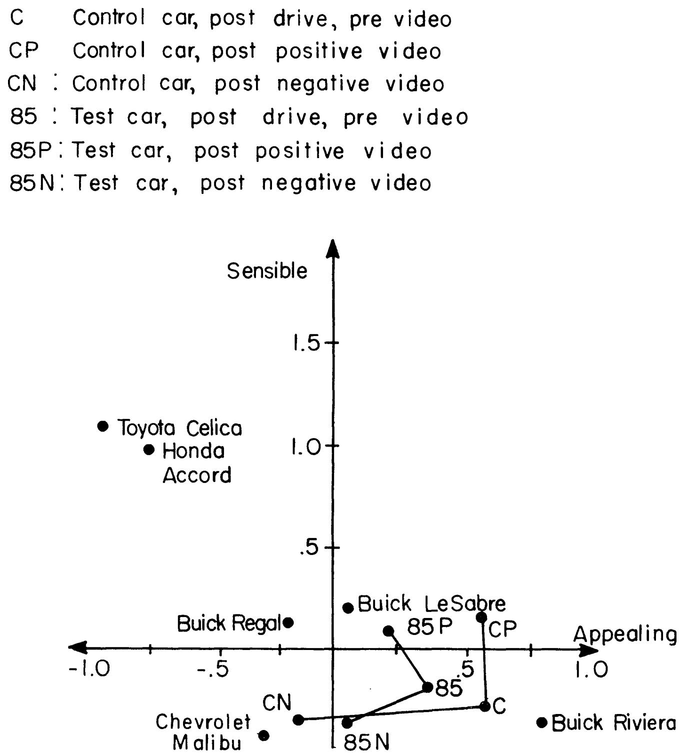

FIGURE 2. Factor Scores.

obtained from the factor analysis at each stage. In all cases the coefficients were significant at the one percent level (all t's greater than 8.9) and the fits were good (the minimum R^2 adjusted for degrees of freedom was 0.30). The appealing and sensible dimensions had about equal importance weight. The relationship of perceptions to value appears to be stable at different information levels.

Uncertainty

The relative uncertainty measures after drive and word of mouth are shown in Figure 3. For both cars uncertainty is substantially increased after negative video and somewhat reduced by positive video. (Note that the positive word of mouth is found to be more typical of what will be said about the brand.)

Choice Probability

Stated probabilities of choice (Juster scale) were higher in all cases for the new car (pre video 0.20 for new and 0.16 for control, and after video 0.20 versus 0.18 with positive word of mouth and 0.18 versus 0.14 for negative word of mouth). In this application value, price, and risk were related to probability using a logit model. Price is included in the regression because when mean value was elicited from respondents it was done irrespective of the product's price. The logit model uses stated probabilities rather than discrete choices as its dependent variable so it was estimated in the following multiple regression form:

$$\log \frac{P_j}{P_1} = \beta_1(X_j - X_1) + \beta_2(Price_j - Price_1) + \beta_3(Risk_j - Risk_1) \tag{20}$$

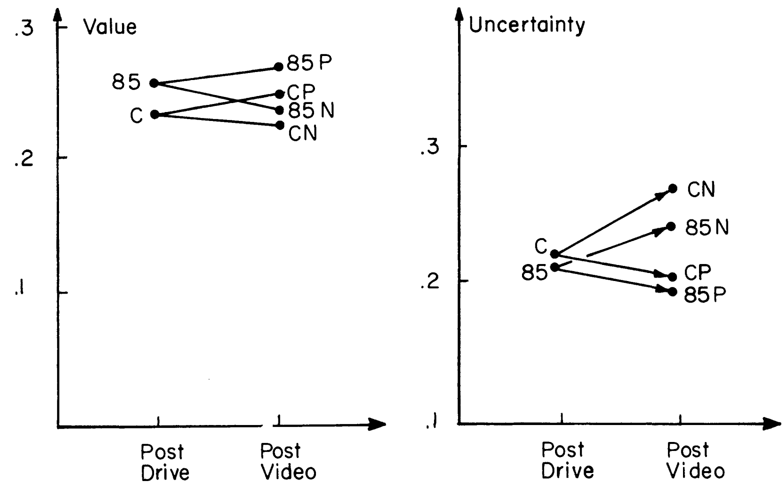

FIGURE 3. Value and Uncertainty Measures.

where subscript 1 represents a reference brand. This technique gave similar results to simulating discrete choice according to stated probabilities and then using a maximum likelihood logit estimation program. The coefficients observed by estimating the regression across respondents for the total sample after drive and video are:

$$\beta_1 = 2.6 \quad (t = 7.7), \qquad \beta_2 = -3.6 \quad (t = -8.8) \qquad \text{and} \qquad \beta_3 = -2.3 \quad (t = -6.8).$$

Overall the t statistics are significant at the one percent level. Risk and price coefficients have the expected negative sign and value points are highly positive. The coefficients were similar across the three estimation situations; existing market, post-drive, and post-drive plus video.

Word of Mouth

As described in the previous section on estimation, pre and post recommendations which respondents gave the cars and those which they perceived the videotapes to be giving can be used to calculate τ/n for each individual (see equation (15)). Average τ/n's for six segments based on current auto ownership and car driven in the experiment are given in Table 1. Overall, the average is 0.874, but some segments had higher τ/n values or more confidence in their prior beliefs. As expected, Buick owners have the highest confidence in their prior beliefs.

Next we estimated the mean and variance of incoming word of mouth by the procedures described above. After drive and before video respondents gave the new car an average of 82.2 value points and a recommendation value of 1.79 (1 = very positive, 5 = very negative). After positive video the recommendation was similar at 1.87 and after negative video 2.27 was observed. We therefore adopted the positive videotape as being more representative of the actual word of mouth that would circulate about the brand. The average number of preference points post video for those people who saw the positive videotape was 92.0 and this was taken as the "true" average preference score which would circulate about the brand. The variance of the incoming word of mouth ($\sigma_{\bar{x}}^2$) was calculated based on equation (16) by the procedures described above with the estimated values for pre and post video uncertainty, updating parameters and inherent product variability. The average value was 1.75 on the 5-point scale.

Fit to Historical Data of Control Car

Remember that the control car against which the new car was tested was currently on the market. Thus, we could then parameterize the model for the control car based on its experimental results and examine how well it fit the historical sales pattern of seasonally adjusted brand share. This provides a test of the model as well as giving an estimate of the amount of word of mouth parameter (k_j in equation (18)). An estimate of k_j is required to provide estimates of n in equation (18) so that, given category purchase and consideration probabilities, each individual's brand choice probability can be recursively projected over time. These are then aggregated to obtain total brand sales and share estimates. Aggregation was performed by setting the forecast number of brand j sales (given an auto purchase) to the sum of the estimated probabilities of individuals in the sample buying the brand. This was done separately by segment and then appropriate expansion factors to extrapolate from the sample to the population were used. The best fitting value of k was found by direct search. k_j was found to be 4.39×10^{-6}. The role of k is to translate the amount of updating which occurred when the respondents were given more information about the control car in a laboratory setting to the amount of updating which occurred as sales of the control car increased in the marketplace. From the recursively estimated values of cumulative adoption, Y_{jt}, equation (18) suggests that in the first month 2.05 owners would be spoken to by a potential buyer (or 2.05 pieces of uncorrelated information were available). This increases to 27 by the end of twelve months suggesting that, at that point, prior information is given a weighting of 54% relative to new information gained since launch.

The corrected $\bar{R}^2$ in the fitting was 0.35 with ten degrees of freedom. The fit followed the overall trend and the correlation of actual and predicted values was 0.59. The overall first year actual sales was 131,700 units and the fitted value 128,870 units. The fits were acceptable and suggested the model was a reasonable structure for forecasting.

Forecasting of Share Dynamics and Managerial Implications

The results of the experimental measures and parameter estimates for the 1985 Merope were then combined with the k from fitting its 1983 predecessor to generate forecasts for the 1985 car. It was assumed that the same levels of consideration and amount of word of mouth communication (k) would be generated by the new car as the control. The new car prediction was for a substantially higher share (month 1 share, 21.5 for new car versus 14.5 for the control; end of year one, 24 versus 19; end of year

TABLE 1
Average Relative Strength of Prior Belief

	Car Respondent Will Replace	τ/n Average
Drove 1985 Test Car	Buick	1.444
	Other US	0.632
	Foreign	0.150
	All Cars	0.823
Drove 1983 Control Car	Buick	1.013
	Other US	0.929
	Foreign	0.250
	All Cars	0.879
Full Sample	All Cars	0.874

two, 25 versus 16) and a similar diffusion pattern. The share growth curves were parallel, but at different levels. This similarity is due to similar measured preference and choice changes with the receipt of word of mouth information. The 1985 Merope model was forecast to sell approximately 25 percent more than the old control car it replaced. This was a positive result, but below the management's objective of a 75 percent increase. The decision was made to introduce the new car, but with considerably more advertising and dealer sales pressure. Advertising was also revised to be very different from previous campaigns and stressed reliability, performance, and economy. This strengthened the positioning in the "sensible" dimension (see Figure 1b) and lowered the risk. Special dealer training effort was directed at getting consumers to drive the car as part of a program of selling the car from the "inside out." That is, get the customer *in* the car and driving it; then sell the smaller *outside* exterior size and style. The after-drive attribute and preference ratings were much higher than the concept evaluations and suggested this as a good strategy. The negative word of mouth penalties (see Figures 1c and 1d) suggested the car should not be introduced with any defects that could result in negative interpersonal communication. A transmission problem was present in the new car and rather than introduce it as scheduled, launch was delayed for over six months.

In developing a new forecasting methodology, particularly one which entails increased complexity, a major consideration must be its forecasting and diagnostic performance relative to other models. It is hard to compare this model to more traditional diffusion models such as that of Bass (1969) because they explain category purchase not brand choice. Comparing this model to static brand choice models one will obtain the same answers as a standard multiattribute model with risk (e.g. Pras and Summers 1978) *at the level of information for which it was calibrated.* However, the dynamics will be lost.

Even comparing the model forecasts to actual sales of the brand is difficult. Based on twelve months of actual sales, observed values were less than one quarter those forecast in the first three months and still less than half those of forecast in the next nine months. This was because the production facility was not operating as planned. Capacity was delayed; only one of three production lines was operational for the first three months and the full capability was not operational until month 12. Validation in these conditions requires additional modeling to account for how production shortfall affects dealer inventories and consumer switching when the desired brand model is not immediately available. This is a topic of current research (see Urban, Roberts and Hauser 1986 for extensions).

Although observed sales were confounded by production constraints, a sample set of data was available to estimate the share of choices for the new car after a dealer visit during month three. Over 10,000 customers were identified as they entered dealers showrooms and then called back to see what car they ultimately purchased. A 22.3 percent share of the luxury car market was observed for the new car (given availability) and this compares favorably with the prediction of 20.9 percent share forecast by the model in period three. This is only weak initial evidence and clearly much effort needs to be devoted to validation before the model can be an operational tool.

Summary and Future Research

This paper has presented a model of brand choice dynamics for a new product in an established product category. Multiattribute utility, information uncertainty, inherent product variability, interpersonal communication, and belief dynamics were modeled by drawing on von Neumann-Morgenstern utility, Bayesian, discrete choice, and diffusion theories. A number of criticisms of current diffusion models are addressed by this paper. In particular, the model accommodated the effect of competitive product positioning, an individual-level explanation of diffusion effects, and the role of information on the adoption process. The model is based on established theoretical constructs and the measurement methodology is designed to enable it to be implemented prior to launch. The proposed measurement and estimation procedures were applied to the launch of a new car based on primary market research data. In its first application encouraging fits and managerial insights were observed. However, this detailed level of prelaunch explanation comes at some cost. The model has a number of theoretical limitations and some of the assumptions required to fit it are quite strong. Among the theoretical and empirical issues which need to be addressed are the appropriateness of Bayesian updating, whether measurement error occurs in risk-adjusted preference (equation (13)) or should more properly be included in expected utility (equation (5)), the adequacy of the normality of beliefs assumption, and the closeness of the preference independence of attributes approximation (equation (5)). The assumption of independence of attributes is particularly important under uncertainty because of the inferencing demonstrated by Johnson and Levin (1985). Meyer (1985) has recently developed a model to incorporate this phenomenon.

Future research is necessary to further test the validity of the model, and to develop other components of the product purchase model. Four new auto clinic studies have now been undertaken to replicate the initial methodology. Over time continued use will build a basis to evaluate the models. These applications are being carried out in a wider framework that supplements this brand choice modeling by category dynamics, competitive entry, dealer visits, and the growth of consideration levels.

Research is underway to extend the model to cases where one brand is creating a new category or both category and brand diffusion are taking place. This research is utilizing nested logit (Ben Akiva and Lerman 1977), value priority (Hauser and Urban 1986), and traditional diffusion models to predict category dynamics. The model proposed here is used to represent brand share dynamics in the category. Models of brand consideration are also being developed.

The work reported in this paper is a first step towards a comprehensive model for premarket forecasting of consumer durables. These initial model results did have impact on decision making and repeated applications will allow the benefits, practicality, and validity of methodology to be established.[6]

[6] We woud like to acknowledge the Buick Motor Division of General Motors and especially John Dabels and Paula Travenia, for their financial and intellectual support of this research. Research assistance and insight was provided by Janny Leung, Larry Lyons, Gail Schlea and Lisa Tenor. Field data collection was effectively executed by Andy Czaka and Lori Anderson. We are grateful to Jim Lattin for ideas and constructive criticism provided during the execution of this research. We would like to thank the Departmental Editor, the Associate Editor, and four anonymous reviewers for their constructive comments on this paper.

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