NEW CONSUMER DURABLE BRAND CHOICE: MODELING
MULTIATTRIBUTE UTILITY, RISK, AND DYNAMICS

by

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ABSTRACT

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 integrates the critical phenomena of multiattribute product characteristics, risk, and dynamics in an individual expected utility framework. The integration is based on established theoretical constructs in utility, Bayesian decision, and discrete choice theory. Measurement and estimation procedures are presented, an application is described, and the managerial relevance of the results is examined.

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 auto makes. 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). These difficulties result from the complexities that underly the purchase of a new consumer durable. Many attributes characterize the product (e.g. in autos: miles per gallon, body style, prestiege, power, durability, price, comfort, etc.) and careful positioning of the product within a market is required for success. Many of these attributes of a new product are known only approximately by the consumer. This uncertainty, as well as the inherent product unreliability underly response. Typically, consumers use media, retail salesmen, and friends as information sources to resolve uncertainty. This interpersonal communication and diffusion of innovation phenomena affect the dynamics of the product's life cycle.

Forecasting the life cycle of a new product is particularly challenging for consumer durables because they are usually not test marketed. In order

to produce enough product 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 product 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 information dynamics in a model to aid in premarket forecasting of a new consumer durable. We restrict our attention to the case of a new durable in an existing category (e.g. new auto, oven, TV or audio system). This work is a component of a wider new durable product forecasting system (Hauser, Roberts, Urban - [1983]) that includes the study of category diffusion effects and of the consumer budgeting process (Hauser and Urban [1984]). The dynamics of brand choice modeled here are utilized in a managerial macro flow model to examine the sensitivity of sales to introductory sales strategies (Urban, Roberts, and Hauser [1984]).

We begin this paper with a perspective on the relevant literature. Then the overall model is developed, measurement and estimation procedures are presented, and an application in the automobile market is reported. We close with a consideration of the use of this model in managing a new entry in an established consumer durable category and a consideration of future research.

PERSPECTIVE

One valuable line of research on consumer durables 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 required usually for accurate forecasts (Heeler and Hustad, [1980]). The original model has been extended to include marketing variables (Horsky and Simon [1983] -- advertising, Robinson and Lakhani [1975], Bass [1980], Dolan and Jeuland [1981] -- price, and Lilien and Rao [1978] -- sales force effort). The Model has also been generalized to incorporate a number of other phenomena; multistate models (Midgley [1976], Dodson and Muller [1978]), target market expansion (Mahajan and Peterson [1978]), risk (Kalish [1982], Jeuland [1983]), states of word of mouth (Mahajan et al, [1984]), and distributions on individual parameters (Jeuland [1979, 1983]). This literature mainly addressed the management problem of bringing a major innovation to 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 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 model new product brand choice dynamics and take category sales as given. In contrast, the single equation diffusion models forecast category sales and do not model brand share diffusion. Our work draws its motivation from the aggregate diffusion work but utilizes a very different model formulation to represent risk, uncertainty, and interpersonal communication.

We also are striving for a model that can be implemented before any national sales history has been accrued rather than a model that describes observed national sales patterns or one which requires substantial in-market sales results. While some category diffusion models have been fit prelaunch (e.g. Hauser [1978], Lawton and Lawton [1979]), there have been few managerial applications and most have been applied after national sales have been observed.

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] and Rosenbergh [1956] in social psychology, and numerous authors in marketing have provided a rich base for modeling multiattribute phenomena. One approach has been to link perception, preference and choice (Urban [1975], Shocker and Srinivasan [1979], Hauser and Simmie [1981]). Another has been to model the direct effect of product attributes to probability of choice with a logit formulation (McFadden [1973]). A third approach is an integration of attributes and risk through von Neumann – Morgenstern utility theory (Hauser and Urban [1979]). While a number of promising multiattribute choice models exist, there is none that combines dynamics with multiattribute choice in a comprehensive individual framework.

Our objective is to integrate diffusion and multiattribute choice theory in a model to forecast new brand share dynamics before national launch.

MODEL DEVELOPMENT

In this paper we are modeling brand choice, conditioned on category purchase and consideration. For a discussion of how this brand choice model

would be integrated into a total brand sales model see Hauser, Roberts and Urban (1983) or Roberts (1983). We may write

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

where $P(N,B,C)$ is the joint probability of the 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 brand N, given a catetory purchase, and

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

It is the last of these elements, $P(N|B,C)$, which this paper addresses. $P(N|B,C)$ will be denoted by P_N for notional simplicity. Note that equation (1) is an individual-level equation and an individual subscript, i, is implicity through out our discussion.

The brand choice model is developed by considering how uncertainty affects a traditional multiattribute consumer behavior model and how beliefs about mean attribute levels and uncertainty will change, as penetration of the new durable brand increases over time. Uncertainty is included by discounting mean attribute levels for risk to form preferences that translate into choice. Dynamics are based on an analysis of beliefs of the consumer prior to receiving word of mouth and the new information they receive. A distribution to characterize the word of mouth information allows prior beliefs to be updated to form a posterior distribution of beliefs after word of mouth communication. The amount of word of mouth communication a consumer receives per period is related to cumulative sales. Knowing posterior brand beliefs we can calculate the consumer's utility after receiving word of mouth and thus his posterior probability of adoption.

Multiattribute Utility and Uncertainty

Expected Utility Function

Theoretical justification for the multiattribute modeling of consumer preference is provided in the growing literature of the Fishbein-Rosenberg (Fishbein [1967]) class of expectancy-value models and the new economic theory of consumer choice advanced by Lancaster [1974]. The most popular of these in marketing is the linear compensatory model in which preference for a good, X_j, is represented by

$$X_j = \sum_{k=1}^{K} w_k y_{jk} \qquad (2)$$

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

In the case of certainty, this measure of preference X_j is the objective criterion which a consumer is assumed to maximize. If price is an important attribute, it may be incorporated in two ways. First, the consumer may be thought to maximize the preference/dollar he gets from his purchase (e.g., Hauser and Simmie [1981]), or second, price may be treated as an attribute (e.g., Dubin and McFadden [1982]). For expositional clarity we treat price as an attribute.[1]

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. Thus, it is necessary to have a method of determining how the consumer moves from his preference function to a utility function which takes account of uncertain outcomes.

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[1]See Roberts (1983) for comparison of these two formulations.

To do this, we appeal to the expected utility tradition, based on the work of Keeney and Raiffa [1979]. A measurable value function (Currim and Sarin [1983]) or strength of preference measure $\tilde{X}$, (Bell and Raiffa [1979]), is one in which for brands a,b,c, and d

$$[a \rightarrow b] \gtrsim [c \rightarrow d] \Rightarrow \tilde{X}_b - \tilde{X}_a \gtrless \tilde{X}_d - \tilde{X}_c \qquad (3)$$

where

$\gtrsim$ means preferred to, or indifferent to,

$[a \rightarrow b]$ means switching from brand a to brand b, and the tilde above the $\tilde{X}$ identifies it as a random variable.

Bell and Raiffa show that for such value functions if the consumer obeys the von Neumann-Morgenstern axioms for lotteries (transitivity, substitutibility, etc.) 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 form was selected for model derivation. Thus, we assume that the linear compensatory model satisfies condition (3) and that the consumer follows the von Neumann-Morgenstern axioms to give the following form for how a consumer allows for uncertainty in his preference function, $\tilde{X}_j$.

$$U(\tilde{X}_j) = \alpha - \beta e^{-r\tilde{X}_j} \qquad (4)$$

where $U(\tilde{X}_j)$ is the utility after allowing for the uncertainty of the value, $\tilde{X}_j$, and α and β are scaling constants ($\beta \geq 0$). For simplicity we set α and β

equal to 0 and 1, respectively. This preserves the required utility difference orderings. Substituting equation (2) in equation (4) with these values we obtain:

$$U(\tilde{X}_j) = -e^{-r\tilde{X}_j} \tag{4}$$

$$= -e^{-r(\sum_1^K w_k \tilde{y}_{jk})} \tag{5}$$

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

r is Dyer and Sarin's [1982] relative risk aversion and Bell and Raiffa's [1979] intrinsic risk aversion. In economics, r is termed absolute risk aversion (Pratt [1964], Arrow [1971]).

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

$$E(U(\tilde{X}_j)) = \int U(x_j) f(x_j) dx_j$$

$$= \int \frac{1}{\sqrt{2\pi}\sigma_j} (-e^{-rx_j}) e^{-\frac{1}{2}(x_j - X_j)^2/s_j^2} dx_j$$

$$= -e^{-r(X_j - \frac{r}{2}\sigma_j^2)} = -e^{-r(\sum w_k y_{jk} - \frac{r}{2} \sigma_j^2)} \tag{6}$$

The normal distribution assumption is based on the proposition that consumers will assign the highest probability of occurance to utility values around the mean and this probability will decrease for values further from the mean, making the bell-shaped normal distribution a reasonable approximation. 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 (6) is greatest.

Expected utility $E(U(\tilde{X}_j))$ is monotonic in $\chi_j = X_j - \frac{r}{2}\sigma_j^2$. We call χ_j the "risk-adjusted estimated net value." The consumer will choose brand j if

$\chi_j > \chi_\ell$ where ℓ is in the consumers consideration set. (7)

In multiattribute terms, this condition may be written

$$\sum_1^K w_k y_{jk} - \frac{r}{2}\sigma_j^2 > \sum_1^K w_k y_{\ell k} - \frac{r}{2}\sigma_\ell^2$$

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.[2]

Inherent Product Variability

Above we represent risk adjusted net value χ, as the weighted mean of attributes and a variance which includes information uncertainty. But even if perfect information were available, the consumer may face some risk due to the inherent product unreliability. For example we usually are uncertain about the level of quality of an auto. However, even if we had perfect information on average quality for a specific brand and all other atributes, we would still be subject to some risk because the quality level of individual cars coming out of the factory is not the same due to inherent production variation. There is a chance you may get a "lemon" even if all available information indicates the brand is of very high average quality.

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[2] An analogous expression to inequality (7) may also be obtained by assuming an ideal point or quadratic measurable value function, together with a linear value to utility transformation (equation (4)). In that case, the normality assuption is not required. See Roberts [1983] for the derivation.

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

Let us posit

$$\tilde{X}_j = \hat{\tilde{\mu}}_j + \hat{\tilde{\epsilon}}_j$$

Where $\tilde{\epsilon}_j$ denotes the inherent product variability the consumer would realize and $\hat{\tilde{\mu}}_j$ is the distribution of means and we assume it to have expectation $\hat{\mu}_j$ and variance $\sigma^2_{\hat{\mu}_j}$. We assume that if the consumer had perfect information, his estimate $\hat{\tilde{\mu}}_j$ would have expectation $\hat{\mu}_j$ and zero variance. The variance of the consumer's estimate of the mean, $\sigma^2_{\hat{\mu}_j}$ 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 the expected value which a consumer estimates that 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

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

The variance of X_j, σ^2_j (the total uncertainty which a consumer expects to realize) is given by:

$$\sigma^2_j = \sigma^2_{\hat{\mu}_j} + \sigma^2_{\epsilon_j} \tag{9}$$

assuming that $\quad \text{cov } (\hat{\tilde{\mu}}_j - \hat{\mu}_j, \tilde{\epsilon}_j) = 0.$[3]

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[3] Zero variance implies inherent variance (e.g. production line) is independent of the consumers level of information uncertainty about various attributes.

where

$$\sigma^2_{\hat{\mu}_j} = \text{information uncertainty}$$

$$\sigma^2_{\epsilon_j} = \text{inherent product variability.}$$

The risk adjusted value function is now:

$$X_j = x_j - \frac{r}{2} \ (\sigma^2_{\hat{\mu}_j} + \sigma^2_{\epsilon_j}) \tag{10}$$

Changes in the Distribution of Beliefs Over Time

Given the objective function (eq. 6) which the consumer is assumed to maximize, diffusion effects at the brand choice level are assumed to occur in two distinct ways. First, word-of-mouth may change estimated mean attribute levels (y_{jk}) with either positive or negative reviews. Second, uncertainty (σ^2_j) may be decreased by a more precise perception of the product, stemming from more information. Updating 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 value function (eq. 10), determination of utility, and probability of brand choice is then examined.

Prior Beliefs of the Consumer

Before receiving word-of-mouth information, a consumer has a set of prior beliefs about the value of the brand. These beliefs were assumed to be normally distributed in the expected utility derivation. We assume that the consumer knows all of the uncertainties necessary to calculate his risk-adjusted net value for a brand (eq. 10); the inherent product variability

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$(\sigma_{\epsilon_j}^2)$, his information uncertainty $(\sigma_{\hat{\mu}_j}^2)$ and the total uncertainty associated with the brand (s_j^2).[4]

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, because then prior beliefs and word of mouth form a normal- normal conjugate pair.

Incoming Word of Mouth

We assume that consumers seek (and receive) word-of-mouth information (WOM) and update their beliefs in a Bayesian fashion. Thus, 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.[5] A number of studies have found Bayesian updating a good approximation to consumer's information integration (e.g., Ajzen and Fishbein [1975], Trope and Burnstein [1975], and Scott and Yalch [1980]).

Let us assume that during a given time period a potential consumer talks to n owners of brand j, (we denote these owners by superscripts i = 1,2,...,...n). Alternatively, we may regard the consumer acquiring n bits of information about the brand's value from current owners, advertisements, and other information sources.

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[4] Updating formulae when variances are not known are derived in Roberts [1983] along with a discussion of when two sets of assumptions are likely to give divergent results.

[5] See Roberts [1983] for how this assumption might be relaxed to allow for homophily, the tendency for the people to whom a consumer talks to hold similar views.

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

$$x^i_j = \mu_j + \epsilon^i_j \tag{11}$$

where μ_j is the mean of the brand's true value and ϵ^i_j is the inherent product variability which owner i realized.[6]

The expected value and variance of owner i's WOM are given by

$E(x^i_j) = \mu_j$ and $\sigma^2_{x^i_j} = \sigma^2_{\epsilon_j}$. For the n owners to whom the potential consumer talks, the expected sample mean $E(\bar{x}_j)$ and sample variance $(\sigma^2_{\bar{x}_j})$ are given by

$E(\bar{x}_j) = \mu_j$ and $\sigma^2_{\bar{x}_j} = \frac{1}{n} \sigma^2_{\epsilon_j}$.

Integration of New Information by the Consumer

Given prior beliefs in time t about the mean of brand j $(\hat{\mu}_j(t))$ and the level of information uncertainty $(\sigma^2_{\hat{\mu}_j}(t))$, the consumer will integrate the word-of-mouth information he receives about the mean $(\bar{x}_j)$ and the sample variability $(\sigma^2_{\bar{x}_j})$ to an extent dictated by the relative strength of his prior beliefs. We also assume no change to the product form over time so, since inherent product variability, σ^2_ϵ, is known and constant and it will not be updated.

DeGroot [1970, p. 168] shows that the updating formulae for the means and the variance are given by the following expressions:

$$\hat{\mu}_j(t+1) = \frac{\tau \hat{\mu}_j(t) + n \bar{x}_j}{\tau + n} \tag{12}$$

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[6] Roberts [1983] extends these results to the case where owner i has a perceptual bias.

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$$\sigma^2_{\hat{\mu}_j}(t+1) = (\frac{\tau}{\tau+n})^2 \; \sigma^2_{\hat{\mu}_j}(t) + (\frac{n}{\tau+n})^2 \; \sigma^2_{\bar{x}_j} \qquad (13)$$

where τ is the relative strength in prior beliefs, also termed the equivalent prior sample size.

Figure 1 illustrates graphically how prior beliefs and sampale information are integrated to form beliefs about the brand after word of mouth. The prior beliefs are updated by incoming word of mouth with equations 12 and 13 to produce a posterior distribution. As word of mouth increases, n becomes large, the consumers' posterior estimate of the mean of beliefs on the brand tends to μ_j, the information uncertainty tends to zero.

Integration of Changing Consumer Beliefs Into the Expected Utility Function

We have advanced a method by which the consumer's beliefs about the mean value of brand j (that is, what an "average" realization of brand j is like) are updated over time (equations 12 and 13).

To relate these beliefs of the mean quality of brand j $(\hat{\tilde{\mu}}_j)$ to what the consumer would expect to obtain if he purchased brand j, we refer to equations 8 and 9.

Substituting 12 and 13 in 8 and 9, we see how beliefs about the value a consumer will realize on purchase get updated over time:

$$X_j(t+1) = \frac{\tau X_j(t) + n\bar{x}_j}{\tau+n} \qquad (14)$$

$$\sigma^2_j(t+1) = \sigma^2_{\hat{\mu}_j}(t+1) + \sigma^2_{\epsilon_j}$$

$$= (\frac{\tau}{\tau+n})^2 \; \sigma^2_{\hat{\mu}_j}(t) + (\frac{n}{\tau+n})^2 \; \sigma^2_{\bar{x}_j} + \sigma^2_{\epsilon_j} \qquad (15)$$

CUSTOMERS' PRIOR BELIEFS

$f(\hat{\tilde{\mu}}_j(t))$

$\sigma_{\hat{\mu}_j}(t)$

$\hat{\mu}(t)$

$\hat{\tilde{\mu}}_j(t)$

INCOMING INFORMATION FROM OWNERS

$f(\bar{x}_j)$

$\sigma_{\bar{x}_j} = \sqrt{\dfrac{1}{n}}\ \sigma_{\varepsilon_j}$

$E,(\bar{x}_j) = \mu_j$

CONSUMERS' POSTERIOR BELIEFS

$f(\hat{\tilde{\mu}}_j(t+1))$

$\sigma_{\hat{\mu}_j}(t+1)$

$\hat{\mu}_j(t+1)$

$\hat{\tilde{\mu}}(t+1)$
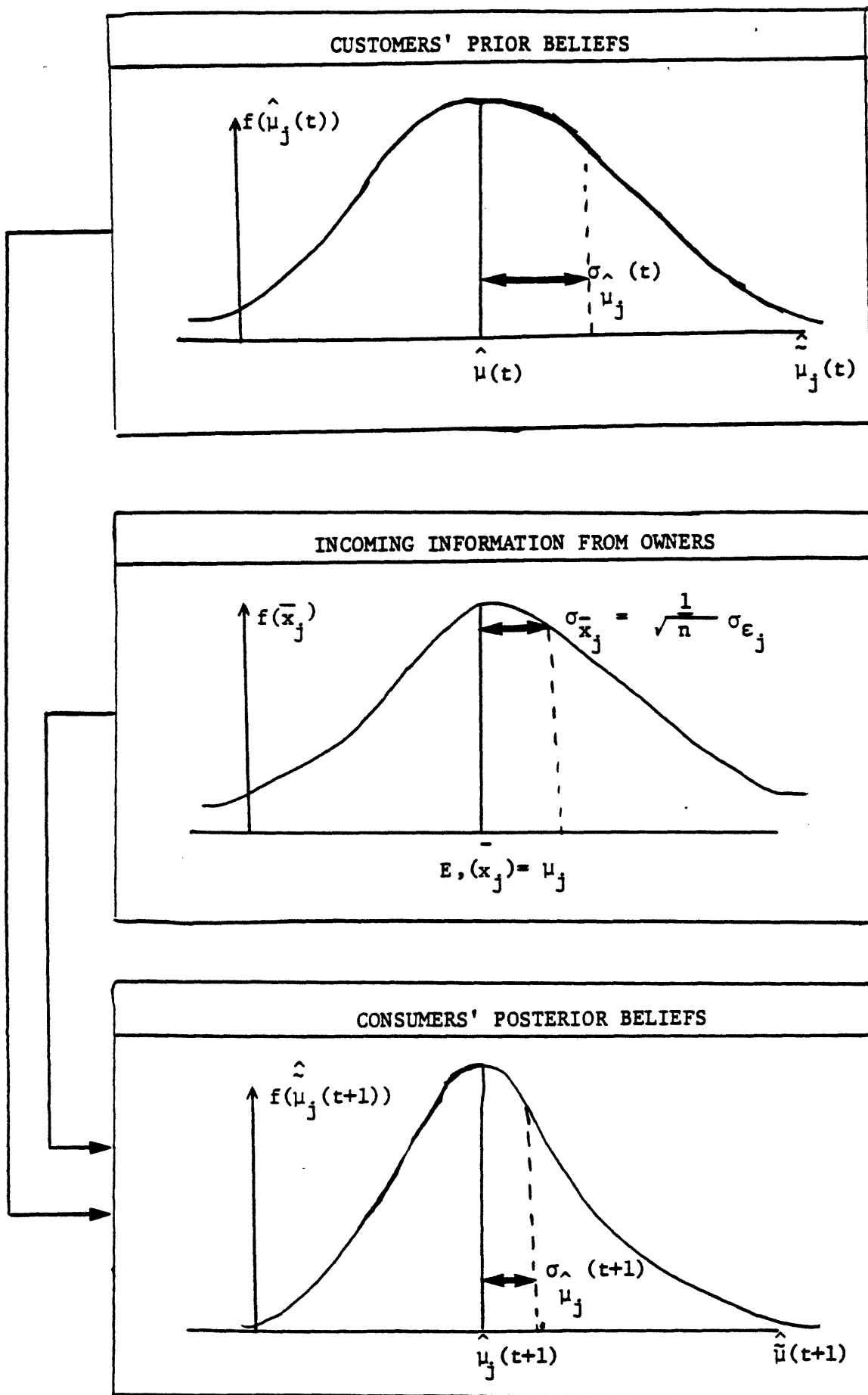
FIGURE 1. UPDATING OF BELIEFS

To relate updating rules to a brand's diffusion over time, we assume that the consumer talks to a proportion, k, of the cumulative adoptors of brand j at time t, Y_{jt}. Thus

$$n_j = k_j Y_{jt} \qquad (16)$$

where k is a constant.[7]

Returning to the formula for expected utility, (eq. (6), and risk adjusted value function (eq. 10), we have

$$E(U(\tilde{X}_j)) = -e^{-r(\chi_j)} = e^{-r(X_j - \frac{r}{2}(\sigma_{\hat{\mu}j}^2 + \sigma_{\varepsilon_j}^2))} \qquad (17)$$

The objective function which the consumer will try to maximize is:

$$\underset{j \varepsilon C}{\text{Max}}[\chi_j] = \underset{j \varepsilon C}{\text{Max}}[X_j - \frac{r}{2}(\sigma_{\hat{\mu}_j}^2 + \sigma_{\varepsilon_j}^2)] \qquad (18)$$

X_j and σ_j^2 are updated according to the Bayesian updating formulae (14) and (15).

Relationship of Expected Utility to Probability

Above, we postulated that the consumer would attempt to choose the brand j that maximizes his estimate of the risk-adjusted net preference, χ_j (equation 18).

We assume that there is some measurement error, e_j, associated with χ_j so that;

$$\tilde{\chi}_j = \chi_j + e_j \qquad (19)$$

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[7] 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 $= (N/M)Y_t = kY_t$.

If we assume that e_j is distributed normally, the multinomial probit model may be used (Hausman and Wise [1978]).

For the stimulus brand, N, the brand choice probability $P(N|B,C)$ is given by

$$P(N|B,C) = Pr\{\chi_N \geq \chi_j; \; j \in C\} \qquad (20)$$

where

$$\chi_N = X_N - \frac{r}{2}\sigma_N^2 + e_N \sim N(X_N - \frac{r}{2}\sigma_N^2, \sigma_{e_N}^2) \quad \text{and}$$

$$\chi_J = X_j - \frac{r}{2}\sigma_j^2 + e_j \sim N(X_j - \frac{r}{2}\sigma_j^2, \sigma_{e_j}^2)$$

In practice, because the number of brands considered may be large, the logit approximation to the probit model (e.g., 20) may prove more tractable. Domenich and McFadden [1975] demonstrate the closeness of the double exponential and normal error distribution assumptions.

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

$$P(N)|B,C = \frac{e^{\beta(X_N - \frac{r}{2}\sigma_N^2)}}{\sum e^{\beta(X_j - \frac{r}{2}\sigma_j^2)}} \qquad (21)$$

Substituting the updating equations (14) and (15) in (21) and introducing a time subscript, we obtain

$$P(N|B,C) =$$

$$\frac{e^{\beta\left[\frac{(\tau X_N(t) + n\bar{X}_N)}{\tau+n} - \frac{r}{2}\left\{\left(\frac{\tau}{\tau+n}\right)^2 \sigma_{\mu_N}(t) + \left(\frac{n}{\tau+n}\right)^2 \sigma_{\bar{X}_N}^2 + \sigma_{\epsilon_N}^2\right\}\right]}}{\sum\limits_{\substack{j=1 \\ j \neq N}}^{J} e^{\beta\left[X_j - \frac{r}{2}\sigma_j^2\right]} + e^{\beta\left[\frac{(\tau X_N(t) + n\bar{X}_N)}{\tau+n} - \frac{r}{2}\left\{\left(\frac{\tau}{\tau+n}\right)^2 \mu_N(t) + \left(\frac{n}{\tau+n}\right)^2 \sigma_{\bar{X}_N}^2 + \sigma_{\epsilon_N}^2\right\}\right]}}$$

$$(22)$$

This equation captures the multiattribute nature of the product (recall $X_N = \sum_{k=1}^{K} w_k y_{Nk}$), expected utility, information uncertainty, inherent risk, and updating for word-of-mouth communication.

MEASUREMENT AND ESTIMATION

Operationalization of the model for premarket forecasting utilizes direct consumer measurement and statistical estimation. The approach of the measurement is based on exposing potential buyers in a clinic environment to successive levels of information about the new product -- advertising, perception, and word-of-mouth communication. Measures of the impact on prescription, risk, preference and choice behavior are taken before and after each information exposure. Advertising is represented by a print or T.V. ad for the new product; product use by actual trial of the prototype new product; and word-of-mouth communication by a video tape of "owners" providing an evaluation of the product. The "owners" are actually actors presenting a script based on verbatums from focus group sessions made up of consumers who tested the new product. Two executions of the video tape are presented on a split sample basis to allow measurement of positive and negative word-of-mouth content. Along with the video, respondents also see a safety and consumer evaluation report that corresponds to the positive or negative video treatment.

A test and control design is used and similar perceptions, preference, and word-of-mouth measures are taken for the control product. The control product is selected to be 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.

The parameters that must be determined to apply the model are shown in Table 1. Some of the new product parameters are measured directly, while others are based on a statistical estimation procedure. A few parameters are obtained by fitting the model to the control product's observed sales results. The fitted parameters may be used as estimated or modified by judgment to reflect differences between the control and new product. This fitting also provides assurance that the model is able to replicate historical results for the control product.

We review the general procedures for estimation of the parameters shown in Table 1 in this section and the reader is referred to the application section for the specifics of the clinic, experimental design, and measurement items.

The multiattribute levels (y_{ik}) and weights (w_k) can be measured and estimated by established procedures (Urban and Hauser [1983]). Typically, many attributes (e.g., 5 point agree/disagree or semantic differential scales) would be rated and preferences measured (e.g., constant sum comparisons) for the existing products consumer would consider. The weights could be estimated by fitting the linear utility model to the preferences (e.g., preference regression). Mean prior belief about the new product ($\hat{\mu}_j$) is measured directly by preference judgements.

The uncertainty σ_j^2 is measured by direct questions or risk (e.g., 5 point scales on "risk", "unreliability", or "uncertainty" or probability distribution on preference judgements). Risk aversion (r) is estimated as one of the parameters of the logit choice models (see below).

TABLE 1. NEW PRODUCT PARAMETER SOURCES

PARAMETER	SOURCE		
MULTIATTRIBUTE UTILITY	MEASURED	STATISTICAL ESTIMATION	FIT TO CONTROL
Attribute level (y_{jk}, eq. 2)	✓		
Weights (w_k, eq. 2)		✓	
Risk aversions (r, eq. 6)		✓	
Prior Beliefs			
Mean of beliefs ($\hat{\mu}_j$, eq. 12)	✓		
Variance of beliefs (σ_j^2, eq. 9)	✓		
Inherent variability ($\sigma\epsilon_j^2$, eq. 9)		✓	
Word-of-Mouth			
Updating (τ, n, eq. 12, 13)		✓	
Mean ($\bar{x}_j$, eq. 12)		✓	
Variance of mean value ($\sigma-\frac{2}{x}$, eq. 13)		✓	
Logit Choice Model			
Probabilities (P|B,C), eq. 21	✓		
ß (eq. 21)		✓	
Risk Aversion (r, eq. 6)		✓	
Amount of word-of-mouth (k_j, eq. 16)			✓

Inherent product unreliability is imputed to give residual estimates of information uncertainty from equation 9. This may be done in a number of ways. If no perceptual bias is expected, production records may be used to estimate the relative inherent product variability. Alternatively, an examination of equation 22, the logit choice model, shows that a brand-specific dummy for the car would capture the relative inherent product unreliability.

Updating parameters (τ, n) can be estimated for each individual based on equation 12. We divide by numerator and denominator by n to get:

$$\hat{\mu}_j(t+1) = \frac{(\tau/n)\,\hat{\mu}_j(t) + \bar{X}_j}{(\tau/n) + 1} \tag{23}$$

and note only one parameter (τ/n) needs to be estimated.

We observe the proper and posterior recommendations which respondents would give to the car 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 is measured by the respondents rating of what recommendation the video tape 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.

The $\bar{X}_j$ in equation 23 used to calculate t/n refelcts the positive or negative video experimental treatment each respondent saw. We also need an estimate of the true value of $\bar{X}_j$ that would occur after dirving the car. This may be either provided as a management input or measured by the average recommendation respondents gave the car after driving it, but before seeing the video tapes. With measured prior and posterior variance of beliefs $(\sigma_{\hat{\mu}_j}^2(t)$ and $\sigma_{\hat{\mu}_j}^2(t+11)$, the estimated updating parameters (t/n) and inherent

product unreliability ($\sigma_{t_j}2$), the variance of incoming information ($\sigma_{\bar{x}_j}^2$) can be calculated directly from equation 15.

Given the multiattribute utility, prior beliefs, and word-of-mouth parameters, we next consider the choice model. These parameters 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 puyrchase (e.g., Juster 11 point point scale) and estimate ß and r for the logit model (e.g., 22).

The final model parameter to estimate reflects the amount of word-of-mouth resulting from the volume of past sales n (k_j, equation 16). This is done by fitting to the first twelve months' sales of the control car with the model. A grid search is used to find the k value that along with the above estimated parameters for the control car and equation 22 best fit the actual sales history. k represents the volume of word-of-mouth transfer and can be used directly for the new product or alternative forecasts can be produced based on assumptions of more or less word-of-mouth than the control product.

In this fitting, category sales and consideration levels must be assumed (P(B), P(C|B) in equation 1). Category sales are usually available from past sales histories and econometric forecasts. The consideration levels may be measured by past surveys or fit to the actual data based on an assumed pattern (e.g., constant consideration) and a scaling parameter (K).

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

APPLICATION

The model has been applied to the pre-launch planning of a new 1985 automobile which we will call the Regada. The auto industry represents an established category in which product differentiation along a number of attributes is common. The 1985 Regada was a total redesign over its predecessor and was viewed as a new entrant in the luxury auto category. The 1985 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 effect. 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. Married respondents 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 Regada was used as a control treatment for one-third of the sample; the remainder drove a pre-production 1985 Regada.

In order to estimate changes in consumers' beliefs over time, respondents were given information sequentially with measures taken after each new

stimulus. Respondents were first shown a concept description of the Regada (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. The concept description was taken to represent the information level corresponding to consideration, test drive represented a dealer visit, and the videotape and the safety reports corresponded to searching for information and word-of-mouth communication.

The respondents supplied preference evaluations before and after the treatments. Preference was measured on an open-ended thermometer scale in which the currently most preferred model was given 100 points. The new car would be rated over 100 points if it was preferred to the current first choice existing car of a respondent and less than 100 if it was not preferred to the existing first choice.

Perceptual attributes were selected on the basis of focus groups and previous auto research (see figure two for attributes). The rating measure used was a five-point scale with verbal anchors from "extremely poor" to "excellent". Attribute ratings were collected before and after each treatment. After the drive, in addition to perceptual attributes, respondents were asked what they would tell their friends about the car and to rate the recommendation on a 5 point-scale (very positive to very negative). This scale was also used after video to represent what respondents felt was the level of recommendation consumers in the video were portraying.

The final measures were risk and purchase probability. Risk was operationalized by "Unreliability" as measured on a five-point verbally anchored scale. Probability of purchase was measured on an eleven-point Juster scale (Juster [1966]). For further details of these measures stimuli,

EXTREMELY
POOR   POOR   AVERAGE   GOOD   EXCELLENT
1   2   3   4   5

LUXURY AND COMFORT

STYLE AND DESIGN

RELIABILITY

FUEL ECONOMY

SAFETY

MAINTENANCE COST

QUALITY

DURABILITY AND RESALE

ROAD PERFORMANCE

————————— = Control
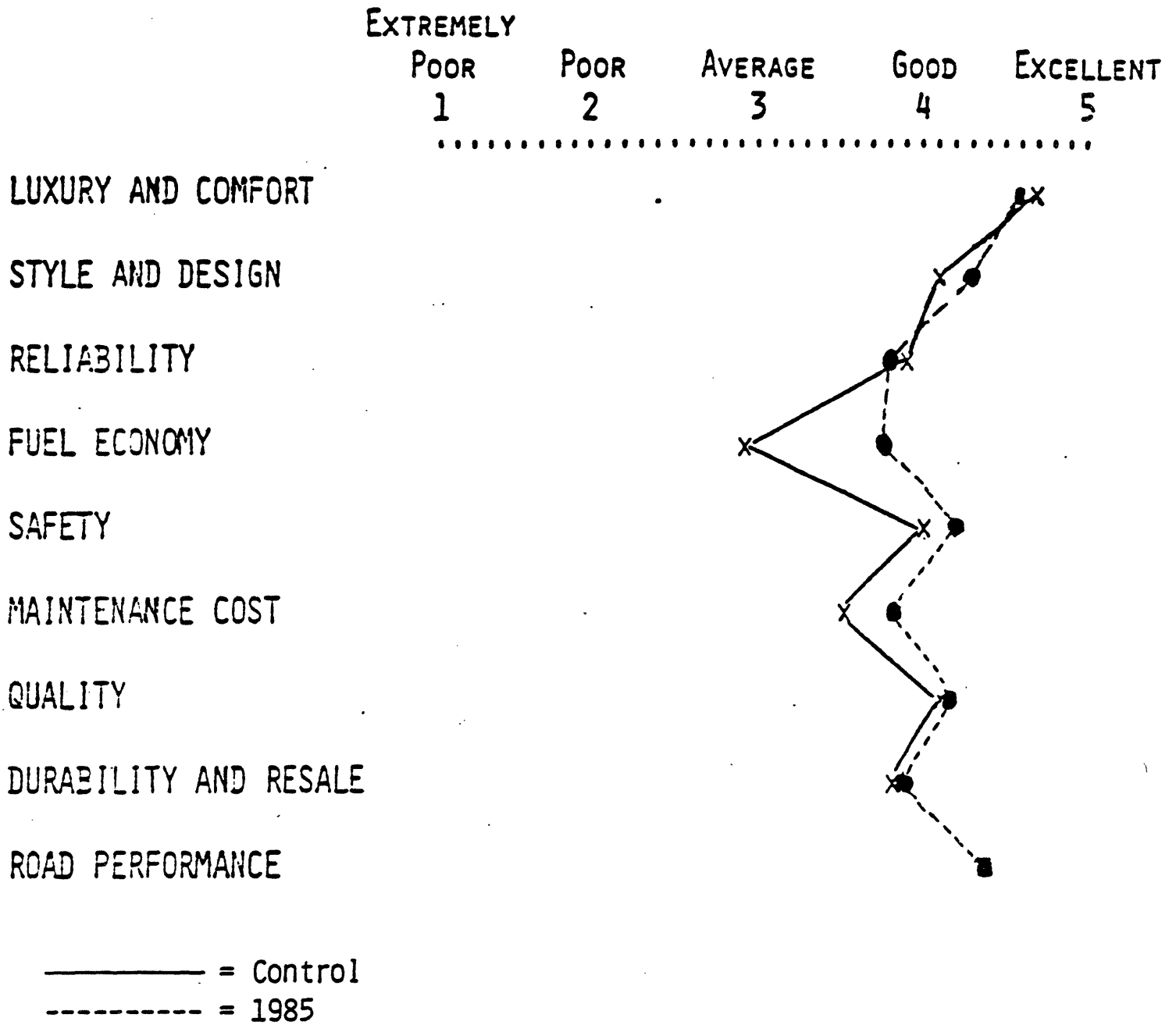- - - - - - - - - = 1985

FIGURE 2.   AVERAGE ATTRIBUTE EVALUATIONS AFTER DRIVE

see Roberts [1983] or Hauser, Roberts, and Urban [1983]. We next report the results for each component of our mode obtained from the measures.

Multiattribute Utilities

The 1985 Regada was down-sized 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 attributes (Figure 2) indicated that the 1985 Regada was a little lower (but not significantly) than the large 1983 Regada control car in luxury and comfort and little higher on style and design. It was perceived as significantly better in fuel economy and equal or marginally better on all other dimensions except reliability. Overall, these reflect favorable ratings.

A principal components factor analysis of the nine 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" (reliable, miles per gallon, maintenance, quality, and durability). These two dimensions accounted for 63.4% of the variance. A third dimension was not considered because its eigen value was less than one $(\lambda_3 = .6)$.

A perceptual map of the market was formed, and the average perceptual position of both the 1985 Regada and the control car to be plotted. Figure 3(a) shows the perceptions after drive and before the videotape. Overall the 1985 is seen as more sensible with less appeal. The 1985 Regada 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 3(b) shows the changes for the after drive position of the 1985 and control car before and after word of mouth. The videotapes had a
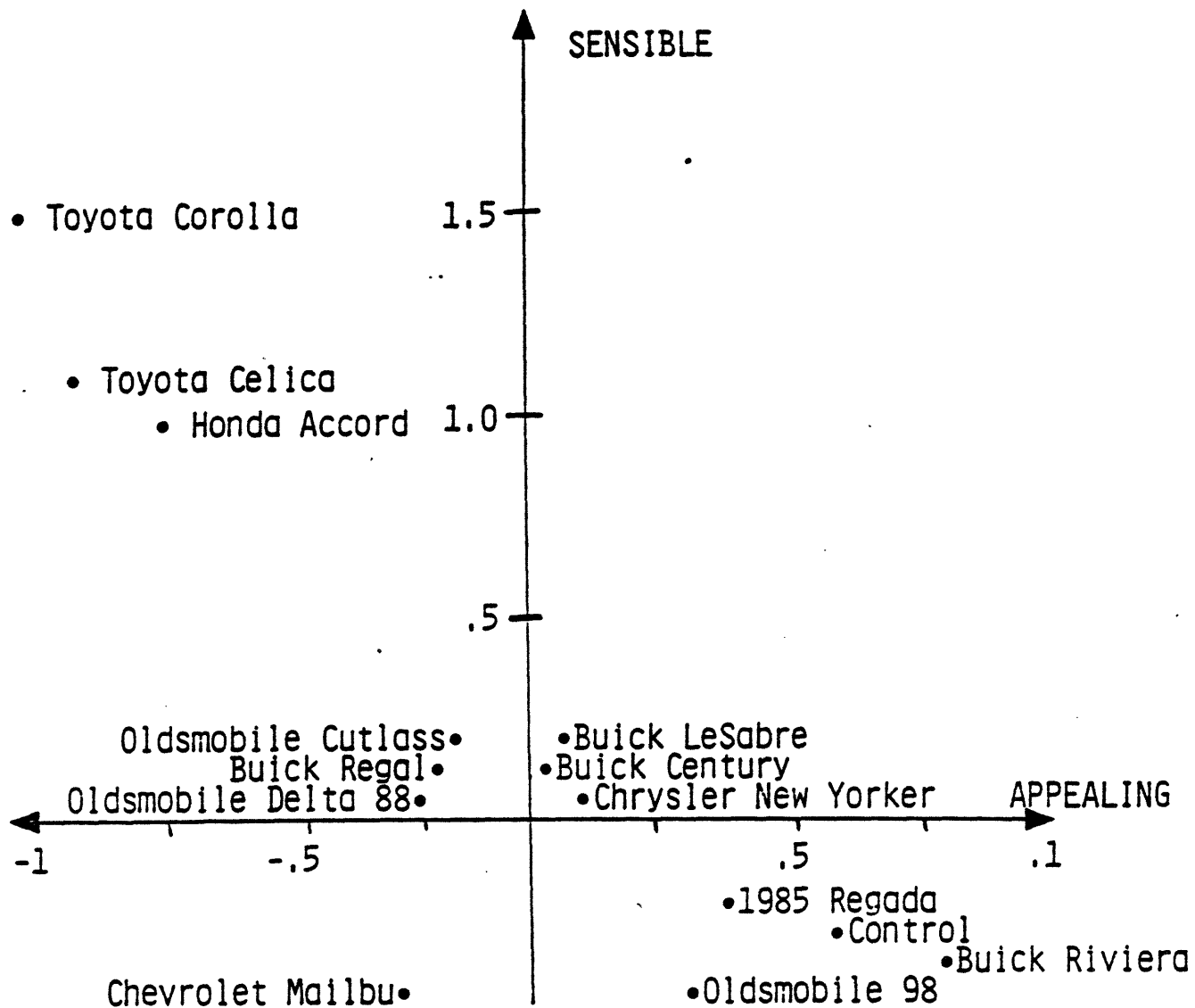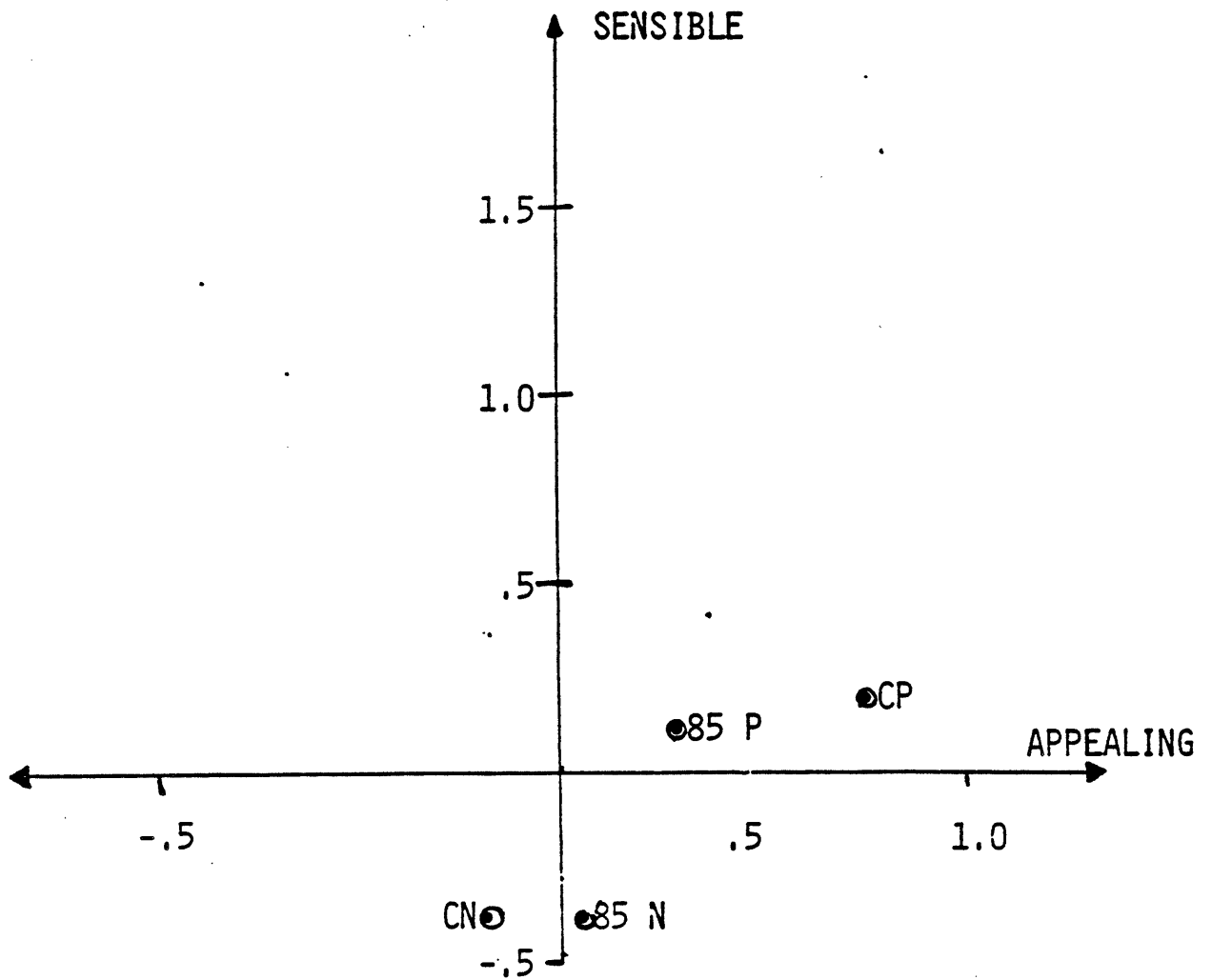
FIGURE 3a. PERCEPTUAL MAP OF AVERAGE POSITIONS OF
BRANDS CONSIDERED BY MORE THAN 10 RESPONDENTS.

SENSIBLE

1.5

1.0

.5

●85 P   ●CP

APPEALING

-.5   .5   1.0

CN●   ●85 N

-.5

CP	:	Control Regada 1983 - post positive video
CN	:	Control Regada 1983 - post negative video
85 P	:	Regada 1985 - post positive video
85 N	:	Regada 1985 - post negative video'

FIGURE 3b.   EFFECT OF VIDEO ON PERCEPTUAL POSITION

substantial effect on perceptions of both cases with the positive treatment
values being higher on both dimensions than after drive position the negative
ratings being lower on both dimensions.

Figure 4 shows the relative preference for the test and control car and
the effects of positive and negative video on preferences. The preference
points (on the thermometer scale) given to the stimuli car are divided by the
total of the points given to the respondents first three choices and the
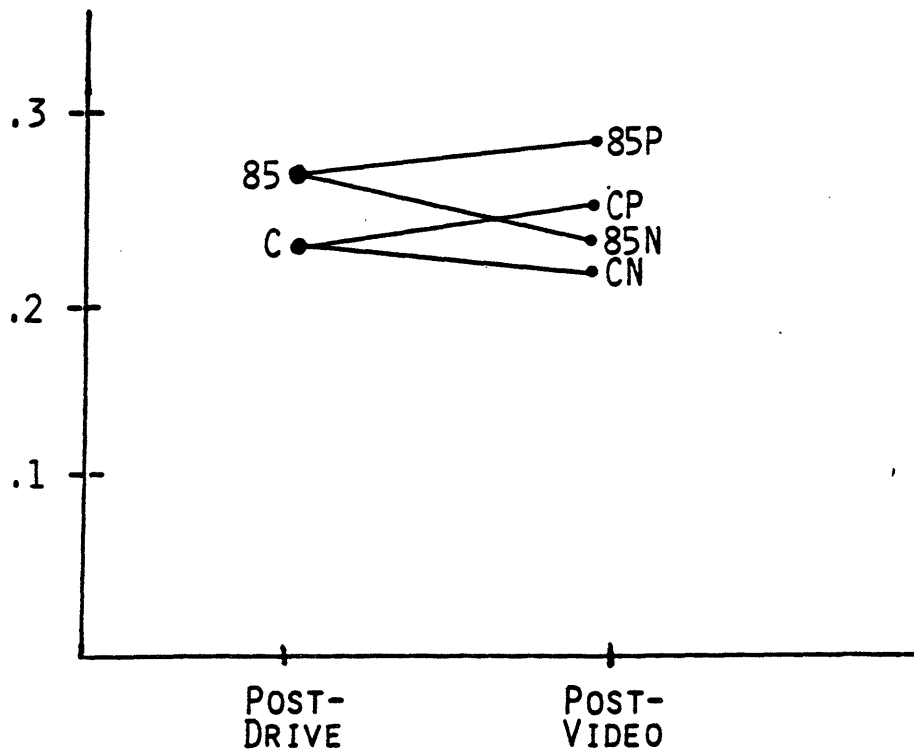stimulus car to calculate the relative preference.

FIGURE 4. RELATIVE PREFERENCE

The new 1985 car is preferred to 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 of relative preference values to the factor scores obtained from the factor analysis was done for existing cars and the new car before and after video (see Table 2). In all cases the coefficients were significant at the one percent level with appealing and sensible dimensions having about equal importance weight.

	EXISTING TOP 3 CHOICES	EXISTING TOP 3 CHOICES AND NEW AUTO AFTER DRIVE	EXISTING TOP 3 CHOICES AND NEW AUTO POST VIDEO
INTERCEPT (T)	.250 (113.59)	.251 (128.87)	.254 (128.54)
APPEALING (T)	.020 (8.90)	.020 (10.55)	.020 (10.03)
SENSIBLE (T)	.026 (11.55)	.028 (13.67)	.028 (14.00)
R^2	.3022	.3083	.3190

TABLE 2. REGRESSIONS OF VALUE POINTS ON FACTOR SCORES

Risk

The unreliability measures after drive and word of mouth are shown in Figure 5. The existing car is seen as less uncertain than the new car. For both cars uncertainty is substantially increased after negative video and somewhat reduced by positive video.
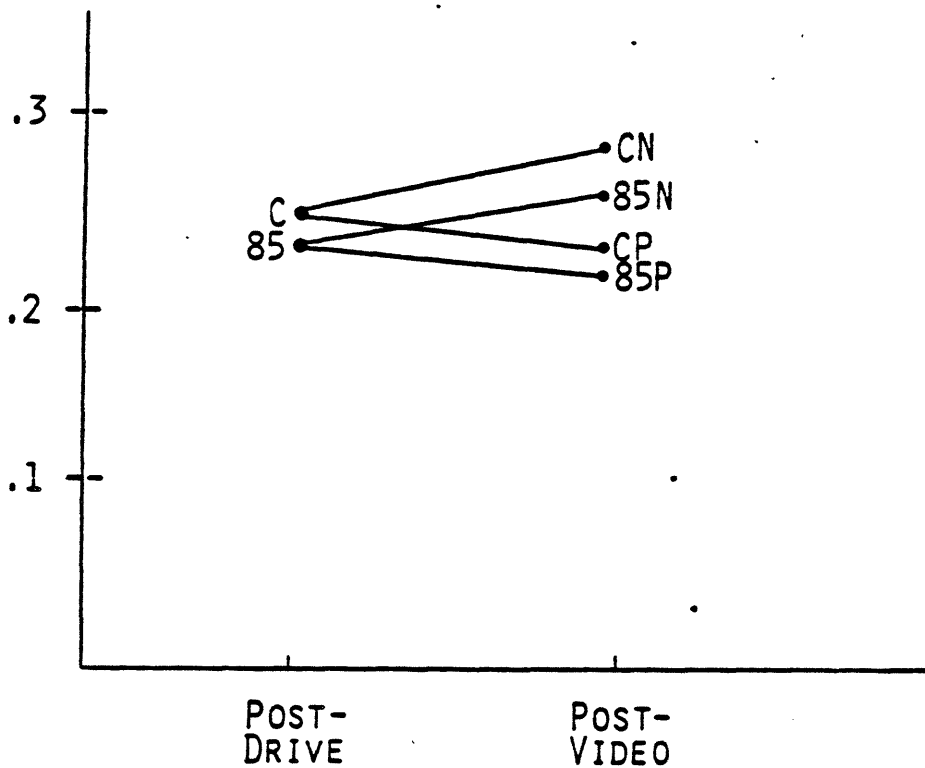

FIGURE 5. PERCEIVED RISK

Choice

Stated probabilities of choice (Juster scale) are shown for the test and control cars in Figure 6. The probabilities are higher in all cases for the new car.
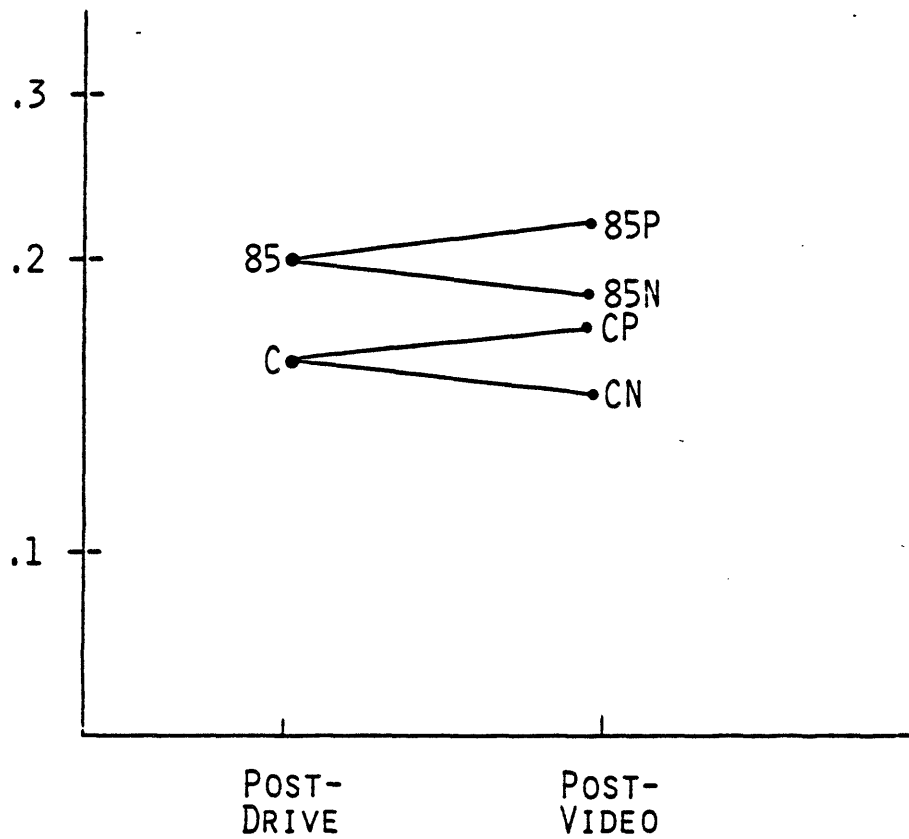
FIGURE 6. PROBABILITY OF PURCHASE

Preference and risk were related to probability using a logit model. The expected price was included in this model to remove price influences from the preference measure. The logit model uses stated probabilities rather than discrete choices as its dependent variable so it was estimated in the following multiple regression form:

$$\log \frac{P_j}{P_1} = \alpha + \beta_1(X_j - X_1) + \beta_2(\text{Price}_j - \text{Price}_1) + \beta_3(\text{Risk}_j - \text{Risk}_1) \quad (24)$$

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 model was estimated at three stages: on the currently available makes, after entry of the new brand, and after WOM of the new brand (see Table 3). The t's are significant in all cases. Risk and price coefficients have the expected negative sign and value points are highly positive. The coefficients are similar across the three estimation situations.

	Top Choice Brands	Top Choice Brands and New Car After Drive	Top Choice Brands and New Car After Video
Value Points	2.20	2.47	2.63
(t)	(6.22)	(10.76)	(7.69)
Price	-2.6×10^{-5}	-3.2×10^{-7}	-3.6×10^{-5}
(t)	(-5.77)	(-0.07)	(-8.82)
Risk	-0.207	-0.162	-0.230
(t)	(-5.40)	(-5.39)	(-6.81)
$\bar{R}^2$	0.0798	0.1503	0.1365

Table 3. Multiple Regression Logit Approximations
to Choice Probabilities

Analysis with the choice model was also used to derive the inherent product unreliability $(\sigma_{\epsilon_j}^2)$. We started with an estimate based on the risk measure obtained for the consumers first choice existing car and assumed it primarily reflected inherent unreliability. This was tested by applying the choice model of equation 22 with a brand specific dummy to represent information uncertainty and the inherent unreliability estimated by the risk measure for

the most preferred brand. The brand specific dummy was not significant in equation 24 for the most preferred existing brand so we adopted the risk for the most preferred brand in a proxy for inherent product unreliability.

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 23). Average τ/n's for eight segments and overall are given in Table 4. Overall, the average is .874, but some segments had higher τ/n values or more confidence in their prior beliefs. MMC is a disguised name for the manufacturer of the test and control cars. As expected, MMC owners have the highest confidence in their prior beliefs, (τ/n = 1.444 and 1.013).

Next we estimated the true mean and variance of incoming word-of-mouth by the procedures described above. After drive and before video respondents gave an average preference point value of 82.2 and a recommendation value of 1.79 (1 = very positive, 2 = positive, 3 = neutral, 4 = negative, and 5 = very negative). After positive video the value was similar at 1.87 and after negative video a value of 2.27 was observed. We therefore adopted the after drive recommendation and corresponding reference preference point value of 82.2 as the true mean of incoming word-of-mouth.

	Car Respondent Will Replace	τ/n Average
Drove 1985 Test Car	MMC	1.444
	Other US	.632
	Foreign	.150
	All Cars	.823
Drove 1983 Control Car	MMC	1.013
	Other US	.929
	Foreign	.250
	All Cars	.879
Full Sample	All Cars	.874

Table 4. Average Relative Strength of Prior Belief

The variance of the incoming word-of-mouth ($s_{\bar{x}}^2$) was calculated based on equation 15 by the procedures described above with the estimated values for pre and post video, risk, updating parameters and inherent product unreliability. The average value was 1.75 preference points.

Fit to Historical Data

We then examined how well the model parameterized for the control car based on its experimental results would 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). The best fitting value of k was found by direct search. k was found to be 4.39 x 10^{-6}. This 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 prior information is given a weighting of 54% relative to new information gained since launch.

The corrected $\bar{R}^2$ in the fitting was .35 with ten degrees of freedom. The fit followed the overall trend and the correlation of actual and predicted values was .59. The overall first year actual sales was 131,700 units and the fitted value 128,870 units. The fits were acceptable and indicated the model was a reasonable structure for forecasting.

Forecasting of Share Dynamics and Managerial Implications

The results of the experimental measures and parameters on estimates for the 1985 Regada 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 word-of-mouth communication (k) would be world generated by the new car as the control. The new car share forecast relative to the first 12 months share fitted to the control car are shown in Figure 7. The new car has a substnatially higher share and a similar diffisuion pattern. This similarity in due to similar measured preference and choice patterns after word of mouth (Figure 3(b), 4, 5, 6), and the assumption of similar consideration and amount of word-of-mouth parameters.

Sensitivity analysis was used to examine alternate assumptions on consideration rates, updating parameters, and volume of word-of-mouth. The final managerial forecast indicated that the new 1985 Regara model would sell approximately twenty-five 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 car, but with considerably more advertising and dealer sales pressure. Advertising was also revised to be very different from previous compaigns and stressed reliability, performance, and economy. This strengthened the positioning in the "sensible: dimension (see Figure 3(a)). Special dealer training effort
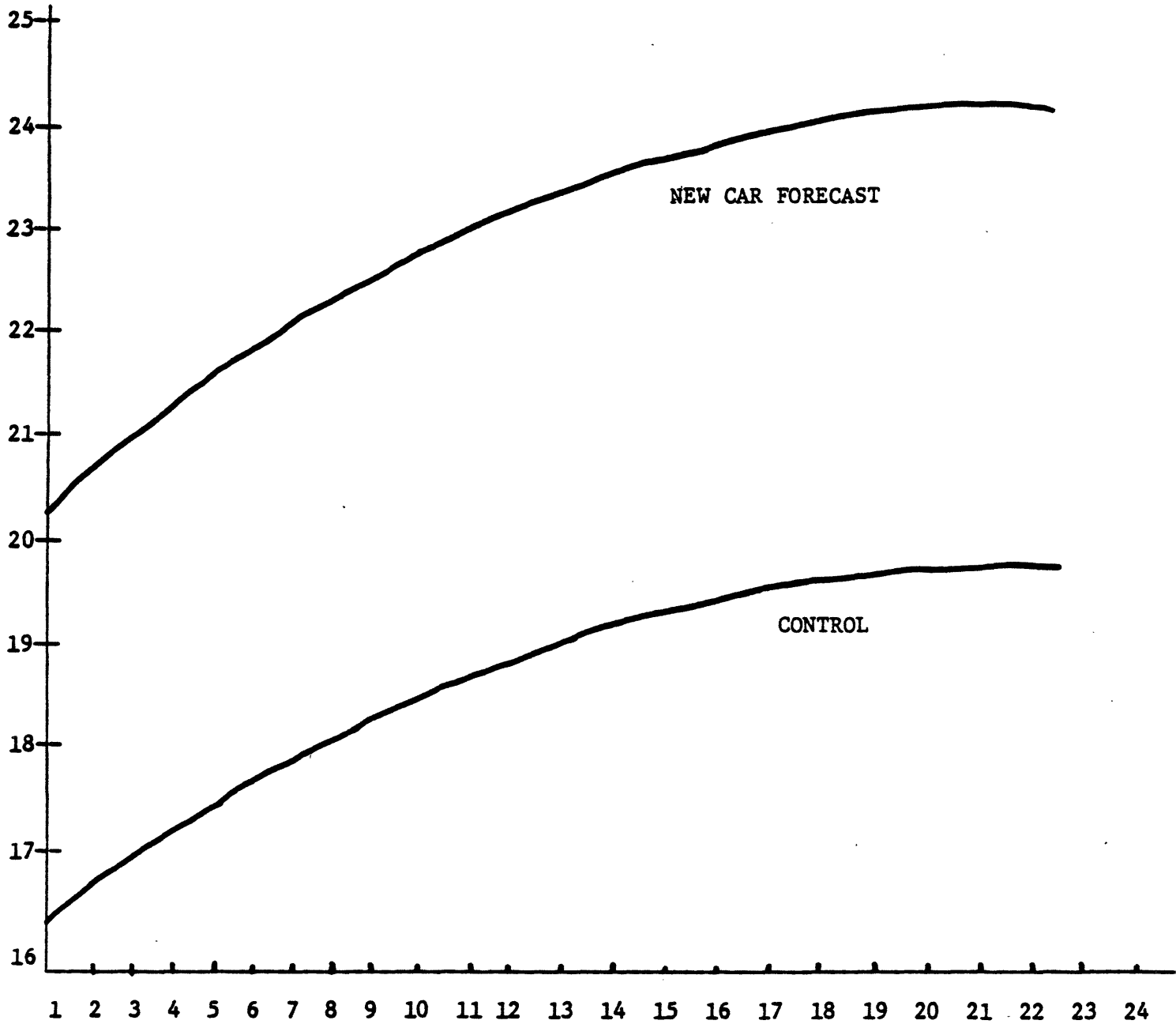
Figure 7. Forecast Evolution of 1985 Regada Brand Share vs. Control

was directed at getting consumers to drive the car as part of a program of selling the car from the "inside out" was developed. 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 suggested this as a good strategy (see Figure 2 and 4).

The negative word-of-mouth penalties (see Figures 3(b), 4, and 6) 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 it was delayed for over six months. The results found in this study suggested this as an appropriate decision even though the delay lost over 100 million dollars.

The model results did have impact on decision making and a comparison of actual sales to the predictions in the future will allow an initial examination of the models validity.

Conclusions

This paper has presented a model of brand choice dynamics for a new product in an established product. Multiattribute utility, information uncertainty, inherent product unreliability, interpersonal communication, and dynamics were modeled by drawing a Von Neuman Morgentern utility, Bayesian, descrete choice, and diffusion theory. 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 impacts were observed. Three new auto clinic studies are now in process. Over time continued use will build a basis to evaluate the models external validity and forecast accuracy. These applications are being carried in a wider framework that supplements this brand choice modeling by category dynamics, competitive entry, dealer visits, and the growth of consideration levels (see Urban, Roberts and Hauser [1984]).

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 (McFadden [1981] and Ben Akiva and Lerman [1977]), value priority (Hauser and Urban [1984]), and traditional diffusion models to predict category dynamics. The model proposed here is used to represent brand share dynamics in the category. The work reported in this paper is a first step towards a comprehensive model for premarket forecasting of consumer durables.

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