A MULTIATTRIBUTE UTILITY DIFFUSION MODEL:

Theory and Application to the Pre-Launch Forecasting of Automobiles

by

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ABSTRACT

This thesis develops a modeling and measurement methodology to forecast evolving preference for a new durable brand in an existing product category, prior to its launch.

The methodology proposes a choice hierarchy approach to modeling individual purchase probability. Brand purchase probability is the product of the probability of brand consideration, the probability of category purchase given consideration, and the probability of brand choice given purchase and consideration. The thesis addresses the problem of forecasting the last of these elements by combining diffusion models with multiattribute utility models using the construct of perceived risk. A decision analysis expected utility framework allows us to model the role of increasing penetration generating more information about the product and thus reducing its perceived risk. This reduction in perceived risk increases the brand's expected utility and thus probability of adoption is updated over time.

Calibration of the model required the development of stimuli to simulate the diffusion process and the design of a questionnaire to measure the model variables. Information stimuli of concepts, test drives, videotapes, and consumer reports were sequentially administered to respondents. Measures of preference, perceived risk, and information levels were taken between stimuli.

An application of the model to the prelaunch planning of a new 1985 automobile is reported. By use of the 1983 version as a control brand, belief changes in the experiment were able to be interpreted in terms of brand diffusion in the marketplace.

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Indeed, this thesis is very much a part of the larger study of developing a prelaunch forecasting system for the sponsoring company. Assistance in data collection and instrument design from Janny Leung, Young Sohn, Fareena Sultan, Nicolas Kojay, and Lisa Tenor all helped ease my burden with the work as well as making it more enjoyable. Support from the sponsoring company (particularly that of John Dabels and Paula Travenia), their advertising agency (Jan Wosnick and Barbara Gaston), and the market research contractor (Andy Czajka, Tom Rose, and Lori Curtis) all helped the project go more smoothly.

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Finally, as I come to the end of the paved road of my formal education and prepare to make tracks of my own, I am bound to reflect on the two people who set me on my journey and who made considerable sacrifice to ensure that I had every natural advantage possible on the way. To my parents, Merle and Robbie, "Thank you."

A MULTIATTRIBUTE UTILITY DIFFUSION MODEL: THEORY AND APPLICATION TO THE PRE-LAUNCH FORECASTING OF AUTOS

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CHAPTER 1: INTRODUCTION

1.1 Overview

Forecasting the sales of a new consumer durable brand is a theoretically interesting and managerially important problem. In this thesis a model is developed to forecast the number of consumers choosing the brand and how this changes over time by drawing on utility and diffusion theory. Measures which allow the calibration of the model and generation of forecasts prior to the brand's launch are described. Finally, an application of the model and the measurement methodology to the launch of a new 1985 auto is presented.

Purchase of the new brand is hypothesized to consist of three components: consideration, purchase within the category, and brand choice. The thesis addresses the third of these elements, brand choice given consideration and a category purchase.

1.2 Objectives and Contribution

As a managerial tool, the thesis aims to provide an important step towards the development of a comprehensive durable forecasting model. From a management science perspective, the specific objectives of the thesis may be summarized as follows:

- to develop a model which explains the diffusion effects of a new brand in a competitive market by combining the product positioning power of multiattribute utility theory with the dynamics of diffusion models, using the construct of perceived risk;
- to present an experimental design and set of measures which allow the model to be calibrated at the individual level, prior to the brand's launch; and
- to demonstrate the feasibility of the methodology and analyze results obtained from an application of the model.

Given those objectives, we believe that the thesis makes the following contributions to modeling and measurement practice.

- A new approach to diffusion modeling is presented. This approach is an individual-level one and directly incorporates such phenomena as information acquisition, perceived risk, and expected utility. It does not rely on an artificial division of the population into innovators and imitators for its justification.
- Diffusion phenomena and multiattribute utility are both combined in the same model by a deductive development of existing theory. A choice framework is developed which allows diffusion

effects to be felt at both the brand level and also the industry sales level.

-- Innovative stimuli to simulate diffusion effects of a new brand, prior to its launch, have been introduced.

-- Innovative measures of preference, uncertainty, and information levels have been developed and tested.

1.3 Approach to Brand Sales Modeling Framework

1.3.1 Context

The problem of forecasting brand preference for a new durable forms an element of the larger problem of forecasting the sales of the product. Together with forecasts of consideration of the brand and purchase incidence within the category, brand preference may be used to provide a forecasting system for the sales of the durable over time. This section reviews the importance of accurate forecasts of brand sales prior to launch. It then develops a framework which allows brand choice conditioned on consideration and category purchase to be studied as one component of brand sales.

The managerial importance of prelaunch forecasts may be seen from the fact that the manufacturer must commit significant capital in plant and equipment to develop and produce a new durable. In the auto market, for example, Ford recently committed approximately one billion dollars for the launch of the Tempo/Topaz line (Auto News, May 1983). This production investment is made prior to launch, prior even to an initial sales history. Furthermore, such investments are high risk. Success can mean large profits (and commensurate rewards to the managers involved). Failure can bring the opposite consequences. Any modeling and measurement methodology that can reduce the risk of failure and provide diagnostic information to enhance the probability and magnitude of success will become a valuable resource to managers.

The value of a forecasting system will be greatly enhanced if it is able to be implemented sufficiently prior to launch to allow changes which might affect the product's appeal. The methodology developed in this thesis may be conducted when first prototypes become available. In the case of the auto application considered, this allows between one and two years prior to launch for the research results to be used. In that time, forecasts may provide diagnostic information for features planning, perceptual positioning, market segment definition and targeting, production scheduling, and profit planning. However, investment in physical plant is likely to already be committed.

Despite the managerial need for accurate forecasts prior to launch, there is no currently published marketing model to allow this at the brand level for consumer durables. Sources from the sponsoring company suggested that industry practice, at least for the auto industry, is to base forecasts more on company objectives than market conditions. This lack of prelauch durable forecasting models contrasts with frequently purchased goods where a number of models have been proposed for product evaluation prior to launch (see Urban and Hauser [1980] for a review). Evidence indicates that these models display good predictive capabilities. For example, Urban and Katz [1983] give a systematic review of one such model.

An examination of why no prelaunch durable forecasting models exist raises a number of interesting modeling and measurement issues. Supply constraints provide one reason for the difficulties, since test marketing for durables often requires a commitment to tooling and production time set-up almost equivalent to a national launch. Even short production runs require the design and production of dies and casts which have a substantial cost, independent of the run size. However, demand phenomena also provide explanations as to why pre-launch forecasting methodologies are difficult for consumer durables. The very fact that durables are not a frequently purchased good makes observation of purchase behavior in a limited period of time more difficult. Less information is available on the behavior of each member of the population since in any reasonable observation period repeat purchase is uncommon and only a small proportion of the population is actively engaged in the buying process.

Consumer behavior phenomena which are particularly prevalent with consumer durables also guide our approach in modeling the sales of a new brand over time. Examples of these include budget effects, existing stock, economic conditions, diffusion and word of mouth, product positioning, and competition. The first three of these largely affect purchase incidence and are described in Hauser, Roberts, and Urban [1983]. The latter three are extremely important in brand preference given purchase and will be central in the development of a model for brand choice here.

1.3.2 Approach to Brand Choice Modeling

The brand choice model should allow the manager to analyze how his product competes against other brands and how this will change over time.

The incorporation of competitive effects using multiattribute models is common in the durable forecasting literature (e.g., Agarwal and

Ratchford [1979], Berkowitz and Haines [1982], Hauser [1983]), described in Section 2.2. Similarly, the use of diffusion models to forecast industry sales in the form of a logistic time series has attracted considerable popularity (Grilliches [1953], Chow [1967], Bass [1969]). These diffusion models have all been at the industry sales level, not at the brand level, and although they have been extended to include price and advertising, until recently none has included product characteristics and perceptual position (see Mahajan and Muller [1979] for a review). Kalish and Lilien [1983] provide an exception with a model which describes industry sales using a diffusion approach and brand share using a logit model (see Section 2.2.1 for a review).

To date, no work has been published combining these two approaches. It is self-evident that competition is important when forecasting the sales of a new brand in a mature market using a diffusion model. That dynamic effects need to be incorporated into static multiattribute utility models is less obvious. Silverman [1982] gives strong circumstantial evidence for a life cycle effect at the brand level for autos when she finds that Bass's model gave satisfactory fits to eleven out of nineteen autos for which it was tried. An example of this effect is provided by the monthly sales of the Ford Granada, illustrated in Figure 1.1

The modeling approach taken in this thesis to include the benefits of both multiattribute models and diffusion models, and to capture the phenomena which they explain, is to use a decision analysis expected utility framework. Through the intermediate construct of uncertainty or

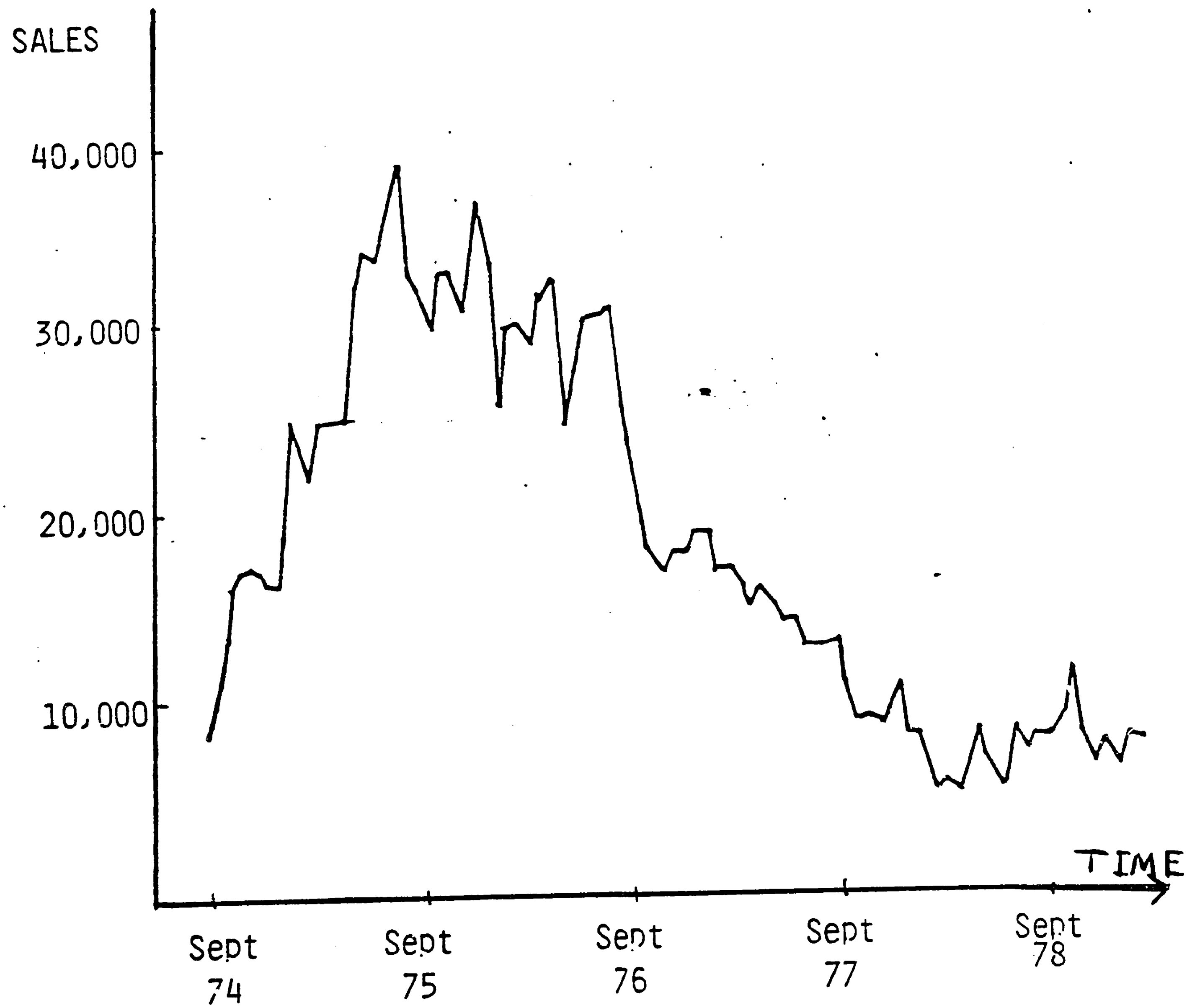

Figure 1.1 Monthly Sales of the Ford Granada 1974-1978 (U.S.)

perceived risk, increasing penetration is hypothesized to generate more word of mouth and thus reducing uncertainty about the product. This increases its expected utility, and can be modeled in a multiattribute framework. We assume that the consumer updates his beliefs about the brand's mean value and his uncertainty of it in a Bayesian manner.

The measurement approach taken to enable such a model to be estimated consisted of getting multiattribute evaluations of the new brand under different simulated levels of penetration (or information availability) based on market research measures gained in a laboratory environment.

1.3.3 Modeling Framework

The approach used to model sales of the brand of interest, N, is a conditional probability one at the individual level. Sales of brand N depend on its consideration by a potential consumer, a category purchase, and the preference of brand N over other considered brands. Thus, at any point in time, a consumer has a set of brands which he or she would consider, C. In deciding whether to buy a durable or not, the consumer does a mental scan of his current consideration set. Work by Day and Deutscher [1982] and Stewart and Punj [1982] suggests that consumers do have a consideration set and perceptions of price and value expected, even before search (although these may change during the search process). The existence of this consideration set is empirically tested in the study associated with this research.

The representation of the brand purchase decision as a category purchase decision followed by brand choice within the category, is commonly accepted in marketing (e.g., Kotler [1980, p. 151], Warshaw [1980, p. 27]), and has been found to give useful results empirically (e.g., Guadagni [1983], Kalish and Lilien [1983]).

This type of model, based on an explicit behavioral hypothesis, is termed a hierarchy of choice structure by Ben Akiva and Lerman [1977]. Since we are attempting to build a predictive model, we do not need to claim that consumers actually go through this process. All that is required is that their behavior may be represented by the model. The use of this hierarchical choice structure permits the development of three different models for consideration, category purchase, and brand choice. These models are called block conditional (Ben Akiva and Lerman [1977, p. 16]).

In mathematical terms the conditional probability model may be written:

$$P_N = P_{CBN} = P_C \cdot P_{B|C} \cdot P_{N|C,B} \qquad (1.1)^1$$

where

P_N = Probability of buying brand N for an individual.

P_{CBN} = Joint probability of considering brand N, buying within the category, and preferring brand N

P_C = Probability of considering brand N.

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1 Note that a complete summary of notation is given in Appendix A.

$P_{B|C}$ = Conditional probability of buying within the category for those consumers who consider brand N.

$P_{N|C,B}$ = Conditional probability of preferring brand N, given that it is considered, and a category purchase is made.

Diagramatically, the conditional probability formulation may be represented as follows:

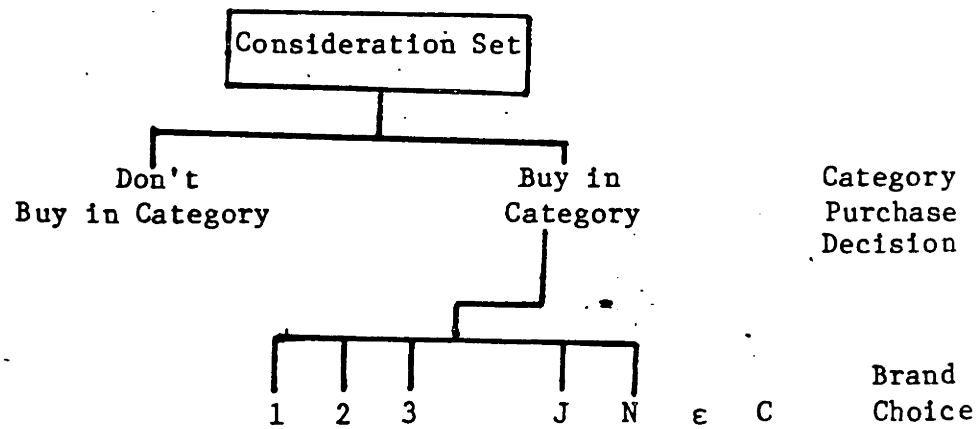

Figure 1.2. Choice Hierarchy for New Durables Purchase.

The utility of purchasing brand j consists of a number of elements specific to j, for example, attributes which it possess not possessed by other brands. It also consists of elements not necessarily specific to j, for example, the disutility of search. If that disutility is the same for all brands, then it may be considered at the category purchase level of the hierarchy rather than having to be considered individually for each brand. This is an example of additive separable utility (Ben Akiva and Lerman [1977, p. 15]).

Formally, durable purchase is said to have additively separable utility if, at different levels of the decision hierarchy, say I and J, the utility of choosing brand j at level J from group i at level I above it, may be expressed:[1]

$$U_{ij} = U_i + U_{j|i} \tag{1.2}$$

where

U_i = that part of utility which is independent of brand choice and,

$U_{j|i}$ = residual utility, i.e., utility of j given that i is chosen at level I.

In the application in this thesis, the form of the separable utility function, equation (1.2), is more specific:

$$U_{Bj} = -C_B + U_{j|B} \qquad \text{(For } j \varepsilon C\text{)} \tag{1.3}$$

where

U_{Bj} = utility gained from buying a durable and choosing brand j.
$-C_B$ = negative utility associated with search and transaction costs (that part of the utility derived only at the durable brand level), and
$U_{j|B}$ = utility of brand j (net of price), given that it is bought.

The relationship between levels in the hierarchy may be gained by considering the utility-maximization process which the consumer undergoes at each level. For example, at the category purchase level in Figure

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1 Note that this definition, used by Ben Akiva and Lerman [1977], varies somewhat from that of Blackorby, Primont, and Russell [1975] who describe a number of separability conditions.

1.2, the consumer will purchase within the category if the expected maximum utility of the right-hand branch exceeds that of the left-hand branch. The expected maximum utility of the right-hand branch comes from equation (1.3):

$$E(\text{Max } U_{Bj}) = -C_B + \underset{j}{\text{Max}}\, E(U_{j|B}) \tag{1.4}$$

Given distributional assumptions about the utilities, the probability of category purchase may be determined. An example of this procedure for Weibull-distributed errors is given in Section 4.5.

Consideration set determination is not included as a level in the hierarchy because possible consideration sets tend to be overlapping and extremely numerous. Methods of treating consideration are proposed in Section 4.5.

1.4 Structure of the Thesis

This thesis describes the development of a brand choice model and how it has been applied in practice. Chapter 1 outlines the nature of the managerial and management science problem in forecasting brand preference. It then proceeds to develop a modeling framework in which brand choice can be identified as one component in the sales of the new brand.

Chapter 2 reviews the literature in the field of durable forecasting, drawing particularly on work in diffusion theory, multiattribute utility, and perceived risk to motivate the model. The model is developed in Chapter 3 under three headings: theory, measurement, and estimation.

An application of the model to the sales of a new automobile is detailed in Chapter 4. A specific model and appropriate measures are developed and then the assumptions necessary to fit the model are discussed. After the presentation of results, we give an indication of how other elements in the forecasting methodology interface with the brand share model.

Chapter 5 summarizes experience with the approach to date and discusses promising areas for future research.

CHAPTER TWO: LITERATURE REVIEW

2.1 Overview

The aim of the literature review is to classify and review research techniques which have been applied to the forecasting of consumer durables, and also other forecasting techniques which have potential application to the development of a methodology for prelaunch prediction. Thus the review covers models such as ASSESSOR (Silk and Urban [1978]) despite its application to frequently purchased goods, because substantial elements of the model offer insight into measuring consumer durable demand. The emphasis is on models of brand choice given purchase incidence, but models which forecast brand sales directly will also be considered.

The review only covers those methologies that are "quantitative" in nature, that is, which use management science techniques for at least part of their forecast generation. Makridakis and Wheelwright [1977] provide an excellent classification of methods which they term qualitative (including decision trees, salesforce estimates, juries of executive opinion (Delphi), exploratory, and normative techniques). Chambers, Mullick and Smith [1971] give an example of the application of these qualitative techniques to the Corning Company and illustrate the use of different methods at differing stages of the product's life cycle.

There are many different ways in which to classify new product forecasting techniques. For example, Wind [1981] suggests eight dimensions: purpose, type of product, units of analysis, format of model, dependent variable, independent variable, required data and analytical procedures. Green and Srinivasan [1978] found it useful to use six criteria to categorize conjoint techniques. Because of the specific nature of the problem addressed by this thesis, two dimensions will suffice to group different methods. Those are format of the model and data collection techniques.

Within each of these, a number of sub-classifications is possible. For example model types could be divided stochastic/deterministic and data collection techniques individual/aggregate. The most useful classification however, which tends to group papers of a similar focus together, is as follows:

Format of the Model		Data Collection Technique
Diffusion models	X	Analogies/DSS/Judgement
Utility models		Exposure to concepts
		Prototype/Field trial
		Early sales data

This split of new consumer durable forecasting methods into diffusion models and utility models represents the two major traditions in the field. It also corresponds quite closely to Wind's [1981] distinction between adoption process models (which have the consumer as their focus) and diffusion-type models (which have the product and its life cycle as the focus). However, the categorization does not represent a perfect fit and boundaries are not always well-defined. The difference between diffusion models and utility models is one which appears to be narrowing. Because they represent the two main traditions in durable forecasting it is interesting to examine their different bases. The foundation of diffusion models comes from epidemiology and rural sociology (e.g. Rogers and Shoemaker [1971]) while utility models have been developed with a different emphasis, grounded in economics, psychology, and decision theory. The essence of diffusion models is a growth curve, that is, univariate analysis or curve fitting. Efforts have been successfully made to model the parameters of such curves in terms of marketing mix variables but the basis remains. Conversely, Lancasterian utility theory is fundamentally multivariate. Component attributes form the core of the theory.

Diffusion is primarily concerned with the dynamic nature of product choice while utility theory has concentrated largely on comparative statics.

Both traditions offer valuable insights; the dynamics of diffusion and the normative ability and descriptive validity of utility models. One possible way to link the two is by the construct of perceived risk or uncertainty; an area attracting considerable attention in both traditions (e.g., Kalish [1982] and Jeuland [1983] incorporate uncertainty into diffusion models while Pras and Summers [1978] introduce perceived risk into a linear compensatory model). Thus, a review of the literature on perceived risk is included as a link between the two schools (Section 2.3).

Data collection may be considered according to level of aggregation of the data (individual or population) or by how early the data is collected in the product development process. Table 2.1 gives an example of how techniques may be classified according to level of aggregation of the data.

	Models of Individual (Data on Individuals)	Models of Population (Aggregate Measures)
Oriented to individual adoption process ("Utility Models")	Attitude/Evaluation models (e.g., Berkowitz and Haines [1982]	Econometric models (e.g., Chow [1956])
Oriented to products' diffusion ("Diffusion Models")	Sociometry (e.g., Coleman et.al. [1957]	Diffusion Models (e.g. Bass [1969]

Table 2.1 Relation of Consumer/Product Model Orientation to Level of Data Collection

Wind [1981, p. 11] usefully classifies data collection techniques by "what people say, what people do, and what people have done." However, more than one technique is often used within the one model, blurring the distinction. Table 2.2 shows a summary of the studies considered in this literature review classified by the primary model used and the data collection method. Data collection methods are divided into: analogies to other products; management/researcher judgment; concept evaluation; prototype or field trial; and use of early sales data.

METHOD	ANALOGIES	DSS/JUDGMENT	CONCEPTS	PROTOTYPE FIELD TRIAL	EARLY SALES DATA
DIFFUSION MODELS (See Table 2.3 for Taxonomy of Methods)					
Bass		Lawton & Lawton [1979]	Hauser [1978]	Lawrence & Lawton [1981] Dodds [1973]	Bass [1969] Nevers [1979] Heeler & Hustad [1980] Silverman [1982] Chow [1967] Bass [1980] Horsky & Simon [1979] Grilliches [1957]
Generalizations of Bass[1]					Mahajan & Peterson [1978] Kalish & Lilien [1983]
Multi-State Diffusion Models (including Macro Flow Models)			Hauser & Wisniewski [1982b]		Mahajan & Peterson [1978] Kalish [1982] Midgley [1976] Urban [1970] Blattberg & Gollanty [1978]

Table. 2.2 Empirical Studies of New Product and other Sales Forecasting Techniques: Classified by Modeling Method and Data Collection Technique. (Part A: Diffusion Models)

1 This table only describes applications of forecasting techniques. Theoretical developments in diffusion models are described in Table 2.3 Thus Jeuland's [1983a, 1983b] contributions to diffusion theory are not included because they are yet to be applied.

METHOD	ANALOGIES	DSS/JUDGMENT	CONCEPTS	PROTOTYPE FIELD TRIAL	EARLY SALES DATA
UTILITY MODELS (See Table 2.3 for Taxonomy of Methods)					
Traditional Utility Models					
Aggregate[1]	Crow and Ratchford [1975]				
Order of Acquisition[2]					Kasulis et al [1979]
Multi-Attribute Utility Modeling[3]					
von Neuman-Morgenstern			Hauser & Urban [1979]		
Perceptions/Preference/Choice	Berkowitz & Haines [1982]		Jain et al [1979] Hauser & Simmie [1981] Tybout & Hauser [1981] Green & Wind [1975]	Silk & Urban [1978] Urban [1975] Ryans [1974]	

Table. 2.2 Empirical Studies of New Product and other Sales Forecasting Techniques: Classified by Modeling Method and Data Collection Technique. (Part B: Utility Models)

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1 Other aggregate econometric models on an established product (autos) include Carlson and Umble [1980], Chow [1960], and Suits [1958, 1961].

2. Other order of acquisition chain studies on established products include Paroush [1965], Brown et al [1965], McFall [1968], Beckwith and Lehman [1980], and Clark and Soutar [1982].

3. Discrete choice models on existing product categories and durable types include Dubin and McFadden [1982], Goett and McFadden [1982], and Berkovec and Rust [1982].

2.2 Major Modeling Traditions Used to Forecast Durable Sales

The previous section outlined a rationale for considering models under the headings of diffusion and utility. This section consists of two subsections which review models of those two types.

Section 2.2.1 introduces diffusion theory briefly (2.2.1.1) before discussing its relevance to the product life cycle (2.2.1.2). Bass' model [1969], outlined in 2.2.1.3, serves as a benchmark for other diffusion models. After a review of the model, its applications, and criticisms of it, extensions are considered. Multi-State Diffusion Models and Macroflow Models are briefly reviewed in Section 2.2.1.4. A summary table of diffusion models is given in Table 2.3.

Utility models are developed in Section 2.2.2, first by considering traditional economic interpretations and recent work by Hauser and Urban [1982] to extend and operationalize them. Empirical studies at the aggregate level are also included. From there, multiattribute utility models are described together with their roots in economics, decision theory, and psychology. Different forms of models of choice, probability and preference on attributes are discussed and applications reviewed.

Section 2.2 completes the review of methods used to forecast demand. A further section (2.3) on perceived risk is included because that construct provides an important link between the two forecasting traditions.

2.2.1 Diffusion Models

2.2.1.1 Introduction. Rogers and Shoemaker [1971, p. 7] define diffusion as "the process by which new ideas are communicated to members of a social system." From this definition, three elements can be identified: the innovation, adoptors, and the process by which the two are brought together. The diffusion phenomenon is usually associated with an upward S-shaped curve of cumulative adoption with respect to time.

There is a rich literature on the characteristics of innovations, members of the adopting population, and the social structure in which the process is embedded, that promote or retard the diffusion process. While useful in marketing, much of the research embodied in the literature comes from the fields of anthropology and sociology and thus must pass an external validity hurdle before being accepted as marketing lore.

Characteristics of the Innovation. The pioneering work of Rogers and Shoemaker [1971], and before that Rogers [1962], has guided much of the research into characteristics of the innovation which shape the diffusion process. They suggest five factors are important in determining the rate and extent of a new product's diffusion. They are: Relative Advantage, Complexity, Compatability, Observability, and Trialability. To these, marketing researchers who have studied the correlates of successful innovations have added perceived risk (e.g., Ostlund [1974], La Bay and Kinnear [1981].

Rogers and Shoemaker [1972, Appendix A] find mixed evidence that their five factors affect the rate of adoption (each receiving support in 60-80% of studies conducted). A number of reasons can be advanced for this. One is lack of uniformity of definitions. The studies are conducted across a variety of disciplines. Another problem is simplicity in the development of constructs. For example Hebb and Leuba's optimal stimulation level (Raju [1980]) would suggest that rate of adoption with respect to complexity should be U-shaped rather than linear. And a final problem with a number of the studies is experimental design, constraints imposed by cross-sectional analysis, and lack of experimental conditions.

<u>Level of Innovativeness in the Adopting Population.</u> Rogers and Shoemaker [1971, p. 27] define innovativeness as "the degree to which an individual is relatively earlier in adopting new ideas than other members of his system." That definition and its philosophical basis have guided most of the research into individual adoptor characteristics. Measures of innovativeness have been based either on the time taken to adopt or the bundle of durables held at a specific point in time (see Midgley and Dowling [1978, p. 280] for a summary).

On the basis of time of adoption, Rogers and Shoemaker divide the population into five groups: innovators, early adoptors, the early majority, the late majority, and laggards. This is illustrated in Figure 2.1.

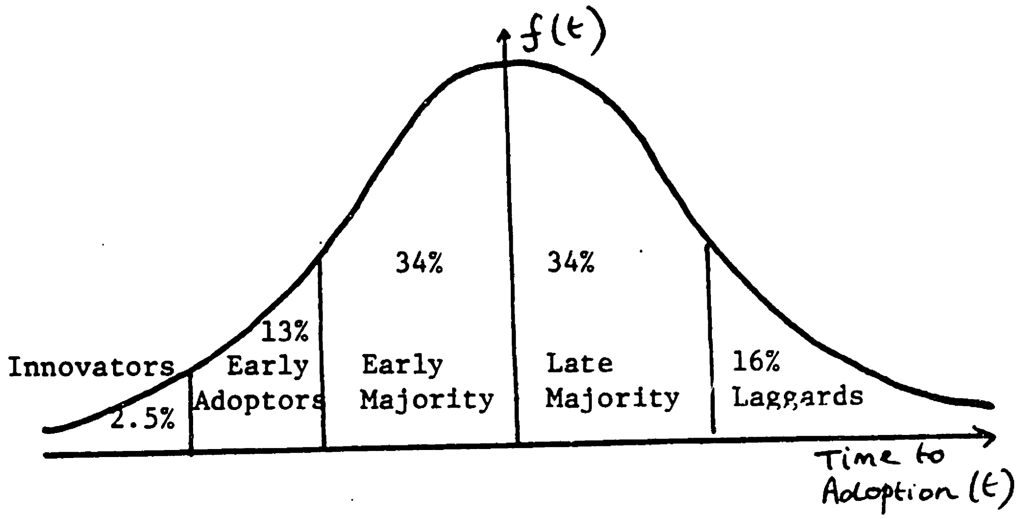


Figure 2.1 Roger and Shoemaker's [1971] classification of adoptor categories.

Rogers and Shoemaker provide 32 "generalizations" about the demographic and psychographic profiles of early adoptors by summarizing available diffusion studies. The level of support for these generalizations varies from 47% of studies surveyed to 100%. In the marketing literature, there is also mixed evidence. (See Robertson [1971] for a summary.) Robertson suggests that even the mixed results in his survey could be upwardly biased by the tendency only to publish statistically significant results.

Midgley and Dowling [1978] cast a shadow on much of the innovativeness work in marketing and other fields. They suggest that because most studies do not control for precocity, that is, when the adoptor learned of the innovation, what is measured is a mixture of social connectedness and innate innovativeness.

<u>Process of Diffusion Through the Population.</u> There is considerable evidence that word-of-mouth communications and direct observation play a

role in generalizing the S-shaped diffusion curve of cumulative sales over time. Perry and Ham [1959] found verbal influence more important for color TV's and autos (whose attributes may not be visually apparent) and observation more important for home furnishings. Midgley and Dowling [1978, p. 233] argue that diffusion effects are more important for durables than non-durables and cite six marketing studies to demonstrate its significance.

Turnbull and Meenaghan [1980] suggest that interpersonal influence and product-related discussions will be important when:

(1) the project investment is high;

(2) the level of objective information surrouding the product is low;

(3) the product has significant social or symbolic value; and

(4) perceived risk is high.

The question arises as to whether awareness and consideration are dichotomous, with an individual either being aware or unaware. The alternative is that there are levels of awareness and each contact with an adoptor increases this awareness. Little research has been addressed to this issue, although for solar systems Leonard-Barton [1980, p. 9] found number of adoptors known to be the single most important determinant of adoption intentions. Thus probability of adoption may increase with penetration not only because the probability of coming in contact with an adoptor increases (as proposed by the contagion models underlying much of the mathematical modeling of diffusion processes), but also because of the cumulative effect of contacts on a susceptible member of the population.

<u>Diffusion Models and The Product Life Cycle</u>. A long held, though controversial, theory in marketing is that product categories go through life cycles involving distinct stages: introduction, growth, maturity, and decline (e.g. Levitt [1965]). The evidence for this is mixed, with Cox [1967] discovering six different types of cycle for 754 ethical drugs and Polli and Cook [1969] finding that only 34% of changes in sales were significantly different from a random model at the 1% level for 140 products and product classes.

Diffusion models are normally applied to the penetration of a new product into the market at the introduction and growth stages of the product life cycle. Most, but not all, models limit their domain to a period before repeat sales occur (e.g. Bass [1969, p. 217]). This makes them less vulnerable to many of the criticisms of the product life cycle, most of which center around the inevitability of the decline stage (e.g. Dhalla and Yuspeh [1976]). Most diffusion models also do not consider competitors but rather model the whole product category. This removes criticisms of the application of product life cycle analysis to brands (e.g. Kotler [1980, p. 292]). One remaining objection to product life cycle analysis and also diffusion models is that growth may never come. Support for this may be found in the sensitivity of Heeler and Hustad's results to early sales data [1980] discussed later in this section.

There have been attempts to fit the entire product life cycle of both brands and product categories (e.g., Brockhoff [1967]). Rink and Swan [1979] in a survey of such models, suggest that fits to the post-growth phase are considerably worse than such models' fits in the early stages of the product life cycle. This is not surprising since the factors which cause the decline are often external to the sales history (for example, new technologies and competition).

Life cycle analysis is primarily an extrapolative, time series technique and thus is not appropriate when exogenous factors are important determinants of sales. Because competitive entry and marketing strategy can have a profound effect on brand's sales, product life cycles have had more success at the product category level or for a monopoly brand. This same constraint has tended to bind diffusion models.

In summary, it may be said that diffusion models represent an attempt to model the introduction and growth phases of the product life cycle. In restricting their attention to a period before repeat sales and decline, they avoid many but not all of the criticisms leveled at product life cycle models.

2.2.1.3 Bass' Diffusion Model

Description of the Model. Mathematical diffusion models have been adapted from those in epidemiology to explain the spread of new products throughout a potential market. Typical of these is Bass' model [1969] which has received more attention than any other and which subsumes a number which preceded it. Bass' 1969 Management Science article gives a rationale for the model and also empirical results.

The model suggests that sales $(\dot{y}_t)$[1] depend on the untapped market $(m - y_t)$ and the likelihood of an individual purchasing, given that he has not already done so. This in turn depends on a diffusion effect, that is it increases with increasing penetration. Bass assumes this effect to be linear (see Jeuland [1983a] for a justification).

Thus

$$\dot{y}_t = (p + q\frac{y_t}{m})(m - y_t) \tag{2.1}$$

where y_t is cumulative sales and m the market potential. The parameter p is called the coefficient of innovation and q the coefficient of imitation. p represents the proportion of the population which adopts independent of external communication and q those that are influenced by the increasing penetration. Jeuland [1979] points out that, as formulated, Bass' model is deterministic. That is, y_t is assumed to be the actual number of sales in time t, whereas according to Bass' interpretation of $p + qy_t/m$, it should only be the expected number of sales. Jeuland derives the result for the stochastic model which does not yield the same solution as Bass and shows the difference to be "not insignificant."

1 The symbol y_t is used for cumulative sales in the Literature Review, consistent with Bass and other researchers. Thus, $\dot{y}_t$ is the first derivative of cumulative sales and is also used to represent sales in a discrete time period. In Chapter 3 Y_t is used for cumulative sales to avoid confusion with attribute ratings.

Closed form solution is possible for Bass' model. Sales as a function of time may be expressed as follows:

$$\dot{y}_t = \frac{mp(p+q)^2 \; e^{(p+q)t}}{(pe^{(p+q)t} + q)^2} \tag{2.2}$$

Cumulative sales (y_t) may be written

$$y_t = \frac{me^{(p+q)t} - 1}{e^{(p+q)t} + \frac{q}{p}} \tag{2.3}$$

which is a logistic curve in time.

Special cases of Bass occur when $p = 0$ which corresponds to a model developed for industrial applications by Mansfield [1961]. The resultant curve is still logistic, but an artificial seed is needed to start the process. When $q = 0$, the imitation effect is zero and an exponential curve results. This is equivalent to a model used by Fourt and Woodlock [1960]. Typically $p << q$ in marketing applications, thus soon after the process is started (that is, y_t/m becomes large relative to p/q), the effect of p is negligible.

The diffusion effect is posited to arise from a number of causes. These include increases in awareness (Kalish [1982]), reduction in uncertainty (Sheth [1968]) and the need for social acceptability (Bass [1969], Nevers (1972]). Additionally, penetration can enhance utility by creating a service infrastructure, networking (e.g. a phone is more useful the more people that have one), and new uses. A simpler explanation of the diffusion effect has been proposed by Russell [1980]. He suggests that traditional economics is quite capable of handling "diffusion" phenomena. He notes that prices normally fall as innovations penetrate and the approximately log normal distribution of income in the community leads to a distribution of reservation prices which generate an S-shaped sales curve as price falls.

Applications of Bass' Model

Applications of Bass' model consist largely of curve fitting excercises on the early years' sales of a number of durables. In his paper Bass examines eleven appliances. All models but one have an R^2 of between .47 and .95 and Bass claims good predictive performance. Applications by Nevers [1972] and Dodds [1973] lend further empirical support to Bass's model using "early" sales data on 13 series.

Nevers applied the model to data relating to 12 product categories and was well satisfied with the fit. It is worth noting that there was an average of eleven years data for each series. Summary statistics were good and peaks were identified accurately with respect to timing and size. However, with the exception of one series his data extend past the peak sales. Nevers makes the excellent point that new products may change in nature significantly in the introductory phase and this may present a confounding effect.

In an interesting application at the brand level, Silverman [1982] fit Bass' model to the nineteen life cycles of nine auto models (including a number of relaunches) using monthly data. Eleven out of nineteen showed significant fits. Of the remainder, some had poor fits while a number of others had large outliers. This is not surprising given the sensitivity of a brand's sales to gas prices, the state of the economy, and competitive offerings, factors not included in the Bass model.

A number of attempts have been made to impute model parameters prior to launch. Eastman Kodak has adopted a method developed by Lawton and Lawton [1979] in which the imitation parameter ,q, is estimated prior to launch from those of similar established products. m is estimated subjectively using managerial judgment. And p may be found as a function of first year sales or also judgmentally before then. In a later paper, Lawrence and Lawton [1981] suggest the use of market research to get better estimates of the parameters, again before launch. The Bayesian updating of parameters would seem to best use early sales data as it becomes available.

Lawrence and Lawton add an interesting twist by suggesting that the model can be "restarted" every time an enhancement to a product occurs. The customer appeal of the enhancement is determined from market research and then the model is rerun with a new $\tilde{m}$ (and no loss of diffusion goodwill y_t/m). They claim excellent results on 30 practical applications (p. 531) but report no data.

Hauser [1978] in a study of narrow band TV also suggests that q may be imputed from other products. He estimates p from market research by examining the situational appeal of the innovation times an innovativeness composite. m is derived using a top-box technique on preference and intent to try. That is, it is assumed that 80% of first preferences and 20% of second preferences will go to the innovation, while 75% of the "definitely will try" respondents would, 30% of the "probables," and 10% of the "mights." Thus, an estimate of the diffusion of the product, as formulated, is available at the concept stage.

Criticisms of the Bass Model

Criticisms have been levelled at the Bass model both at an empirical level and also with respect to interpretation of the diffusion process.

In a critical review of the forecasting ability of the model, Heeler and Hustad [1980] report fits to seven further U.S. annual appliance sales histories as well as those from up to 15 countries for 15 different durables. They conclude that the temporal stability of Bass' model is not good unless data are included past the sales peak, that Bass' estimates of p,q, and m are biased, and that though the model fit series extremely well ex post it was difficult to use as a forecasting tool. Fits on international data were not as good as those on American data. While forecasts were good after the peak, this is cold comfort since at that stage forecasting by any method is easier and also replacement sales tend to confound the data and the marketplace.

A related criticism was made by Bernhardt and MacKenzie [1982] who suggested that Bass' "successes have been due to judicious choices of situation, population, innovation, and time frame on analysing the data. These choices have been made post hoc. They have been made for successful innovations."

Jeuland [1983a] points out that

> "The problem of interpretation of Bass' model lies in the fact that the equations
>
> $$P(T) = p + \frac{q}{m} y_t \text{ and } \dot{y}_t = (p + \frac{q}{m} y_t)(m - y_t)$$
>
> do not by themselves formally define the dichotomy innovators/imitators with which Bass at times describes the model. In fact, even if p were related to the size of the innovator group, it is not clear that this would be very useful since there is no operational definition of the innovator group (the 2.5% cutoff point of Rogers is arbitrary as pointed out by Bass)."

2.2.1.4 Extensions to Bass' Model.

A number of extensions to Bass' model have been proposed to remove the criticism that it is not responsive to environmental changes and variables under management control. These may be considered under the headings of (1) Increasing the Model's Normative Application (introducing price and advertising); (2) Modeling the parameters; p, q, and m (in terms of population characteristics); and (3) Generalizations of the Model.

Increasing the Model's Normative Application. Early work to incorporate the effects of adversiting and price is well summarized by Mahajan and Muller [1979] and will not be reviewed in depth here.

Early attempts to incorporate price (p_t) may be briefly summarized by noting that a price factor ($D(p_t)$) was multiplied by the probability of adoption, thus giving sales of

$$\dot{y}_t = (p + \frac{q}{m} y_t)(m - y_t)D(p_t) \tag{2.4}$$

Bass [1980] assumed the form of $D(p_t)$ to be $D(p_t) = p_t^{\varepsilon}$, while Robinson and Lakhani [1975] and Dolan and Jeuland [1981] considered $D(pt) = e^{-\beta p_t}$. Jeuland [1979] points out that one of the shortcomings of both of these formulations is that neither allows the price to affect the ultimate population size, m.

Horsky and Simon [1979] incorporated the effects of advertising into their model by assuming that the parameter p is a function of advertising, specifically:

$$p = a + b \log A$$

where a and b are parameters, and A is advertising.

<u>Modeling p, q, and m in Terms of the Population's Characteristics.</u> In a pioneering work on hybrid corn, Grilliches [1957] fit a logistic model to the 31 corn-growing states separately. This allowed him to perform a cross- sectional analysis on his diffusion parameters. He modeled the time till "take-off" (10% penetration) and found that this depended largely on supply factors (or the attractiveness of the area to producers). However both the rate parameter (p + q) and the ultimate population size, m, were extremely closely related to the average size of the farm, the yield increase expected, and the a priori yield. Fits of m and (p + q) on these variables across geographic regions had R^2s of .89 to .99. The variables used were similar to those used in the diffusion literature in sociology and marketing. For example, Arndt [1968] found that heavy users are early adoptors, while the work on relative advantage as an adoption determinant has already been discussed.

Another economist to apply product attributes as a determinant of diffusion parameters was Chow [1967]. Although he fit both Gompertz and logistic curves he reports primarily on the former because of the better fits. His rationale for including explanatory variables has a strong econometric base. Bass's model with q = 0 may be written

$$\dot{y}_t = p(m - y_t)$$

or with p = 0

$$\dot{y}_t = q\, y_t(m - y_t)$$

The differential equation specifying a Gompertz curve may be written

$$\frac{d(\log y_t)}{dt} = q(\log m - \log y_t)$$

All three of these are of the form of a stock adjustment model for which the standard treatment is to model the "desired" stock as a function of economic variables (Cagan [1956]).

Chow's formulation of $m(t) = a - bp_t$ is proposed after finding that price changes were almost perfectly correlated with performance changes over the period and thus there was collinearity in including both price decreases and quality increases in the model. He obtained excellent fits to his model and price was a significant predictor of market size.

Generalizations of the Bass Model

A number of generalizations of the Bass model have recently appeared. These include work by Jeuland to allow non-constant probabilities of adoption within the population (Jeuland [1983a]), by Kalish and Lilien [1983] to model brand share as well as industry diffusion, and by Jeuland [1983b] to incorporate the effect of diffusion of information on the perceived risk of a product. The latter two are relevant to this thesis and will be briefly described.

Kalish and Lilien use a diffusion model to represent industry sales:

$$\dot{y}_t = (m(p_t) - y_t^*) \cdot \frac{e + aA + bW}{1 + aA + bW} \tag{2.5}$$

where

y_t = sales in time t

$m(p_t)$ potential market at price p_t, $= m_o e^{dp_t^c}$

y_t^* = cumulative sales, after allowing for attrition (replacement)

A = sum of past advertising, exponentially discounted

W = sum of past sales, exponentially discounted.

e, a, b, m_o, d, c are parameters.

Equilibrium <u>share</u> of industry sales is then predicted with a nested logit model using three levels of nesting: price range, company, and brand. Product characteristics, company image, price, and advertising are used as attributes. Dynamics at the brand level are introduced by assuming that market share next period will be a weighted average of market share this period and equilibrium market share predicted by the logit model.

The model gives very good fits ($R^2 = 0.995$) although the parameters e and a are not statistically significant. The model is an appealing method of combining diffusion at the brand and industry levels. It does not, however, allow feedback between the brand share model and the industry sales model in terms of the repositioning of any brand. From equation 2.5, above, only price, advertising, and cumulative sales affect industry sales. It also requires sufficient historical sales data to allow the estimation of its ten industry-level parameters and however many logit parameters are used. Some of these may be able to be estimated using management judgment (and were in Kalish and Lilien's application).

Jeuland [1983b] takes Schmalensee's pioneering brand framework to incorporate information uncertainty into a diffusion model. Schmalensee [1982] assumed that

(1) that a product is either of value v or kv and the consumer has some uncertainty ($P_v = 1-\pi$, $P_{kv} = \pi$);

(2) that uncertainty may be totally removed in one step (Schmalensee suggests by trial, Jeuland by word-of-mouth communication);

(3) consumers are risk neutral; and

(4) there is a distribution of reservation prices throughout the population $m \cdot Q(p)$, where $Q(p)$ is the proportion of the population for whom the expected value exceeds p.

Given this framework, Jeuland shows that

$$\dot{y}_t = (Q(p) - Q(\tfrac{p}{\lambda})) . I(t) \qquad (2.6)$$

where $\lambda = 1 - (1-k)\pi$. Note that the expected value to the consumer is

$(1-\pi)v + \pi kv = \lambda v$. $I(t)$ is the proportion of the population totally informed about the product. $I(t)$ is given by

$$I(t) = \frac{m e^{\beta m t}}{e^{\beta m t} - 1 + Q(\frac{p}{\lambda})^{-1}} \tag{2.7}$$

Jeuland also considers the effect of price changes over time.

The model is interesting because it explicitly incorporates information uncertainty into a diffusion model in a rigorous way. Its application to the practical forecasting of a number of durables is limited by the restriction of total learning in one step, homogeneity of perceptions of value, lack of inherent product unreliability, and risk neutrality. However, it provides the first analytical framework to incorporate information uncertainty into a diffusion model.

It is worth noting that the "risk reduction" driving the model occurs because of a change in the mean expected level of the product, not due to any risk aversion. Before information, the product has expected value $\lambda v < v$. After information, it has value v. The consumer was specifically defined to be risk neutral.

2.2.1.4 Multi-State Diffusion Models

Bass' model may be thought of as a two-state transition probability model in which adoption is a trapping state and the probability of transition is a function of the number of people in the two states. A number of authors have extended diffusion models to more than two states. For example, Mahajan and Peterson [1978] in a three-state model, allow diffusion from the population into the market potential and then diffusion from the market potential to adoption to allow dynamic populations. Kalish [1982] allows diffusion from unaware to aware and from aware to adoption to account for consideration. Dodson and Muller [1978] use the same framework to allow repeat sales (flows of adoptors to aware and unaware). Finally, Midgley [1976] has four states: unaware, aware (passive), active adoptor, and active rejector to allow a negative diffusion process to take place simultaneously.

When viewed as transition state models, these multistate diffusion models are generally related to Urban's SPRINTER framework (Urban [1970]). In its most sophisticated form, the model uses 77-states with some five hundred equations detailing movement between states, demonstrating the level of detail that can be incorporated using a transition state approach. SPRINTER III considers the effects of advertising, sampling, couponing, word of mouth, and availability in the purchase decision. Consumers are also classified according to brand loyalty and depth of repeat. The level of complexity of the model can be tailored to the requirements of the situation. Urban and Karash [1971] point out how a three-state model can evolve continuously to a more complex one. Hauser and Wisniewski [1982a, p. 459] note:

> "Although he combines data from panels, questionnaires, and store audits, Urban's model requires a large number of non-stationary parameters which put a strain on data resources. Furthermore the flows are estimated independently and period by period and thus do not make full use of the stochastic properties of the Markov model."

Hauser and Wisniewski [1982a] also allow transition state probabilities (including self flows) to be (linear) functions of marketing mix variables. The probability of a transition is modeled as

Erlang or exponential to capture the "purchase" incidence element. They are able to derive closed form solutions for cumulative awareness, cumulative trial, penetration, expected sales and purchases due to promotion. The incorporation of word-of-mouth communication suggests that this model could also be considered a diffusion model.

An application of the model to travel mode choice is reported on Hauser and Wisniewski [1982b]. The model is illustrated below in Figure 2-2. Perceptions in the four left boxes are assumed to influence preference which together with intervening factors (direct mail, publicity, word of mouth communication, availability, transport as a perceived percentage of the household budget, and Neslin's preference inertia) determine state to state flow rates. In the final model word of mouth, budget allocation, and preference inertia were deleted due to lack of significance. The model fit reasonably well ($R^2 = .82$) and had a correlation of .94 with ridership.

AUTHOR	FUNCTION FORM	COMMENT
Bass-Based		
Bass [1969]	$y_t = (p+qy_t/m)(m-y_t)$	Benchmark
Fourt and Woodlock [1960]	$y_t = p(m-y_t)$	Bass with q=0
Mansfield [1961]	$y_t = qy_t/m(m-y_t)$	Bass with p=0
Hermes [1976]	$q = q_1{}^t, p = p_1{}^t$	Bass with decay
Price Incorporation:		
Chow [1967]	$m = m(pr)$	Gompertz and Bass
Robinson and Lakhani [1975]	$p = p'\exp(\beta pr), q = q'\exp(\beta pr)$	$m = m(pr)$
Dolan and Jeuland [1981]	$p = p'\exp(\beta pr), q = 0$	$m = m(pr)$
Bass [1980]	$p = p'pr^{-\epsilon}, q = q'pr^{-\epsilon}$	$m = m(pr)$
Advertising and Sales Effort:		
Horsky and Simon [1979]	$p = a + b\log(\text{Advert})$	
Lilien and Rao [1978]	$p = a + bS + cS^2$	S = Sales Effort
Position variables (not dynamic):		
Grilliches [1957]	$q = q(\pi), m = m(\pi)$	π = Relative advantage
Hurter and Rubenstein [1978]	$q = q(\pi), p = 0$	π = Profit
Hauser [1978]	$m = m(\text{Position})$	from logit analysis
Generalizations of Bass		
Peterson and Mahajan [1978]	$y_t = (p+qy_t-q'y_t')(m-y_t)$	y_t': Competitive sales
Jeuland [1981a]	$y = (p+qy_t/m)(m-y_t)S_i$	S_i: Beta through population
Kalish and Lilien [1983]	$y_t = f(y_t^*, \text{Adv}), (m(pr)-y_t^*)$ (y^* = discounted past adoptors)	Industry diffusion; Brand logit
Multi-State Diffusion Models		
3-State Dynamic Populations:		
Bernhardt & MacKenzie [1972]	$m(t) = m(0)e^{\alpha t} + \lambda m(t-1)$	Entry and exit
Mahajan and Peterson [1978]	$m(t) = [a+bm(t)][P-m(t)]$	Double Bass
3 & 4 State, Unaware/Aware/Adoptor Models:		
Dodson and Muller [1978]	Bass/Fount and Woodlock, Between states	
Kalish [1982]	Bass awareness, Adoption complex	
Midgley [1976]	Bass between states	Includes rejector group
Urban [1970]	Up to 500+ equations	77-State Model
Hauser & Wisniewski [1982a]	$Pr_{ij} = f$ (relative appeal of j) (Pr_{ij} = probability of next flow being i to j)	n-states

Table 2.3 Summary of Mathematical Diffusion Models of New Product Acceptance.

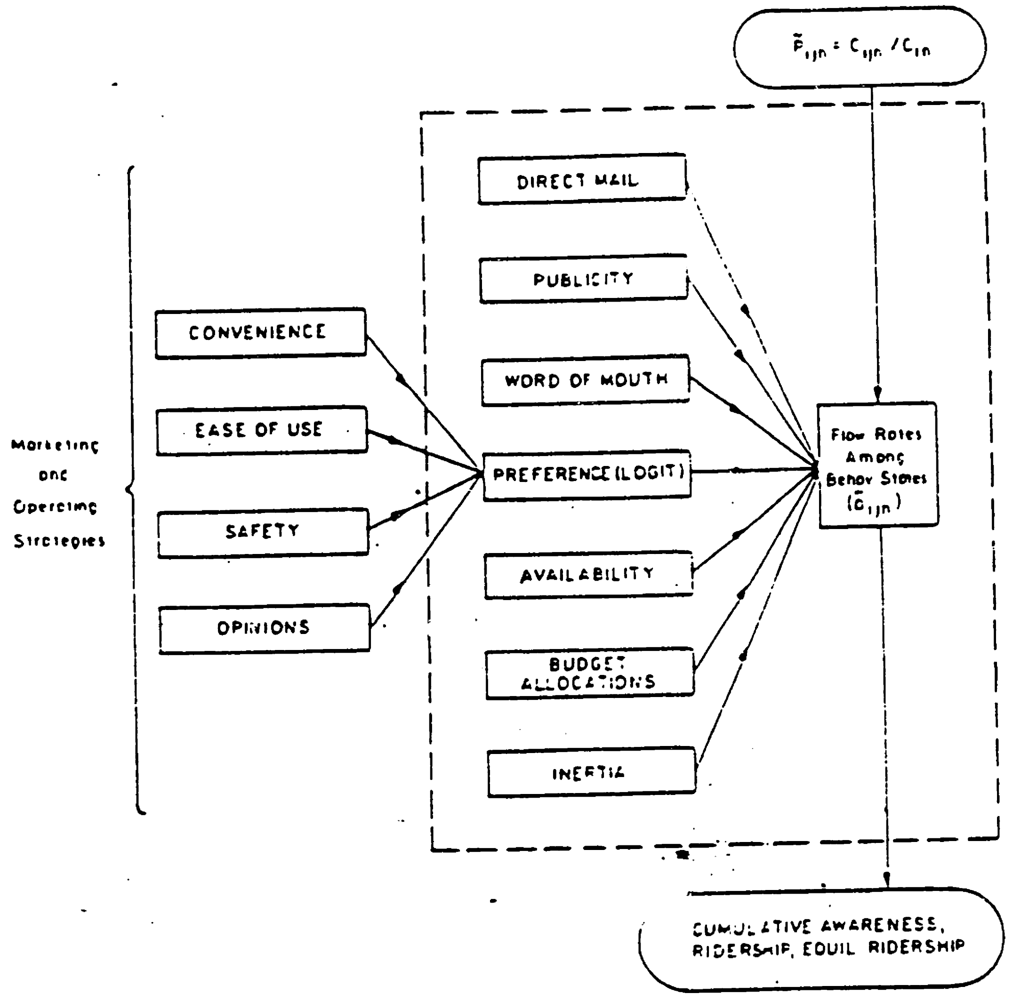


Figure 2-2 Hauser and Wisniewski's Model of Transition State Probabilities between Transport Modes.

2.2.2 Utility Measurement Models

An important class of model for forecasting product choice is that involving utility measurement.

Utility theory has a long history in the field of economics. Its modern use may be traced back to Jeremy Bentham (Stigler [1950, p. 308]) in the late eighteenth century. Traditional utility theory considers a consumer's tradeoff between various goods, or one good against a composite of all other goods. The theory addresses indifference between quantities of n goods using an n-dimensional space to determine marginal rates of substitution (see, for example, Nicholson [1979]). "Traditional" is used in contrast to Lancaster's approach of considering the utility of a good as arising from its component attributes (Lancaster [1966]).

Using such a traditional approach, Gossen showed in the mid-nineteenth century that an individual's utility is maximized under a budget constraint when

$$\frac{\partial u_j}{\partial p_j} = \lambda \text{ (constant)}$$

where continuous u_j is the utility of the j the (continuous) item ($j = 1,2,\ldots,n$) and p_j its price Stigler [1950, p. 315].

(2.8)

It is this relationship which can be used to derive an individual's demand curve and also to perform comparative static equilibrium analysis to study the effect of price and income changes at the individual level.

However, there is little empirical work at the individual level using this framework. Recent research by Hauser and Urban seeks to extend the model. They consider household consumer durable purchase plans with a view to studying how the budget constraint imposes a substitution effect between durables. They note three properties of durables; their individual significance in the budget, their discrete nature, and their long life. The budget constraint is already included in Gossen's formula cited above. They incorporate the discrete nature of durables by making utility maximization a mixed integer program, rather than a continuous one. The multiperiod nature of the problem is overcome by optimizing over a finite planning horizon with suitable discount factors, depreciation and borrowing assumptions.

Purchase is determined by considering the utility per dollar gained from each durable and also that of a composite good. The utility of the composite good (U_y) is assumed to be piecewise linear and it is scaled to have unit price.

Hauser and Urban propose that consumers minimize search by a using a heuristic of choosing the durable with maximum utility per dollar, then that with second most, etc. until the utility per dollar no longer exceeds that of spending an equivalent amount on the composite good. Under these conditions they show that durable j will be purchased in time period t if

$$\frac{u_j}{P_j} \left[\sum_{q=0}^{\tau-t} \gamma_j^q/(1+r)^{\tau-t} \right] \geq \mu \qquad (2.9)$$

where τ is the planning period, r the discount rate, γ the depreciation rate, and μ the Lagrange multiplier associated with the debt repayment constraint and also that

$$\frac{\partial u_y(y)}{\partial y_t} = \mu(1+r)^{\tau-t} = \lambda_t \tag{2.10}$$

Hauser and Urban propose extensions to allow for future price expectations to affect plans (by the inclusion of a time subscript on price) and product interactions (complements and substitutes). That is achieved by the consumer myopically choosing the first complement or substitute only if its individual utility per dollar dictates and then considering subsequent purchases on the basis of their utility per dollar conditional on the purchase of the first.

A number of methods are proposed to measure these cross-durable utilities. Logit estimation is proposed to fit the probability of purchase. An application of the technique is discussed in Hauser, Roberts, and Urban [1983] and briefly reviewed in Section 4.5.1.

Order of Acquisition Chains

When consumers have homogeneous tastes, the order of acquisition of durables can be expected to follow a uniform pattern from one household to the next. This approach may be viewed as a particular case of Hauser and Urban's algorithm and it has found considerable application. The order of acquisition technique has only had one reported application to new durables. A study by Kasulis, Lusch, and Stafford [1979] attempted to fit microwave ovens into priority buying patterns to investigate order of acquisition chains as a method of using early sales data to forecast sales of newly launched durables.

They reported disappointing results:

> "The order of acquisition scale does not do a good job in predicting innovative behavior. Of the 52 households owning a microwave, 32 households or 61.5 percent did not own all lower order durables. Comparable results are found in the other analyses. Thus, it appears that ownership of microwaves is cutting across established priority or acquisition patterns in that the innovators are not necessarily households that have accumulated all other durables on the scale. In general, it can be concluded that the derived order of acquisition scale fails to precisely identify the adopters of microwave ovens."

However, poor results are not surprising since the authors make no attempt to measure dynamic effects of the new durable sales, and they take no account of innovativeness characteristics other than current holdings.

As Pickering [1977, p. 10] points out, in their current form order of acquisition chains are not well suited for replacement purchases. The theory could be adapted by the inclusion of a stochastic element for repeat purchases, but the more general framework of Hauser and Urban [1982] appears more appropriate for this. However, the model may well have application for forecasting first purchases of different types of durables as a complement to a repeat forecasting model. Indeed, position on the chain seems a natural measure for the concept of susceptibility advanced in Chapter 4.5.2.

Aggregate Econometric Models

The above discussion centers around a single household's propensity to purchase durables. It is possible to derive individual demand curves for a commodity as a function of price and income and to aggregate these across consumers, thus forecasting industry sales at the aggregate level (e.g., see Nicolson [1979], Chapters 4 and 5). Personal disposable income, average auto prices, and other macroeconomic determinants of demand may thereby be related to sales.

There is a fine distinction between these models and those in the next section on multiattribute utility models measured at the aggregate level. The separation of aggregate regression models from that group is done largely to reflect their origin from classical utility theory. Generally, aggregate models motivated by traditional utility theory have price, income and other macroeconomic indicators as explanatory variables, but not product attributes.

Such models have been developed by Chow [1960], Nerlove [1957], and Suits [1958, 1961]. Typical of these models is that of Nerlove:

$$x_t = .0046 - \underset{(-3.0)}{.018p_t} + \underset{(+1)}{.006p_{t-1}} + \underset{(+6.5)}{.013y_t} - \underset{(-2.3)}{.007y_{t-1}} + \underset{(+1.68)}{.268x_{t-1}} \qquad (2.11)$$

where

x_t = sales of new autos in time t (U.S., per capita)

p_t = index of new auto prices (GDP deflator)

y_t = personal disposable income (per capita)

Fitted to annual data between 1922 and 1953, the model gave an R^2 of 0.91.

The advantages of these techniques are that they use data which is normally readily available or cheap to obtain. Estimation at the aggregate level also skirts the problem of how to generalize from a sample to a population. Use of actual sales rather than self-reported data removes reporting biases. However, they are largely appropriate for category sales forecasts, not brand choice. At the brand level, we must be able to compare brands in terms of their different attributes which form the basis on which they are compared. This leads to a consideration of the utility of a good arising from its constituent attributes.

Multiattribute Utility Models

Motivation for multiattribute utility models has come from the disciplines of economics, decision theory, and social psychology. In economics, the traditional concept of utility developed in the previous section, that of preference and indifference between goods and commodities has been extended by Lancaster [1966] to consider component attributes of products. Lancaster considers not only the goods necessary to sustain a certain level of activities, but also the component characteristics of those goods (the consumption technology). He postulates that utility is derived not from goods, per se, but from their characteristics.

The consumer's problem is:

$$\begin{aligned}
&\text{Maximize } U(z) \\
&\text{subject to } px \leq k \\
&\text{with } z = By \\
&\qquad x = Ay \\
&\qquad x,y,z \geq 0 \qquad\qquad (2.12)
\end{aligned}$$

where z is the vector of characteristics providing utility

x is the vector of goods at price p,

y is the set of activities undertaken,

k is the budget constraint, and

B and A are the matrices representing the constituent characteristics and goods respectively, necessary to sustain level of activity y.

A consumer's choice is thought of as buying a required mix of characteristics at minimum total cost (an "efficiency choice"), and choice between characteristics mixes (a "private choice"). This allows substitution to be defined in terms of switching within efficiency choices. The approach has a number of advantages over traditional theory. One is that it is possible to model changing utility of durables over the life cycle more easily. Another is that the introduction of a new good (or modifications and retirement of existing ones) does not require changing the number of axes and hence, the surfaces of individuals' utility functions.

In order to be applied to a group of products, Lancasterian theory demands that those chacteristics of products in the group which vary between members are not possessed by any goods outside the group. The need to have comparable characteristics within the group of goods under consideration together with the separability requirement, dictate that these multiattribute models are usually used to study brand choice within product classes, or at the most general, product forms within generic product groups (e.g. choice between modes of transport).

<u>von Neumann-Morgernstern Utility</u>

Lancaster assumes ordinal utility. The work of von Neumann and Morgenstern [1953] developed an alternative view of approaching utility theory. By considering different probabilities of obtaining outcomes and by assuming that individuals can "compare not only events, but even combinations of events with stated probabilities," they show that with certain assumptions about behavior, a measurable utility function (unique up to a linear transformation) can be derived.

von Neumann-Morgenstern's work allows the operationalization of cardinal utility with a flexible range of utility functions. Hauser and Urban [1979] operationalize von Neumann-Morgenstern utility theory to derive utility functions based on consumer perceptions of existing and proposed health maintenance organizations. The method uses lotteries to assess the shape of consumer's utility function by asking a series of questions to determine indifferences between lotteries with different outcomes.

The approach has the advantage of being perfectly general in its assumptions about the shape of utility curve with respect to attributes. Also interaction between attributes is not restricted in form. While relatively strong assumptions must be made to make the method tractable, at least these may be tested. The wide range of utility functions available means that a remarkable variety of different utilities may be modeled parsimoniously. Hauser and Urban found that the technique did reasonably well in predicting preferences (better than logit analysis and preference regression).

Certainly this method is the most powerful and flexible of any considered in the measuring of consumer preferences. It easily allows for product insertion and it can be modified to consider any factors at all (e.g., scenario analysis of changing environmental conditions). Risk neutrality or even constant risk aversion is not required.

The method's major drawback is its onerous data collection requirements and limited theoretical work on associated error structures.

Linear Compensatory Multiattribute Models

The most usual assumption concerning the utility function is that of additive independence which implies a utility function of the following form (Keeney and Raiffa [1976, p. 295]).

$$u_j = \sum_i w_i x_{ij} \tag{2.13}$$

where w_i are termed importance weights of the attributes (characteristics) i, and x_{ij} is the amount of attribute i possesses by good j.

Motivation for this form can be found in the field of social psychology. Models by Rosenburg [1956] and Fishbein [1967] have a similar mathematical form. For example, Rosenburg's model can be expressed:

$$A_j = \sum_i V_i I_{ij} \tag{2.14}$$

where

A_j = attitude toward object j

V_i = value importance of value i

I_{ij} = perceived instrumentality of the object j for attaining or blocking value i

Wilkie and Pessemier [1973] point out that "It is clear that marketing adaptations have significantly departed from the original proposals of Roenburg and Fishbein," and an examination of the two sets of variable definitions above shows this different emphasis. Nonetheless, Fishbein and Rosenburg's work provides a rationale for "overall affect reflecting net resolution of an individual's cognitions (beliefs) as to the degree to which given objects possess certain attributes weighted by the salience (importance) of each attribute to the individual." (Wilkie and Pessemier [1973]).

Two variants of the linear compensatory model above are common. The first is the ideal point model, in which

$$u_j = -\Sigma w_i (x_{ij} - x_j^{'})^2 \qquad (2.15)$$

where $x_i^{'}$ is the ideal level of attribute i.

The second variant is the part worths model in which

$$u_j = \sum_i \sum_{k_i} w_{ik} x_{ijk} \qquad (2.16)$$

where attribute i is categorical with k_i levels and $x_{ijk} = 1$ if j possesses i at the kth level, 0 otherwise.

Green and Srinivasan [1978] give an excellent review of the data collection requirements, scaling assumptions, estimation methods, and reliability and validity tests for these models. Shocker and Srinivasan [1979] compare multiattribute models for evaluating new product ideas on the basis of market determination, attribute determination, creation of the perceptual space, modeling of preference, and ability to generate new ideas. Finally Jain et al. [1979] conduct an experiment to compare data collection methods and estimation techniques to measure consumer prefereuces for banking services.

Application of the linear compensatory model to the prediction of preferences are given by Hauser and Simmie [1981], Tybout and Hauser [1981], and Agarwal and Ratchford [1979] (discussed in more detail below).

A good review article and application of the part worth model is given by Green and Wind [1975].

Ideal point models were used by Urban [1973] in his development of PERCEPTOR to aid in the design of new frequently purchased consumer products. Both probability of purchase and probability of repeat are modeled as linear functions of squared distance from the ideal point. He reports a close relationship between predicted and actual share as well as the source of share gained by a new entrant. In a similar application to a consumer durable Ryans [1974] clustered respondents on the basis of existing brands, and then used perceptions of a new product to estimate its share and the draw of that share. By using different price levels across the sample he was able to determine a price elasticity for the new insertion. Exposure to the new product (a blender) was by the examination (but not use) of a prototype model. The method gave significant improvements over a naive one but no comparison to actual sales were possible.

Linking Preference to Choice

Green and Srinivasan [1978] point out that the decision whether to relate overall preference or probability to attribute levels depends on the purpose of the study. Many studies which look at the comparative appeal of different formulations of a product may have no need for a probability measure, preference may be sufficient.

For studies requiring a sales forecast a probability estimate is required. Shocker and Srinivasan [1979, pp. 172-173] give a good review of techniques which have been applied. Many researchers assume that the most preferred brand is purchased or that some percentage of first, second, and third preferences will be translated into choice. For example, Hauser [1978] uses 80% of first preferences and 20% of second preferences in calculating a convergent measure of share for a proposed narrow band TV service. Kalwani and Silk [1982, p. 279] provide evidence to suggest that such "top box" methods may be reasonably accurate in practice. Pessemier et al. [1971] found that assuming that the most preferred product was always chosen, gave aggregate predictive results almost as good as more complex models.

Another popular method of relating preference to choice is by an assumption that probabilty of choice will be proportional to preference (for example, see papers by Rao and Soutar [1975], Shocker and Srinivasan [1974], and Lehman [1971]). Pessemier et al. [1971] propose raising preference to a power to minimize scaling problems.

Recently, more formal models to relate preference to choice have appeared. By assuming suitable error structure on the consumer's estimates of utility, probabilities of purchase may be derived analytically. For example, McFadden [1974] has shown that if utility is measured with Weibull distributed errors which are independent between choices, the probability of choosing brand j is given by

$$P_j = \frac{e^{\beta u_j}}{\sum_k e^{\beta u_k}} \tag{2.17}$$

Successful applications of the model are manifold. In the area of marketing, Tybout and Hauser [1981] use it to predict mode of travel in a Chicago suburb, incorporating both physical attributes and affective attitudes. Hauser and Simmie [1981] use it to model narrow band television to allow the estimation of the position of the product relative to Lancaster's efficient frontier. Silk and Urban [1978] use the logit model to estimate the market share of new frequently purchased products based on perceptions of evoked existing products and likely awareness of the new product. In their ASSESSOR model they also have a trial-repeat module to obtain convergent validity. Berkowitz and Haines [1982] report an application to a new durable (solar heating). The model was calibrated on existing heating methods (oil, gas, and electricity) and extrapolated to solar on the assumption that the market structure would remain the same. Perceptions of solar were collected. No attempt was made to measure how much information respondents had about solar energy, nor to fit diffusion effects. Fits on neither the logit model nor on the relative shares model (an adaption of that of Crow and Ratchford, discussed below), had high fitting or predictive ability, although all predictor variables were significant.

Using data on currently available autos, Agarwal and Ratchford [1979] compare logit models based on utilities obtained from fitting preferences by LINMAP, logit based directly on product attributes, logit estimated separately on two clusters, and a naive model consisting of choosing the first preference. The top preference model did not perform well at the aggregate level, overstating some popular makes' shares. Logit on attributes performed considerably better at the aggregate level than logit on fitted utilities. Using clustering based on estimated preference weights gave comparable fits to attribute-based estimation on the whole sample at the aggregate level and somewhat higher percentage of correct classifications (9% as opposed to 6%,).

Logit models have also received extensive application by economists and transportation researchers to forecast demand for appliances, automobile type and brand choices, and travel mode studies. Most of these studies estimate probabilities directly on attributes rather than using the intermediate construct of utility or preference in the estimation. However, multiattribute utility is an integral part of the derivation of these models. Examples of these models are provided below.

Berkovec and Rust [1982] model vehicle type purchase and usage decisions for one vehicle households. They use a nested logit model in which sequential decisions are made to keep the current auto or to purchase a new one, and then vehicle class and vehicle type. The model based on a vehicle miles driven/purchase choice optimization algorithm includes a number of product-related and household-related variables (subjectively selected and objectively measured). Anticipated interactions are incorporated by transformation of exogenous variables. For example, seating size is defined as household size times the square root of the number of seats in the auto, thus increasing its level for large households. Operating costs, the prime exogenous determinant of utilization, are included by the use of a gasoline price.

Reasonable results were obtained using an 11-variable version of the model. The model is able to impute transaction costs which are significant and greatly improve the log likelihood function. The model seems to be valuable in its treatment of the purchase/keep decision, in terms of its strong theoretical basis, and for the incorporation of future usage utility into the purchase decision explicitly (if only through the relatively weak mechanism of gas prices).

Another example of such an economic model is that of Dubin and McFadden [1982]. In an analysis to determine electricity usage and appliance purchase they use a nested logit model to determine holdings of various appliances taking account of capital and operating costs as well as availability and other holdings. In analyzing a similar nested logit model Goett and McFadden [1982, p. 1-15] point out the normative uses of such a model. One nice feature of the Goett and McFadden model is that stochastic failure is incorporated so that replacement due to breakdown can be predicted.

Aggregate Models Incorporating Product Attributes

Aggregate models of demand on component attributes resemble those which relate demand to a price index and personal disposable income discussed earlier. However, their roots lie in the aggregation of individual Lancasterian attribute-level optimizations, rather than the sum of individual's demand curves related to price and income.

An interesting example of such an application is one by Crow and Ratchford [1975] using a relative shares model to examine specific brands of auto. Their model may be written:

$$\log\left(\frac{x_{jt}}{x_{1t}}\right) = \alpha+\beta_o \log\left(\frac{p_{jt}}{p_{1t}}\right) + \sum_{i}^{r}\beta_i \log\left(\frac{y_{jit}}{y_{1it}}\right) + \sum_{\ell}^{k-1} \gamma_\ell M_\ell \tag{2.18}$$

where

x_{jt} = sales of brand j

j=1 represents the base or reference brand (a full-sized Chevrolet)

p_{jt} = price of price j, time t

y_{jit} = level of attribute i in brand j, time t

M_ℓ = manufacturer's dummies.

The Crow and Ratchford paper is noteworthy in that it attempts to estimate the effect of a major innovation; the electric auto. To do this it has to make strong assumptions about perceptions of electric autos. For example, the model assumes that such a vehicle would possess no new attributes not estimated from existing autos, and that it would not disrupt the market. Without collecting data from potential consumers, the reasonableness of these assumptions cannot be tested. Because data for the model are at the aggregate level, only objective attributes can be used (price, front leg room, rear leg room, acceleration, passing speed, fuel consumption, transmission, ride, handling, and frequency of repair). The latter three attributes were imputed after reference to popular auto magazines. The manufacturers' dummies explained more of the variation than the other attributes, suggesting that some variables, possibly perceptual, are missing from the attribute specification. Fits without the manufacturers' dummies were mediocre with an R^2 of 0.123 and only leg room, price, and fuel economy were statistically significant, the last being of the wrong sign.

However, the methodology provides an imaginative way of calculating the effect of a new brand insertion given only publicly available, aggregate data.

2.2.3 Summary of the Major Forecasting Traditions

Mathematical diffusion models have been shown to offer a high degree of explanatory power to new product sales trajectories over time. Problems which arise in their application include the difficulty of estimating the model prior to peak sales, the lack of normative variables in Bass' model [1969], and the general restriction of the models to new categories and industry sales. Each of these problems has attracted considerable research attention.

Lawrence and Lawton [1981] and Hauser [1978] propose methods of conducting market research prior to launch to gain early estimates of the parameters in Bass' model. These may be updated as early sales data become available.

Research to increase the normative ability of Bass' model largely centers around incorporation of advertising and price. However, Grilliches [1959], Chow [1967], and Hauser [1983] suggest ways in which the underlying parameters may be modeled in terms of the products' characteristics.

Kalish and Lilien [1983] have made a useful start in their efforts to include competition at the brand level into diffusion models by their use of two stages: an industry diffusion model and a logit brand sales model. Although some feedback is allowed from brand strategies to industry sales, the treatment of sales of all brands as equivalent in stimulating industry diffusion may be biased against the diffusion effects of a major innovative new brand.

All of these models are specified in terms of differential equations relating sales to past cumulative sales. None considers a choice modeling framework in which changes in expected utility cause changes in probabilities of adoption (with the partial exception of Jeuland [1981b]).

Utility models have had a wide range of application to durable forecasting problems. Traditional utility which addresses how consumers make tradeoffs between different goods has been largely applied at the aggregate level, although Hauser and Urban [1982] propose a method to operationalize it at the individual level.

The alternative utility approach, proposed by Lancaster [1966], has been extensively used at the individual level. The approach regards utility of goods as arising from their component attributes and it has analogues in decision theory and social psychology. Models based on such a view are most appropriate for comparing brands with the same characteristics (in differing proportions). Hence, multiattribute utility models have found more application in the area of brand choice than for purchase incidence. Various formulations of the model have been proposed, for example, relating attributes to preference, attributes to choice, (e.g., Dubin and McFadden [1982]), and a full set of modules relating attributes to perceptions, perceptions to preference, and preference to choice (e.g., Tybout and Hauser [1981]). Generally, these multiattribute models have not considered the dynamics of utility as the brand diffuses.

This section has examined models commonly used for forecasting durable goods and found valuable insights from both diffusion models and utility models. In a desire to incorporate the best features of both traditions in our models, we are naturally led to ask what causes changes in the probability of an individual to purchase over time. Changes in awareness are obviously one factor, while changes in expectations about the mean value of a product are clearly another. The third, decreasing perceived risk, has received considerable attention in the literature. It deserves a discussion since together with awareness and expectation changes, it can help to explain the diffusion phenomenon of both product classes and individual brands.

2.3 Perceived Risk

2.3.1 Definition and Importance

Bauer [1960] is generally credited with introducing the concept of perceived risk. Since then his original ideas on the notion have attracted a considerable amount of research interest in marketing, decision theory, communications science, social psychology, and psychometrics. Perceived risk is important because it affects relative preferences for different brands (and in that sense is like a negative valued attribute) and because its dynamic nature with search and product diffusion causes changes in preferences over time. While it is not a method of forecasting the sales of a new durable by itself, because it is an important phenomenon and because it promises to offer a link between multiattribute utility and diffusion models, a review of the relevant literature has been included.

In its role as an "attribute", a number of researchers have found it to be an important determinant of preference (e.g., Pras and Summers [1978], Meyer [1981]). Taylor [1974] cites a major oil company which found that low perceived risk was the primary determinant of gas brand choice. Perceived risk offers a possible explanation for choice of familiar brands over unfamiliar ones with higher expected attribute levels (Neslin's [1976] preference inertia, Hershey _et al_'s [1982] inertial effect, and Bernhardt and McKenzie's [1976] safety margin). Schmalensee [1982] shows that uncertainty and information acquisition can be used to explain the enduring market share advantages enjoyed by the first entrant into a product category as demonstrated by Urban, Johnson, and Brudnick [1982].

The importance of the dynamics of perceived risk has also been highlighted in both empirical results and theoretical developments. Rogers [1973] and Roselius [1971] cite evidence that perceived risk reduces as word-of-mouth communications about the product spread. Cox [1967] speculates that consumer-dominated channels (word-of-mouth communication) will be important when

> "(1) performance risk has been aroused (perhaps by being stimulated by information supplied by the marketer) and is sufficiently high; and/or when;
> (2) psychosocial risk is sufficiently high to justify the time and effort required to obtain information from these informal channels; and when
> (3) perceived risk is high and consumers are anxious to avoid mistakes (hence want negative or unfavorable information if it exists)."

Sheth [1968] ties the importance of perceived risk to diffusion when he suggests:

> "Depending upon the magnitude of risk perceived in an innovation, two products may exhibit widely different patterns of diffusion on aspects such as rate of adoption, word-of-mouth communication, and importance of two-step flow of communication."

From this base Kalish [1982] incorporated uncertainty in the model in his Ph.D. thesis by inflating a consumer's reservation price depending on the uncertainty (see later in this section). Also, as reviewed in the previous section, Jeuland [1983b] has recently incorporated uncertainty in a diffusion model.

A third reason for the importance of perceived risk is a methodological one. Schmittlein [1981] shows that failing to account for uncertainty in linear compensatory models leads to inconsistent parameter estimates and tends to equalize preferences for all stimuli. He draws the parallel to work in errors in variables in econometrics.

The considerable body of literature which is now available on perceived risk, together with the diversity of disciplines which have examined the concept, has led to a confusing array of meanings and definitions.

I shall follow Taylor [1974, p. 56] in using perceived risk and uncertainty synonymously. Uncertainty may be defined as the effect of consumers' expectations not being at a single point; there are a number of values which the variable with uncertainty could take and the consumer is unsure as to which one will materialize. It is capable of decision theoretic operationalizations such as the certainty equivalent or differences between the value function (utility under uncertainty) and the utility function (utility under certainty). See Keeney and Raiffa [1976] for a theoretical development and examples of these constructs. Bell and Raiffa [1982] and Dyer and Sarin [1983] discuss the relation between the value function under certainty and the utility function. This work is outlined more fully in a discussion of the model in Chapter 3.

A number of definitional distinctions are also drawn in the consumer behavior area which will prove useful in our consideration of perceived risk. As Bauer [1960] points out in his pioneering work on the subject, it is perceived risk in which we are interested, rather than any actual physical uncertainty. Bettman [1972] distinguishes between inherent risk and handled risk;

> "Inherent risk is the latent risk a product class holds for a consumer, the innate degree of conflict the product class arouses in the consumer. Handled risk is the amount of conflict a product class engenders when the buyer chooses a brand from that product class in his usual buying situation. Thus, handled risk includes the effects of information and risk reduction processes as they have acted on inherent risk."

Bettman notes that these two different types of risk have been confused in the research literature. A different usage of "inherent" will be made in this thesis. Inherent product variability will be taken to mean risk associated with the product given perfect information. Total uncertainty will be taken to mean the uncertainty associated with the product at any time, including both information uncertainty and variability inherent to the product. This is equivalent to Bettman's "handled risk." Thus, Bettman's inherent risk is higher than handled risk because cues such as brand and store are not present. Our inherent product variability is a lower bound on total uncertainty (or handled risk).

Work on perceived risk may be considered under four headings: studying the components of perceived risk; incorporating the effects of perceived risk into the preference structure; measurement; and dynamics.

2.3.2 Components of Perceived Risk

Classifying types of perceived risk has attracted much attention, but is not central to the topic of this thesis. Typical of such classifications is that of Jacoby and Kaplan [1972] who identified five types of risk: financial, performance, physical, psychological, and social.

Of more relevance is a debate between Cunningham [1967] and Bettman as to the underlying dimensions of perceived risk (Bettman [1975]). Cunningham proposes certainty and consequences as the two relevant dimensions, whereas Bettman advances probability of acceptabiliy and importance. The expected utility framework incorporates all of these factors: probability (the consumer's distribution of beliefs about a brand), consequences (shape of the marginal value function), and importance (the risk aversion parameter), in an axiomatic way.

2.3.3 Incorporating the Effects of Perceived Risk into the Preference Function

Uncertainty has been incorporated into models of preference in three distinct ways.

First, Schmalensee [1982], Jeuland [1983b], and Peter and Tapley [1975] assume that the product can have one of two levels of performance: basically, that the product works as expected, or it does not. Given probabilities of these two outcomes and an assumption about risk aversion, expected utility may be maximized.

The second method of incorporating risk is by an algebraic manipulation. For example, Kalish [1982] multiplies the reservation price by a factor related to uncertainty, R, of the form $\frac{\alpha + 1}{\alpha + (y_t/m)^2}$. This functional form is chosen for fit rather than for theoretical reasons.

Third, a number of researchers have incorporated uncertainty into expected value models. These incorporations have been based on the belief that expected utility should be discounted geometrically or linearly by risk, rather than by reference to the literature in decision theory or finance.

Pras and Summers [1978] suggest the form

$$U_{\tilde{X}} = U(E(\tilde{X})) - r.R_{\tilde{X}} \qquad (2.19)$$

where

U	= utility
$\tilde{X}$	= vector of component attributes of the good
r	= lack of risk tolerance, or risk aversion, and
$R_{\tilde{X}}$	= risk

Meyer [1981] adds a cross-product term, reminiscent of a multiplicative value function

$$U_{\tilde{X}} = k_1 U(E(\tilde{X})) + k_2 R_{\tilde{X}} + k_{12}\, U(E(\tilde{X}))R_{\tilde{X}}$$

This suggests that he more has in mind risk as a dimension of the attribute rather than an integral part of the evaluation of the distribution of beliefs.

2.3.4 Measures of Perceived Risk

Four types of measures of perceived risk are considered: elicitations of the distributions of beliefs, direct questions about the level of risk, measures of the relative difference in risk between two products, and Wilton and Pessemier's derived measure.

The most thorough measure of the distribution of expectations was developed by Woodruff [1972a, 1972b]. In observing that some people could give prior distributions easily, while others could not at all, he tested a two step procedure for eliciting the probability distributions of possible outcomes. The first task for respondents was to mark on a 19 point scale the highest and lowest possible value for each attribute of a product. Using these as benchmarks, in the second step respondents allocated points to each graduation "so that the relative number of points for each represented judgments of the relative likelihood of the accuracy of the evaluations."

Even with this scale, Woodruff reports some people had difficulty, that all had to exert considerable effort, and generally respondents found the task "unpleasant." He noticed strong evaluation apprehension and most subjects tried hard to ensure that their distributions looked bell-shaped. After an information stimulus subjects were remeasured and almost exactly half had a range of values outside (at least in part) the range which they had previously called the possible range. However, the measure was not without its success. The mean and the variance of scales were shown to measure independent dimensions of evaluation. And 65% of respondents did decrease the variance of their beliefs when presented with more information. Woodruff suggests that with more practice examples and more detailed explanations his results would be further improved.

A variant of the Woodruff scale used by Pras and Summers [1978] also had moderate success. Using a seventeen point scale they had subjects assess eight attributes on each of 5 auto makes and found risk measured by this method to significantly discount the utility of expected attribute levels. They also note "the burden of the Woodruff scale might result in more random error than is produced by the other less demanding rating procedures." Indeed Hagerty and Aaker [1981, p. 25] call for "adequate and more practical measures based upon one or two questions." That may be achieved if one is prepared to impose a distributional assumption on beliefs. For example, if beliefs are normally distributed, then Hogarth and Teboule [1973] suggest methods of estimating the mean and variance by asking for fractiles. Additional questions may be included to test consistency with the normal distribution.

Given the distribution, a risk measure in terms of dispersion may be calculated. For Pras and Summers [1978], the amount of risk is measured by the positive semi-standard deviation for risk takers (i.e., $[\Sigma(x_i-\mu)^2 f_i]^{1/2}$ where f_i is the distribution function at x_i) and the negative semi-standard deviation for risk avoiders. They suggest that otherwise higher-order moments will not be adequately fit. Their form with equal degrees of freedom as the variance or standard deviation would just do better in some distributional shapes and worse in others.

Although he presents no theoretical justification for it, Meyer's [1981, 1982] use of the variance to measure uncertainty appears more sensible (and is shown to be optimal in Chapter 3 under suitable conditions). Meyer also suggests discounting the expected utility by a factor of $(1 + r\sigma_x^2)^{-1}$ as an alternative formulation (Meyer [1981], p. 8).

The second type of risk measurement, direct questioning, has been applied to different facets of risk including risk itself (Bettman [1975], Jacoby and Kaplan [1972]), certainty of evaluation (Arndt [1968]), danger (Cunningham [1967]), and confidence in choice (Deering and Jacoby [1972], Day and Deutscher [1982]). Typical of the questions and scales involved are those of Bettman [1975]:

> "To you, choosing a brand of this product class in an imaginary store would be:
>
> Not risky at all 1 2 3 4 5 6 7 8 9 10 11 Exceptionally Risky"

The third type of measurement also devised by Bettman [1973] involves (n-1)n/2 pairwise ratings of the relative risk of a group of n objects. The respondent picks the object from a pair which he or she considers to be the more risky and then estimates the degree on a ten-point scale. 0

represents indifference and 9 much more risky. This allows the relative risks for each brand to be calculated.

The final measure of "risk" is proposed by Wilton and Pessemier [1981]. They suggest that the variance of an estimate of preference across the population may be taken as an index of perceptual clarity if the population is homogeneous. Clearly, if the population were segmented, this would help the homogeneity assumption. In a conversation, Pessemier suggested to me that this population measure might make a good surrogate for uncertainty.

In an interesting experiment Wilton and Pessemier deliver different messages about auto brands to consumers using split cable TV (low/intermediate/high information levels and hire/purchase availability). They hypothesize that both the complexity and clarity of beliefs will increase with more information and they take pre and post-information stimulation measures. Their proposed index of perceptual clarity improves over time. In addition they find that a probit model with parameters fitted on initial perceptions but with predictions based on informed perceptions gives a good fit to stated preference. They point out that stated preference may not be a good indicator of actual purchase. They suggest that their approach may be used to estimate ultimate market shares. Although the method does not attempt to show the dynamics of attitude change at the individual level during the purchase process or at the aggregate level as penetration occurs and diffusion effects grow, it does seem a useful start to trying to simulate post-launch conditions to calculate ultimate acceptance.

2.3.5 Dynamics of Perceived Risk

Most of the research studying changes in perceived risk has involved a controlled information stimulus with pre and post measures. However diffusion researchers have also measured it (e.g., Sheth [1968]). No relationship has been established between the two schools. While uncertainty can theoretically increase with increasing information (Hagerty and Aaker [1981, p. 7], Cunninghman [1967, p. 265]), theory and evidence dictate that in general it should decrease. Sheth [1968], Cunningham [1967], Arndt [1967, p. 289], and Woodruff [1972a] all provide evidence of this. Bauer [1960] relates this to group influences increasing the probability of social acceptability of adopting, while Sheth [1968] relates it to decreasing risk of adverse product performance. Both effects are probably normally at work.

The diffusion process consists of two dimensions; a process one and an individual one. At an individual level a consumer goes through the purchase stages from awareness to post-purchase feelings (over time). At the process level, at any point in time there is a distribution of consumers in each state influencing others. Perceived risk is an individual phenomenon which feeds on the state of the process (e.g. the cumulative number of adoptors and rejectors).

Dickson and Wilkie [1978, p 84] cite statistics which show that at purchase an average consumer is aware of about 40% of the relevant information concerning the brand he is purchasing. Therefore any model which follows the dynamics of risk with increasing information must be able to predict the stage at which purchase will occur. Generally this will be considerably less than full information.

2.4 Literature Summary

In Section 2.1, a framework for classifying new product forecasting techniques by modeling approach and data collection methods was given. Section 2.2 considered the two major traditions in forecasting consumer durables: diffusion models, and utility models. Both traditions were shown to have appealing features: the product positioning explanation of multiattribute utility, and the dynamics of diffusion models. The chapter closed with a consideration of the construct of perceived risk or uncertainty since this appears to offer a method of marrying the two major traditions. Multiattribute utility has been extended to include risk by a number of researchers (e.g., Pras and Summers [1978]), while the dynamics of risk have been considered by research diffusion theory research (e.g., Jeuland [1981b], Kalish and Lilien [1983]).

CHAPTER 3: MODEL

3.1 Theory Development

The objectives in developing the model of brand choice are twofold. First, the model aims to provide a vehicle which combines the benefits of diffusion models' dynamics with the product characteristic explanation of relative advantage at the individual level offered by multiattribute utility models. Second, it attempts to show how diffusion effects are felt at the brand level and to show how specific brand diffusion effects can influence product class sales.

To achieve these objectives, it is useful to consider what causes changes in the sales of a new brand over time. The behavioral diffusion literature reviewed in Chapter 2 suggests that increasing adoption stems from both growing awareness of the brand and (generally) increasing preference for it. Increasing awareness is included in the probability of consideration component of the model, briefly addressed in Section 4.5. Increasing preference stems from changes in expected utility which are generally assumed to have two components: changing mean expectations about the product (which may move either up or down), and changing perceived risk or uncertainty of the product's benefits as more information becomes available.

While a number of researchers have identified the importance of risk or information uncertainty on choice (e.g., Pras and Summers [1978], Wilton and Pessimier [1981], and Meyer [1981]), and some have modeled risk as a determinant of sales dynamics (e.g., Jeuland [1981b], Kalish [1982]), none has combined risk in its static role of discounting multiattribute utility choice between brands with risk in its dynamic role of explaining the changing rate of adoption of a specific product in isolation. (See Chapter 2 for a review of this literature). This chapter uses the concept of expected utility from decision theory to model the magnitude and effect of changes in mean and uncertainty of a new brand as its penetration increases.

We call this model the "Multiattribute Utility Diffusion" model or MAUD.

3.1.1 Form of the Expected Utility Function

Theoretical justification for the multiattribute modeling of consumer preference is provided in the growing literature of the Fishbein-Rosenburg class of expectancy-value models and the new economic theory of consumer choice advanced by Lancaster (see Section 2.2.1 for a review).

The most popular of these in marketing is the linear compensatory model (or vector model) in which a measure of preference for good j, v_j is represented

$$v_j = \sum_{k=1}^{K} w_k y_{jk} \tag{3.1}$$

where w_k, k = 1, 2, ... K, represent the importance weights of the K attributes and y_{jk} is the amount of attribute k contained in product j. The application described in Chapter 4 gives a specific example of the model using a framework adapted from Tybout and Hauser's [1981] Integrated Model of Consumer Choice.

In the case of certainty, this measure of preference, v_j, is the objective criterion which a consumer attempts to maximize. If price (p_j) is an important criterion in the choice, it may be incorporated into (3.1) by one of three assumptions. First, the consumer may be argued to maximize the preference/dollar which he gets from his choice (v_j/p_j). Second, if all other goods are grouped as a composite good and the consumer uses preference per dollar to choose among the composite, he may be thought to maximize his total consumer surplus of choosing a brand within a category ($v_j - \lambda p_j$, where λ = marginal utility/dollar of the composite good in some reference budget). Last, price may be treated as a negative- valued attribute (so the objective function becomes $v_j - w_p p_j$, where w_p is the importance weight of price). If λ is not available from external data, then for practical estimation, the second and third methods become equivalent.

There is substantial empirical justification for the third approach (e.g., Dubin and McFadden [1982], Berkovec and Rust [1982], Train and Lohren [1982]), and so the theory is developed in terms of that formulation. However, both are included in the analysis and Chapter 5 suggests this as a promising area for future research.

On the basis of these arguments, we define net preference for brand j, X_j, by

$$X_j = v_j - \lambda p_j = \sum_{1}^{K} w_k y_{jk} - \lambda p_j \tag{3.2}$$

The preference function X_j assumes that the attribute levels are known with certainty. As suggested in the literature review, consumers generally make decisions with some uncertainty about the true level of attributes 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 (3.2) to a utility function which takes account of uncertain outcomes.

Bell and Raiffa [1979] define a strength-of-preference measure (measurable value function in Currim and Sarin's terms [1983]), $\tilde{X}$, to be one in which for brands a,b,c, and d

$$[a \to b] \gtrsim [c \to d] \Rightarrow \tilde{X}_b - \tilde{X}_a \geq \tilde{X}_d - \tilde{X}_c \tag{3.3}$$

where

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

[a→b] means switching from brand a to brand b, and the tilde above the X identifies it as a random variable.

They show that for such value functions that if the consumer obeys the von Neumann-Morgenstern axioms for lotteries (transitivity, substitutability, etc.) and if a utility function exists, it should show constant risk aversion with respect to the strength of preference measure. Thus, the utility function should be either linear or negative exponential. That is:

$$u(\tilde{X}_j) = a + b\tilde{X}_j \tag{3.4}$$

or,

$$U(\tilde{X}_j) = a - be^{-r\tilde{X}_j} \tag{3.5}$$

where U( ) is the utility after allowing for the uncertainty of the value, $\tilde{X}_j$, and a and b are scaling constants ($b \geq 0$).

If we assume that the linear compensatory preference function (3.2) satisfies condition (3.3) and that consumers follow the von Neumann-Morgenstern axioms, $\tilde{X}$ is a strength-of-preference or measurable-value function and utility follows either (3.4) or (3.5).

There is little empirical evidence to choose between (3.4) and (3.5). In a study of forty-three subjects evaluating simulated job offers, Currim and Sarin [1983] found that the exponential model gave better fits than the linear model in forty cases. Therefore, the negative exponential utility form (3.5) was selected for derivation. However, footnote 1 at the end of Section 3.1.1 shows that a similar result to the one obtained here with linear marginal value (equation (3.2)) and exponential utility (equation (3.5)) may be obtained with quadratic marginal value (an ideal point model) and linear utility (equation 3.4)).

Using exponential utility and arbitrarily setting a=0 and b=1, the model for utility becomes:[1]

---

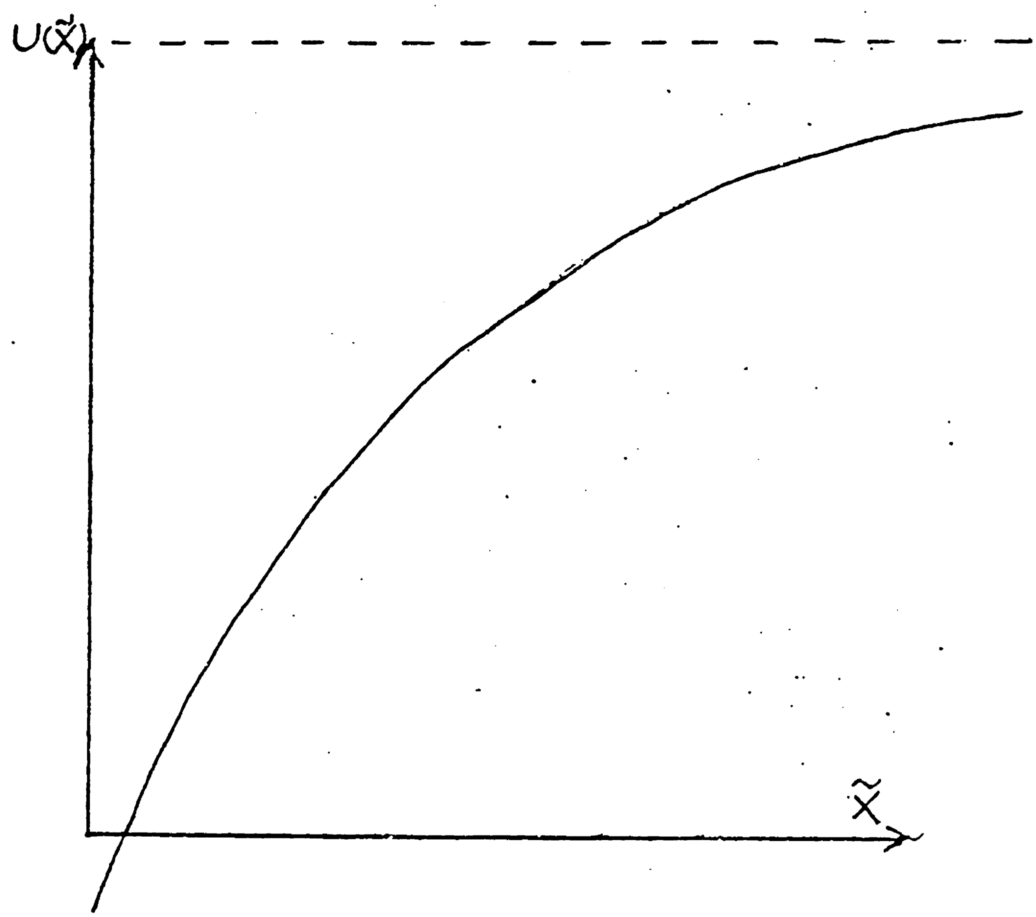
1 As discussed in Chapter 5 this formulation does not correspond to maximizing $E(U)-\lambda p$ across categories since we have discounted value by price in equation 3.6, not utility. The behavioral assumption implied by this equation is that when a consumer looks at a category what is important to him is the surplus value that he would get under certainty integrated across levels of uncertainty. This is not quite the same as $E(u)-\lambda p$.

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

$$= -e^{-r(\sum_{1}^{K} w_k \tilde{y}_{jk} - \lambda p_j)} \tag{3.6}$$

where r is Dyer and Sarin's [1982] relative risk aversion, or Bell and Raiffa's [1979] intrinsic risk aversion. In economics, Pratt [1964] and Arrow [1971] term this parameter absolute risk aversion. Arbitrarily setting the scaling constants a and b will not affect the utility orderings of different products.

A graph of utility as a function of preference is given below as Figure 3.1



Graph of $U(\tilde{X}_j) = -e^{-r\tilde{X}_j}$

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

$$
\begin{aligned}
E(U(\tilde{X}_j)) &= \int u(x_j)f(x_j)dx_j \\
&= \frac{1}{\sqrt{2\pi\sigma_j}} \int (-e^{-rx_j}) \, e^{-\frac{1}{2}(x_j - X_j)^2/\sigma_j^2} dx_j \\
&= -e^{-r(X_j - \frac{r}{2}\sigma_j^2)} \qquad (3.7)
\end{aligned}
$$

The normality distribution assumption is based on the proposition that consumers will assign the highest probability to 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 or she will choose the brand for which (3.7) is greatest.

It should be noted the expected utility, (3.7), is monotonic in $X_j - \frac{r}{2}\sigma_j^2$. We call this term risk-adjusted estimated net value. The consumer will choose brand j if

$$X_j - \frac{r}{2}\sigma_j^2 > X_\ell - \frac{r}{2}\sigma_\ell^2 \qquad \ell \varepsilon C \qquad (3.8)$$

We denote risk-adjusted estimated net value $X_j - \frac{r}{2}\sigma_j^2$ by χ_j. In multiattribute terms, this condition may be written

$$\sum_1^K w_k y_{jk} - \lambda p_j - \frac{r}{2}\sigma_j^2 > \sum_1^K w_k y_{\ell k} - \lambda p_\ell - \frac{r}{2}\sigma_\ell^2 \qquad (3.9)$$

Equations (3.8) and (3.9) imply that the consumer will select the brand of maximum expected value, after discounting for the variability or uncertainty associated with each brand. Being able to use variance as a measure of uncertainty is an implication of the assumption of the consumer's belief about value being normally distributed. Normality implies that mean and variance are complete statistics. The linearity of inequalities (3.8) and (3.9) follow from the functional form assumed for utility.

An analogous expression to inequality (3.9) may also be obtained by assuming an ideal point or quadratic strength-of-preference function (described in Section 2.2.2), together with a linear value to utility transformation (equation 3.4). In that case, the normality assumption is not required.[1]

1 A quadratic marginal value model may be written without loss of generality as:

$$x_j = c - \Sigma\, w_i (y_{ij} - y_i')^2$$

If we let the distribution of ranges on each attribute be $f_i(y_{ij})$, mean μ_{ij}, variance σ^2_{ij}, and assume mutual utility independence, then using expression (3.4) for utility (a linear transformation of value), we obtain:

$$\begin{aligned}
U(\tilde{y}_{ij}) &= E(a + b\tilde{X}_j) \\
&= a + b(c - \Sigma w_i E(\tilde{y}_{ij} - y_i')2) \\
&= a + b(c - \Sigma w_i \textstyle\int (y_{ij} - y_i')^2 f_i(y_{ij}) dy_{ij}) \\
&= a + b(c - \Sigma w_i \textstyle\int \{(\mu_{ij} - y_i')^2 + (y_{ij} - \mu_{ij})^2\} f_i(y_{ij}) dy_{ij}) \\
&= a + b[c - \Sigma w_i (\mu_{ij} - y_{ij})^2] - b\Sigma w_i \sigma^2_{ij} \\
&= u_j(\mu_{ij}) - b\Sigma w_i \sigma^2_{ij}
\end{aligned}$$

Thus, the expected utility is again the utility of expected attribute levels, linearly discounted by variance.

3.1.2 Changes in the Distribution of Beliefs Over Time

Given the objective function in equation (3.8) or (3.9), diffusion effects at the brand choice level are assumed to occur in two distinct ways. First, word-of-mouth may change estimated attribute levels (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. Hagerty and Aaker [1981] note that under some conditions, uncertainty may increase and conditions for that phenomenon are derived in Appendix B.2. Because we assume known variances in our model, variance is monotonic decreasing (see footnote 2, following equation 3.20).

<u>Distinction Between Beliefs About Brand's Mean Value and Value to be Realized on Purchase</u>

All products are subject to some variability in quality, however small. At any point in time a potential consumer has a distribution of beliefs about the mean value of brand j, averaging over these quality differences.

We denote this mean distribution by $\tilde{\hat{\mu}}_j$ and assume it to have expectation $\hat{\mu}_j$ and variance $\sigma^2_{\mu_j}$. We assume that if the consumer had perfect information, his estimate $\hat{\mu}_j$ would have expectation $\hat{\mu}_j$ and zero variance. We call $\sigma^2_{\hat{\mu}_j}$ the information uncertainty.

If the consumer were to purchase brand j, not only would he have uncertainty because he did not know the true mean, he would also realize some inherent product variability. If we denote by $\tilde{X}$ the distribution of value which he believes he would obtain on purchasing the brand, we may examine the relationship between $\hat{\tilde{\mu}}_j$ and $\tilde{X}_j$.

Let $\tilde{X}_j$ have expectation X_j and variance σ_j^2. Let ε_j denote the inherent product variability which the consumer would realize. That is:

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

$$E(\tilde{X}_j) = X_j = E(\hat{\tilde{\mu}}_j) + E(\tilde{\varepsilon}_j) \tag{3.10}$$

$$= \hat{\mu}_j + E(\tilde{\varepsilon}_j)$$

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 $E(\tilde{\varepsilon}_j) = 0$.

Thus $X_j = \hat{\mu}_j$ (3.11)

To obtain the variance of X_j, we may write

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

$$= \mu_j + (\hat{\tilde{\mu}}_j - \mu_j) + \tilde{\varepsilon}_j$$

Assuming μ_j does not change over time and suppressing the brand j subscript for notational ease:

$$\sigma^2 = E(\tilde{X} - X)^2$$

$$= E((\hat{\tilde{\mu}} - \mu) + \tilde{\varepsilon})^2 \quad \text{since} \quad X_j = \hat{\mu}_j$$

$$= \sigma^2_{\hat{\tilde{\mu}}-\mu} + \sigma^2_{\tilde{\varepsilon}} + 2 \operatorname{cov}(\hat{\tilde{\mu}} - \mu, \tilde{\varepsilon})$$

$$= \sigma^2_{\hat{\tilde{\mu}}-\mu} + \sigma^2_{\tilde{\varepsilon}} \qquad \text{if } \operatorname{cov}(\hat{\tilde{\mu}} - \mu, \tilde{\varepsilon}) = 0$$

The assumption of zero covariance is equivalent to the assumption that successive samplings of brand j are independent.

We may rewrite σ^2, the total uncertainty which a consumer expects to realize;

$$\sigma^2_j = \sigma^2_{\hat{\mu}_j} + \sigma^2_{\varepsilon_j} \qquad (3.12)$$

Consumer's Total Uncertainty	=	Information Uncertainty	+	Inherent Product Variability

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 (Section 3.1.1).

For measurement and model development simplicity, we assume that all variances (uncertainties) are known to the consumer (though not necessarily constant). Updating formulae when variances are not known are derived in Appendix B.2. The assumption is not necessary in deriving the updating model, but it does simplify the measurement task by not having to measure the dynamics of perceptions of inherent product variability. A discussion of when two sets of assumptions are likely to give divergent results is included later in this section.

We assume that the consumer knows all of the uncertainties necessary to calculate his risk-adjusted net value for a brand. From equation (3.12) we assume that he knows the inherent product variability (σ_ε^2), his information uncertainty ($\sigma_{\hat{\mu}_j}^2$) and the total uncertainty associated with the brand (σ_j^2). (We will also assume when we discuss word-of-mouth integration that he knows the variance of owners' perceptual biases, σ_ν^2.) Because we assume no change to the product form over time, since σ_ε^2 is known and constant, it will not be updated. $\sigma_{\hat{\mu}}^2$ will be updated as more information becomes available.

The consumer has normally distributed beliefs about the value of brand j.

$$\tilde{X}_j \sim N(\hat{\mu}_j, \sigma_j^2)$$

$$\tilde{\hat{\mu}} \sim N(\hat{\mu}_j, \sigma_{\hat{\mu}_j}^2)$$

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. (Prior beliefs and word of mouth form a normal-normal conjugate pair.)

Following DeGroot [1970, p. 168] we define τ, the relative strength in prior beliefs, by:

$$\tau = \frac{\sigma_X^2}{\sigma_{\hat{\mu}}^2} \qquad (3.12)$$

τ is often termed the equivalent sample size.

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 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. Appendix B.1 suggests how this assumption might be relaxed to allow for homophily, the tendency for the people to whom a consumer talks to hold similar views. While a number of studies have found Bayesian updating a good approximation to consumers' information integration (e.g., Ajzen and Fishbein [1975], Trope and Burnstein [1975], and Scott and Yalch [1980]), Slovic and Lichtenstein [1971] suggest that consumers tend to be conservative by underweighting later pieces of information. Alternative information integration algorithms are discussed in Chapter 5 under Future Research.

Let us assume that a potential consumer talks to n owners of brand j, indexed owner 1,2,...,i,...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). For notational ease, the brand subscript j is suppressed for the development of updating formulae. All means and variances implicitly refer to brand j.

Consider Owner i who provides word-of-mouth to the consumer. His report of his durable's value, x^i, may be represented:

$$\hat{x}^i = x^i + \nu^i \tag{3.14}$$

where

x^i is the true value (as the decision maker would see it) and

ν^i is a personal bias.

The true value x^i, of his particular durable's value is given by

$$x^i = \mu + \varepsilon^i \tag{3.15}$$

where μ is the mean of the brand's true value and ε^i is the inherent product variability which Owner i realized. Combining (3.14) with (3.15) yields

$$\hat{x}^i = \mu + \nu^i + \varepsilon^i \tag{3.16}$$

We have already assumed $E(\varepsilon) = 0$ and it has variance σ_ε^2. We assume $cov(\varepsilon,\nu) = 0$. We also assume that ν^i has a zero mean; that is, the population as a whole perceives the brand the same way the consumer does.[1] This may be relaxed at some cost to clarity of exposition.

Let ν^i have variance σ_ν^2. Then the mean and variance of owner i's report of his durable is given by

$$E(x^i) = E(\mu + \nu^i + \varepsilon^i) = \mu \qquad \text{and}$$

$$\sigma_x^2 = \sigma_\nu^2 + \sigma_\varepsilon^2$$

The expected value and variance of the sample mean are given by

$$E(\bar{x}) = \frac{1}{n} \Sigma E(x^i) = \mu \tag{3.17}$$

$$\sigma_{\bar{x}}^2 = \frac{1}{n} \sigma_x^2$$

$$= \frac{1}{n} (\sigma_\nu^2 + \sigma_\varepsilon^2) \tag{3.18}$$

1 The implication of this may be seen by examining equation (3.10) where we assumed $\tilde{X}_j = \hat{\tilde{\mu}} + \tilde{\varepsilon}_j$, that is, that the consumer did not realize a perceptual bias in his purchase. That may be easily included in the model, though in practice it would be hard to measure. To the extent that it is the same across considered brands, it will only have small effect on the choice probability, equation (3.36).

Integration of New Information by the Consumer

Given prior beliefs $(\hat{\mu}(t), \sigma^2_{\hat{\mu}}(t), \tau)$ and the receipt of word of mouth information, $(n, \bar{x}, \sigma^2_{\bar{x}})$, De Groot [1970, p. 168] shows that the updating formulae for the mean and the variance are given by the following expressions:[1]

$$\hat{\mu}(t+1) = \frac{\tau\hat{\mu}(t) + n\,\bar{x}}{\tau+n} \tag{3.19}$$

$$\sigma^2_{\hat{\mu}}(t+1) = \left(\frac{\tau}{\tau+n}\right)^2 \sigma^2_{\hat{\mu}}(t) + \left(\frac{n}{\tau+n}\right)^2 \sigma^2_{\bar{x}} \tag{3.20}$$

These updating formulae may be contrasted to those in which the variance is not assumed known. Those formulae (B.12 and B.13) are given in Appendix B.2. Comparing (3.19) to (B.12), it may be seen that the updating formula is unchanged for the mean. The variance formula has a change in the weighting of the prior variance estimate and the sample variance estimate from $2(\alpha-1) + n$ to $\tau+n$. Additionally, the bias term, $(\bar{x}-\hat{\mu})^2$ is absent. Thus, the approximation will not be good $2(\alpha-1) >> \tau$ or $2(\alpha-1) << \tau$, that is, the strength of belief in the mean varies from the strength of belief in the precision. The formula will also fare poorly when the prior estimate of the mean, $\hat{\mu}(t)$, is very different from the sample mean. Hauser, Roberts, and Urban [1983] provide an alternative approximation in the latter case, using a different behavioral model.

---

1 In order for the consumer to continue to know his information uncertainty $\sigma^2_{\hat{\mu}}$, he must know $\sigma^2_{\bar{x}} = \frac{1}{n}(\sigma^2_{\varepsilon} + \sigma^2_{\nu})$. Since he knows σ^2_{ε}, by implication we assume he knows σ^2_{ν}.

The variance updating formula 3.20 implies that information uncertainty will always decline.[1]

The updating formulae (3.19) and (3.20) may be shown equivalent to other minimum variance unbiased weighting models. Appendix B.1 shows the relationship to simple exponential smoothing, partial adjustment models, and Granger and Newbold's [1977] combination of forecasts. These alternative formulations of the updating rules suggest how the model might be extended to include systematic variation in the perceptual bias (ν^i) and homophily (correlation amongst the information providers). An outline is provided in Chapter 5 under Future Research.

1

$$\sigma^2_{\hat{\mu}}(t+1) - \hat{\sigma}^2_{\hat{\mu}}(t)$$

$$= \left(\frac{\tau}{\tau+n}\right)^2 \sigma^2_{\hat{\mu}}(t) + \left(\frac{n}{\tau+n}\right) \sigma^2_x - \sigma^2_{\hat{\mu}}(t)$$

$$= \frac{1}{(\tau+n)^2} \left[n^2\sigma^2_x - (2\ \tau n + n^2)\sigma^2_{\mu}(t)\right]$$

$$\text{But } \tau = \frac{\sigma^2_x}{\sigma^2_{\hat{\mu}}} \Rightarrow \sigma^2_{\hat{\mu}} = \frac{1}{\tau}\sigma^2_x = \frac{n}{\tau}\sigma^2_x$$

$$\therefore \sigma^2_{\hat{\mu}}(t+1) - \hat{\sigma}_{\hat{\mu}}(t)$$

$$= \frac{1}{(\tau+n)^2} \left[n^2\sigma^2_x - 2n^2\ \sigma^2_x - n^2\ \sigma^2_{\hat{\mu}}(t)\right)$$

$$= \frac{-n^2(\sigma^2_x + \sigma^2_{\hat{\mu}})}{(\tau+n)^2} < 0$$

Example

A numerical example illustrates how these formulae might be used in practice. Changes in belief structures may also be illustrated diagramatically (see Figure 3.2).

As an example, consider the net value for an automobile (in a thousand dollar metric).

Let $\hat{\mu}(t) = 8$, $\hat{\sigma}^2_{\hat{\mu}} = 8$, $(\sigma_{\hat{\mu}} = 2.83)$

therefore:

$$h \simeq \sigma_{\hat{\mu}}^{-2} = \frac{1}{8}$$

Assume τ, the equivalent sample size, equals 3.

If the consumer receives four pieces of sample information, with $\bar{x} = 8.5$, $\Sigma (x_i - \bar{x})^2 = 31$, then we may apply (3.19) and (3.20) to obtain the posterior beliefs about the mean and variance of the mean

$$\hat{\mu}(t+1) = \frac{3 \times 8 + 4 \times 8.5}{3 + 4} = 8.29$$

$$\sigma^2_{\hat{\mu}}(t+1) = \frac{2.5 - 1}{2.5-1+2} \cdot \frac{3}{3+4} \cdot 8 + \frac{2}{2.5-1+2} \cdot \frac{3}{3+4} \cdot \frac{31}{3x4}$$

$$= 1.47 + 0.63 = 2.10$$

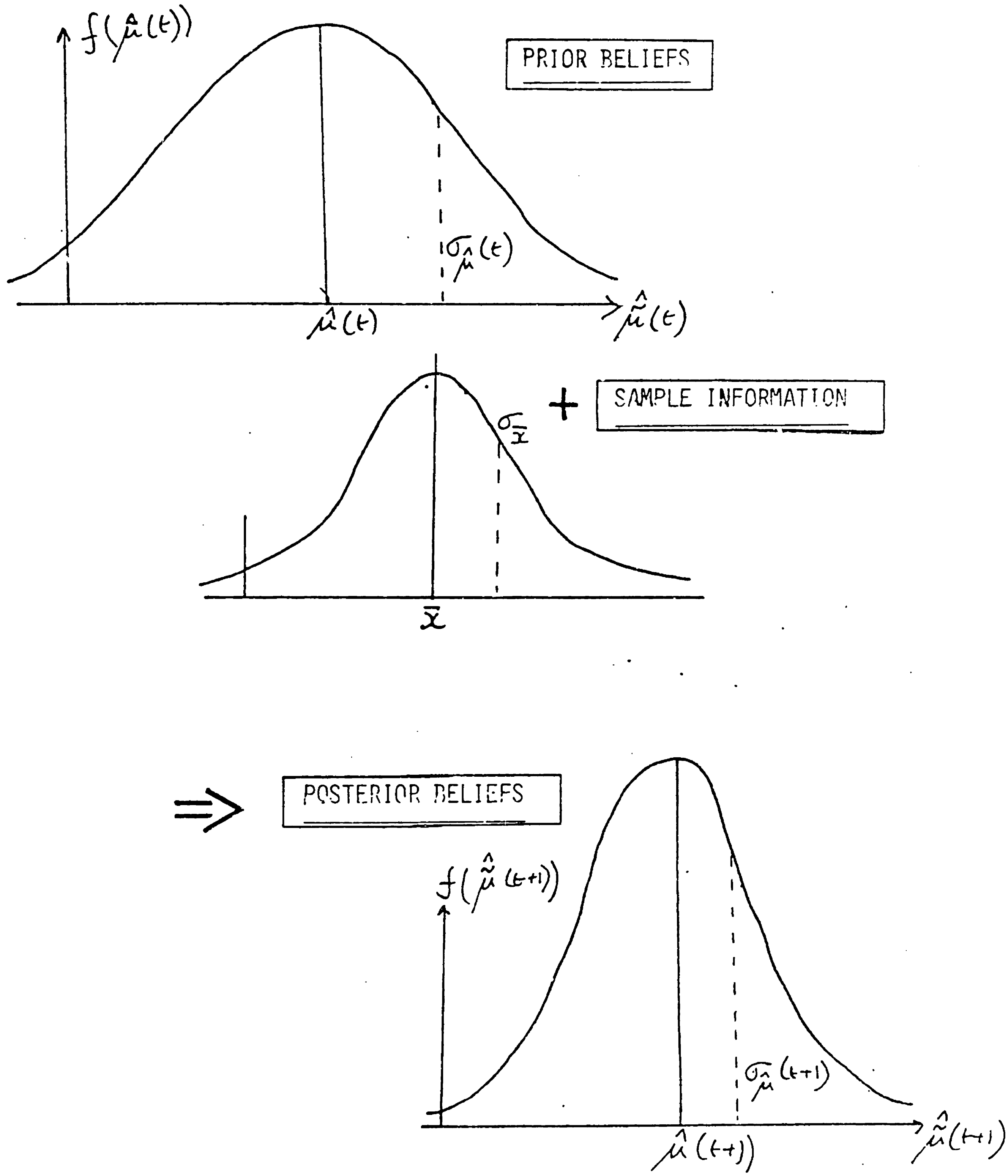


Figure 3.2 Illustration of Integration of New Information by Consumers (known variance)

3.1.3 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 (3.19) and (3.20)).

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 (3.11) and (3.12):

$$X_j = \hat{\mu}_j \tag{3.11}$$

$$\sigma_j^2 = \sigma_{\hat{\mu}_j}^2 + \sigma_{\varepsilon_j}^2 \tag{3.12}$$

σ_ε^2 was assumed known and thus since the product is assumed not to change during the diffusion process, σ_ε^2, the perceived inherent product variability is constant.

Therefore, substituting (3.11) and (3.12) in (3.19) and (3.20), we may readily see how beliefs about the value a consumer will realize or purchase get updated over time:

$$X_j(t + 1) = \frac{\tau\, X(t) + n\bar{x}}{\tau + n} \tag{3.21}$$

$$\begin{aligned} \sigma_j^2\,(t+1) &= \sigma_{\hat{\mu}}^2\,(t+1) + \sigma_\varepsilon^2 \\ &= \left(\frac{\tau}{\tau+n}\right)^2 \sigma_{\hat{\mu}}^2\,(t) + \left(\frac{n}{\tau+n}\right)^2 \sigma_{\bar{x}}^2 + \sigma_\varepsilon^2 \end{aligned} \tag{3.22}$$

If it were not for the idiosyncratic reporting error in word-of-mouth, ν, shown in equation (3.14) and its effect on the variance of word-of-mouth (equation 3.18), information uncertainty would quickly become small relative to inherent product variability since an examination of (3.20) shows

$$\sigma^2_{\hat{\mu}} = 0(\frac{1}{n})\ \sigma^2_x + 0(\frac{1}{n^2})$$

$$= 0(\frac{1}{n})(\sigma^2_\varepsilon + \sigma^2_\nu) + 0(\frac{1}{n^2}) \qquad \text{(see footnote 1)}$$

While the σ^2_ν term is also $0(1/n)$, if it is large relative to σ^2_ε, then it will take a large n before σ^2_ε dominates $\sigma^2_{\hat{\mu}}$.

To relate updating rules to a brand's diffusion over time, it is useful to re-introduce the brand subscript, j. We assume that the consumer talks to a proportion, k, of the cumulative adoptors at time t, Y_t.

Thus $n_j = k_j Y_{jt}$ (3.23) where k is a constant.[2]

Returning to the formula for expected utility, equation (3.7) we have

$$E(U_j) = -e^{-r(X_j - \frac{r}{2}(\sigma^2_{\hat{\mu}_j} + \sigma^2_{\varepsilon_j}))} \tag{3.24}$$

The objective function which the consumer will try to maximize, given inequality (3.8) is

$$\underset{j\varepsilon C}{\text{Max}}\ [\chi_j] = \underset{j\varepsilon C}{\text{Max}}\ [X_j - \frac{r}{2}\ \sigma^2_j] \tag{3.25}$$

1. $f(n) = 0(1/n)$ is a notation which suggests $f \to 0$ as $n \to \infty$. Note that n is implicitly a function of time.

2. This algebraic form is based simply 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 = $(N/M)Y_t = kY_t$.

From equation (3.12), σ_j^2, total uncertainty about the value of brand j may be expressed as the sum of information uncertainty and inherent product variability.

Thus, (3.25) may be written

$$\underset{j \varepsilon C}{\text{Max}} \left[X_j - \frac{r}{2}(\sigma^2_{\mu_j} + \sigma^2_{\varepsilon_j}) \right] \tag{3.26}$$

X_j and $\sigma^2_{\mu_j}$ get updated according to the Bayesian updating formulae, (3.21) and (3.22).

If the objective of the model is to produce monthly forecasts, then the preference for brands in the consideration set may be calculated at discrete periods of time. Observing this inherently continuous process at discrete intervals is analogous to Bass's treatment of time intervals in his logistic model [1969]. Schmittlein and Mahajan [1982] demonstrate a number of problems with this approach and it is a topic deserving of future research, as discussed in Chapter 5. The problem is less severe for monthly data than for annual data.

3.1.4 Relationship of Expected Utility to Probability

We postulated that the consumer would attempt to choose the brand j that maximized his estimate of the risk adjusted net preference,

$$\chi_j = \underset{j \varepsilon C}{\text{Max}} \left[X_j - \frac{r}{2} \sigma_j^2 \right].$$

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

$$\tilde{\chi}_j = \chi_j + e_j \tag{3.27}$$

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

$$P_{N|B,C} = \Pr \{\tilde{\chi}_N \geq \tilde{\chi}_j \qquad j \varepsilon C\} \tag{3.28}$$

where

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

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

The updating formulae can be used to update brands other than the stimulus brand. They may also be used to incorporate the effects of information obtained during active search as well as passive information gathered during the passage of time.

3.2 Measurement

This section gives a general overview of the way in which data are gathered for the model outlined in Section 3.1. It refers to durables in general. Details and an example of an application of these measures are presented later in Section 4.2.

In designing a measurement instrument, we must take not only detailed measures of consumer perceptions of brands' utility and risk at present, but also how they will change over time. These are particularly relevant for the stimulus brand. Therefore, we need an experimental design which allows enough information to calibrate the model, but also one which allows a simulation of the diffusion process and different levels of information about the brand.

The measurement task should satisfy a number of desiderata. For the model and results which come from it to be useful for management planning, and for the methodology to be capable of implementation, we need:

(1) the measurement task to be feasible for respondents;

(2) the managerial inputs (e.g., prototypes, advertising copy, etc.) to be available;

(3) the measurement and analysis cost to be reasonable; yet

(4) sufficient measures must be taken to deal with the variables in the model over time; and

(5) sufficient redundancy must be built into the measurement to provide estimates of convergence and allow us to have faith in strategic plans based on our analysis.

Feasibility for respondents is measured by reliability of measures from the experiment. Reasonable cost may be taken to be less than $100,000, approximately twice the cost of a pre-test survey for a frequently purchased product (Urban and Hauser [1980]). Estimates of convergence include alternative brand share, consideration, and industry sales models outlined in Section 4.5. Experience with the model will also allow predictive accuracy to be tested.

Just as the modeling of brand preference was developed within a framework which included all the components of the brand's sales, so in designing a calibration system for brand preference, it is necessary to keep in mind that it forms a part of a total vehicle to forecast sales of the new brand. Thus, we must ensure consistent measures across model components. For example, utility is also an important construct in the durable purchase decision and the utility of existing stock must be able to be measured in a way comparable to brand utility. The need to consider other elements in the measurement system also has ramifications for the amount of information which can be gathered.

In discussing the measurement task, we first discuss the stimuli which might be used to simulate the diffusion process and then go on to the measures used to quantify variables in the model.

3.2.1 Experimental Design

Simulation of the diffusion process may be undertaken by giving the respondent progressively more information about the new brand and measuring his or her beliefs at each stage. Clearly, some correspondence relationship between the stimuli and the brand's actual diffusion must also be established.

The most basic information about the brand is a concept description (Urban and Hauser [1980], p. 237). The respondent views a factual description of the brand including maker, attribute levels, and a picture.

Experience with the product provides another level of information. For small durables such as a food processor, this may be able to be gained by allowing the consumer the opportunity to purchase the product in a manner similar to that used with frequently purchased goods (Silk and Urban [1978]). For somewhat larger durables, a trial in the home might be possible, for example, with a projection television. For some such durables, the supply of complementary goods may present a problem to implementation (e.g., a new model personal computer may be limited in its trial by the software available). In other cases, features of the new product need not be available as a prototype, they may be simulated. For instance, facilities on a new "intelligent" telephone such as call forwarding, holding calls, etc., may be provided by the local telephone office without the consumer being aware.

For highly expensive durables for which prototypes are difficult to construct, highly confidential, or likely to require significant maintenance, testing by respondents at a central site is an alternative way of providing direct experience with the brand. The product used in the application chapter of this thesis, a new auto model, fell into this latter category.

In addition to physical experience with the product, it is necessary to simulate other informaton which a consumer might get about a new brand. Cox [1971] classifies such information which a consumer will receive about a product into three categories according to source: marketer-dominated, consumer-dominated, and neutral. Examples of stimuli to stimulate these three types include advertising copy, videotapes of "owners" discussing the new brand, and consumer reports about the brand, respectively. These stimuli should be tried at different levels to allow an estimate to be made of the effect of different contents and to permit a sensitivity analysis to various valences of word of mouth.

Because of the potential for a methods effect, a control brand whose sales are known, but which is not readily identifiable, should also be used. To minimize demand effects, response sets, and other sources of unwanted methods distortion, it is desirable to embed the new brand at the concept description stage in a group of other descriptions. A conjoint analysis provides a good vehicle for this as well as providing valuable information on the effect of competitive entry and responses. For some small durables, it might also be possible to develop competitive prototypes for testing.

Data about the consumer's perception of the current market and his or her beliefs about the brand as he or she gains more information about it are best collected in a face-to-face interview, though this could be modified for the testing of a new brand in the home.

Details of sampling designs and typical modules involved in the measurement task are provided in the description of an application of the methodology in Section 4.3.

3.2.2 Measures for Variables in the Model

Equation (3.25) provides the objective function which a consumer will try to optimize in his brand choice decision:

$$\max_{j \epsilon C} [X_j - \frac{r}{2} \sigma_j^2] \tag{3.8}$$

Thus, we need estimates of the mean value of each brand in the consideration set, together with the total uncertainty in buying it (the sum of information uncertainty and inherent product variability). We also need to work out how these will change over time. Equations (3.19) and (3.20) show how estimates of the mean value and information uncertainty of each brand are updated:

$$\hat{\mu}_j(t+1) = \frac{\tau_j \hat{\mu}_j(t) + n_j \bar{x}_j}{\tau_j + n_j} = \frac{\tau_j \hat{\mu}_j + n_j \mu_j}{\tau_j + n_j} + \text{normal error} \tag{3.29}$$

$$\sigma^2_{\hat{\mu}_j}(t+1) = \left(\frac{\tau_j}{\tau_j + n_j}\right)^2 \sigma^2_{\hat{\mu}_j}(t) + \left(\frac{n_j}{\tau_j + n_j}\right)^2 \sigma^2_{\bar{x}_j} \tag{3.30}$$

To apply these formulae, we need estimates of the mean and variance of incoming word of mouth. For the stimulus brand, which is the one in whose diffusion effects we have the most interest, these may be obtained as a managerial input, describing the word of mouth which the manager believes will circulate about his product. Alternatively, the views of the total sample after full information may be used to estimate true values, as detailed in Section 4.3.

The variables for which we need to develop measurement scales include expected value (utility), uncertainty (risk), and information levels (strength of beliefs, τ/n). In addition, to estimate the model, we need probabilities of brand purchase. Some of these values were measured directly, some were derived. An overview of the measurement and estimation procedures is included in Section 4.3.2. A complete set of the measures used is included as Appendix D.

Value

A number of measures of value are possible. Ranking considered brands gives an ordinal scaling, while constant sum paired comparisons, graded paired comparison, and Pessimier's dollar metric give potentially interval- or ratio- scaled measures (Urban and Hauser [1980], p. 272, Hauser and Shugan [1980]). For this application, we developed a thermometer scale of value using two reference points, indifference about owning a brand being zero points and top brand from those currently available being 100 points.

Attribute ratings, when suitably weighted, also provided a preference or value measure. Selection of attributes is discussed in Chapter 4.2.

Secondary data may be able to be used for some of the measures. For example, the dynamics of the value of brands currently in the consideration set may be modeled as a function of that brand's position in the product life cycle.

Uncertainty/Risk

A number of ways have been postulated to measure risk or uncertainty of beliefs, as described in Section 2.3. Pras and Summers [1978] use Woodruff's [1972a,b] method of eliciting the whole distribution of beliefs by asking respondents to place counters next to possible values in proportion to their probability of occurrence. Hogarth and Teboule [1973] provide an even more comprehensive range of probability assessment techniques.

The advantage of such methods is that they allow us to examine the reasonableness of the normality assumption. Their problem lies in the time intensiveness and fatigue involved in their administration. A compromise is to use a fractile method to just establish two or three data points and use the normality assumption to determine the variance of the distribution of beliefs (Hogarth and Teboule [1973]).

An alternative approach is direct assessment of risk. For example, Bettman [1975], uses a fifteen point scale from "Not risky at all" to "Exceptionally risky". To these we added "confidence in choice" as a measure of information uncertainty.

Probability

Probability of brand choice was measured on an eleven point (0-10) Juster scale, since that scale has had substantial validation in the marketing research literature (Juster [1966], Kalwani and Silk[1983]).

Information Levels

The strength of beliefs which a respondent has (τ/n) may be measured either directly or indirectly. Direct measures are of the form "How much information do you have on this brand relative to the information you would need when you next purchase?" (relative information), and "How much knowledge do you have about the durable category market?" (absolute).

An indirect measure of the strength of beliefs about a brand may be gained from showing the respondent a stimulus, taking pre- and post-measures as well as his perception of the stimulus, and thus determining his relative movement by estimation (see Equations (4.4) and accompanying explanation).

3.3 Estimation of the Model

The objective function of the consumer in the brand choice problem was taken to be (3.27)

$$\underset{j\varepsilon C}{\text{Max}} [\tilde{\chi}_j] = \underset{j\varepsilon C}{\text{Max}} [X_j - \frac{r}{2} \sigma_j^2] + e_j, \text{ where } e_j \text{ is measurement error.}$$

$\tilde{\chi}_j \sim N (\hat{\mu}_j - \frac{r}{2} \sigma_j^2 , \sigma_{e_j}^2)$, since the distribution of measurement errors in the risk adjusted net value of each brand were assumed to be normal.

Since the consumer has a normal distribution of $\tilde{\chi}_j$ for each brand j in his consideration set, the choice problem may be fit by the multinomial probit model. Details of brand choice probability estimates for both currently available brands and the new brand, as well as value and risk measures can be collected from respondents in a survey (as detailed in Chapter 4).

The Multinomial Probit Model

The multinomial probit model may best be illustrated by considering the case of two alternatives, j and k. This case corresponds to Thurstone's Law of Comparative Judgment, Case V (McFadden [1976]). Thurstone showed that if a consumer observed one drawing (or took one measurement) on each of two alternatives whose values were distributed normally mean χ and variance σ^2 that the probability of preferring j over k, P_j, is given by:

$$P_j = \Pr\,(\chi_j - \chi_k > 0) \tag{3.31}$$

$$= \Phi\,\{\frac{\chi_j - \chi_k}{(\sigma_j^2 + \sigma_k^2 - 2\sigma_{jk})^{\frac{1}{2}}}\} \tag{3.32}$$

where Φ is the standard normal cumulative distribution function. This is based on the fact that the difference of two normal variables is itself normal.

The multinomial probit can be generalized to J alternatives with equation (3.31) becoming

$$P_j = \Pr(\chi_j - \chi_k > 0 \quad \text{for } k=1,2, \ldots J \quad \text{and } k \neq j) \tag{3.33}$$

However, it should be noted that because the maximum of a number of normal variates is not, in general, normal, the simplicity of equation (3.32) cannot be gained for greater than two alternatives. McFadden [1976] notes:

> "with judicious choice of the joint distribution to reflect expected or hypothesized variations in tastes and perceptions in the population, this approach has the potential of yielding flexible and realistic selection probability functions. Unfortunately, the problem of computing selection probabilities computed in this way is usually formidable, particularly for multinomial response."

McFadden [1981] suggests that the multinomial probit is reasonable for up to three alternatives but largely impractical for greater than five. To the problems of computational difficulty and cost he adds the problem that the multinomial probit does not guarantee a global optimum for its parameter estimates (in contrast to the logit model, for example).

In order to use the full power of the multinomial probit in explaining variance-covariance structure between alternatives and their errors, Albright, Lerman, and Manski [1981] point out that many degress of freedom are lost and empirically they find that this hurts the standard errors of their probit parameter estimates.

Logit Approximation to Probit Model

McFadden [1973] has shown that, given the utility maximization problem implicit in equation (3.33), a necessary and sufficient condition for Luce's form of the selection probabilities,

$$P_j = \frac{e^{\chi_j}}{\sum_{k=1}^{J} e^{\chi_k}} \tag{3.34}$$

is that the errors in observing the values are independently and identically Weibull-distributed. That is:

$$f(\tilde{\chi}_j - \chi_j) = e^{-e^{-(\tilde{\chi}_j - \chi_j)}} .$$

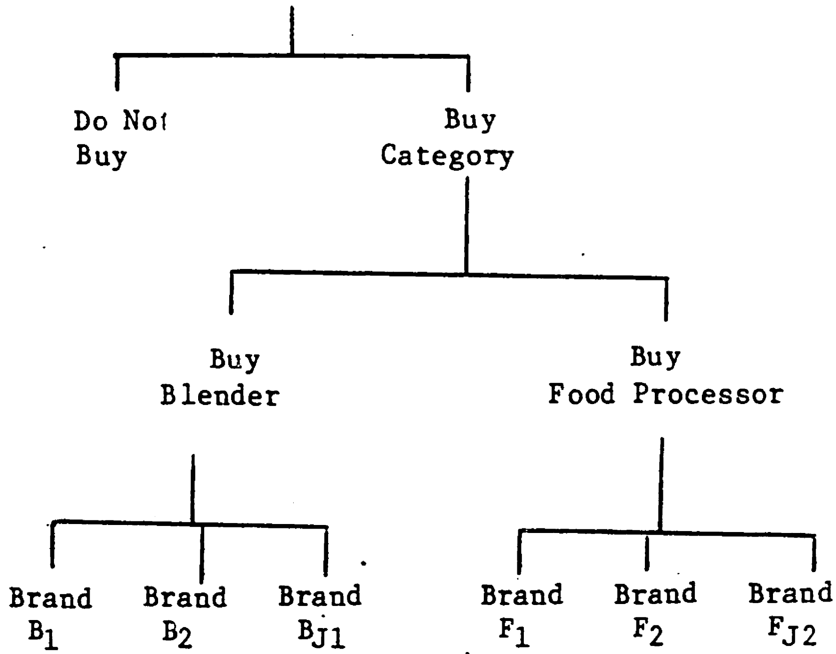
This distribution is similar in shape to that of the normal distribution. It is usual to include a scaling parameter for the χ so that 3.34 becomes

$$P_j = \frac{e^{\beta\chi_j}}{\sum_{k\varepsilon C} e^{\beta\chi_k}}$$

To use a logit approximation to the probit model when the number of considered alternatives is large has wide acceptance in the discrete choice literature (e.g., Hauser and Simmie [1981]). Gensch and Recker

[1979] claim that the two methods give the same results and an empirical comparison by Albright, Lerman and Manski [1981] suggests that "the probit estimates do not differ greatly from their logit counterparts" and the difference in log likelihoods for probit and logit is small. Domencich and McFadden [1975] show the similarities of the two distributions on their Figure 4.5 and Table 4.1

Studies which have found substantial differences between logit and probit estimates (e.g., Currim [1981], and Hausman and Wise [1978]) appear to do so because of the breakdown of the irrelevance of independent alternatives (IIA) assumption implicit in logit. That is, $\mathrm{cov}(x_j, x_k) \neq 0$ for some brands j and k. The IAA assumption requires that the relative probabilities of all existing alternatives stay the same if a new alternative is added. Both Currim, and Hausman and Wise, were looking at transport mode choice where the number of alternatives are few and the differences between them are quite marked. It is thought that IIA should not be a problem for most durables which are generally reasonably similar in terms of attributes, particularly when conditioned by the consideration set. To the extent there are distinct differences in the market (for example, between food processors and expensive blenders in the category of mixers), a further level of nesting can be used in the brand choice framework (Urban, Johnson, and Hauser [1983]). Thus, the choice hierarchy would become:



Under suitable error assumptions, this is a nested logit model and its estimation does not present a problem (Ben Akiva and Lerman [1977]).

Maximum likelihood programs are readily available to estimate logit models; a partial list is provided by McFadden [1976, (footnote 4)]. Similarly, a number of different maximum likelihood algorithms are available. Again, a detailed discussion is given by McFadden [1976]. He has shown the maximum likelihood estimates to be unique.

3.4 Summary and Discussion

3.4.1 Model Summary

We have developed a model to explain the diffusion of a new brand, the basic elements of which may be summarized as follows.

Utility for the brand is a function of its estimated mean net value (X_j) and the variance of beliefs about the value (σ_j^2):

$$E(U(\tilde{X}_j)) = -e^{-r(X_j - \frac{r}{2}\sigma_j^2)} . \tag{3.7}$$

Utility across brands will be maximized if the following expression is maximized:

$$X_j = X_j - \frac{r}{2}\sigma_j^2 \tag{3.8}$$

$$= \sum_1^K w_k y_{jk} - \lambda\, p_j - \frac{r}{2}\sigma_j^2 \tag{3.9}$$

We call this variable risk-adjusted estimated net value. An analogous expression to (3.30) may be obtained by considering quadratic rather than linear marginal value combined with a linear rather than exponential value to utility transformation.

When a consumer purchases the brand, he or she is uncertain about the value which he or she will realize. The mean of the consumer's beliefs about this value is X_j and it equals the belief about the mean value of brand j durable (μ_j). The variance of value that a consumer expects to obtain has two components; information uncertainty ($\sigma_{\hat{\mu}}^2$) and inherent product variability (σ_ε^2):

$$\sigma_j^2 = \sigma_{\hat{\mu}_j}^2 + \sigma_{\varepsilon_j}^2 \tag{3.12}$$

Beliefs about the mean value and variance are updated in a Bayesian way according to:

$$\hat{\mu}\ (t+1) = \frac{\tau\ \hat{\mu}(t) + n\ \bar{x}}{\tau+n} \tag{3.19}$$

$$\sigma_{\hat{\mu}}^2\ (t+1) = \left(\frac{\tau}{\tau+n}\right)^2 \sigma_{\hat{\mu}}^2\ (t) + \left(\frac{n}{\tau+n}\right)^2 \sigma_{\bar{x}}^2 \tag{3.20}$$

Inherent product variability, σ_ε^2, is assumed known and thus does not get updated.

The assumption of normality for risk-adjusted estimated net value including measurement error, $\tilde{\chi}_j$, implies that we can use a multinomial probit model to fit reported brand choice probabilities (Hauser and Wise [1978]). A logit approximation is proposed as an alternative because of the large number of brands in many consumers' consideration sets. Under the logit formulation, the probability of brand choice is given by

$$P_j = \frac{e^{\beta\chi_j}}{\sum_k e^{\beta\chi_k}} \tag{3.35}$$

We call this model the Multiattribute Utility Diffusion Model (MAUD).

Definition of an Innovation. By considering an entrant in an existing product class and its position relative to currently available brands, we have finessed the issue of "What is new enough to be considered an innovation?" which plagues many diffusion models (Rink and Swan [1979], Zaltman and Lin [1971]). Very new products are likely to have high initial information uncertainty and (potentially) very inaccurate mean estimates. They will therefore show marked diffusion effects. "Me-too" brands in a static market are likely to elicit accurate prior beliefs and low information uncertainty suggesting little diffusion effect. Thus, an innovation and its diffusion have been made a matter of degree.

3.4.2 Flexibility of the Model

The model has considerable flexibility in explaining different diffusion patterns. A graph of diffusion shapes which may be algebraically generated by the model is provided as Figure 3.3. A number of these imply increasing variance (uncertainty) and thus only have an interpretation if the known variance assumption is relaxed (as in Appendix B.2).

The figure was generated by assuming that industry sales and brand consideration were constant. Purchase probabilities were generated recursively using the equation

$$P_{N|B,C} = \frac{e^{\beta\left(\frac{\tau X(0)+ky_t\mu}{\tau+ky_t}\right)-r\left\{\left(\frac{\tau}{\tau+ky_t}\right)^2\sigma_0^2+\left(\frac{ky_t}{\tau+ky_t}\right)^2\frac{\sigma_x^2}{ky_t}+\sigma_\varepsilon^2\right\}}}{\kappa+e^{\beta\left(\frac{\tau X(0)+ky_t\mu}{\tau+ky_t}\right)-r\left\{\left(\frac{\tau}{\tau+ky_t}\right)^2\sigma_0^2(0)+\left(\frac{ky_t}{\tau+ky_t}\right)^2\frac{\sigma_x^2}{ky_t}+\sigma_\varepsilon^2\right\}}} \qquad (3.36)$$

where $X(0)$ is the initial preference, σ_o^2 the initial uncertainty. Equation 3.36 is obtained by substituting equation (3.23), $n_j = k_jY_{jt}$, in equations (3.21) and (3.22) and in turn substituting these in equation

(3.35), the logit model. No diffusion effects were assumed for other brands in the consideration set. All members of the population were considered to have the same probabilities of adoption.

The first graph shows a case of no diffusion. This corresponds to a mean known to consumers and no information uncertainty (or no communication with adopters).

The second two graphs (II) show the effect of the mean being updated, but no uncertainty reduction. The third graph in II shows information uncertainty reduction with no change in the mean. These three graphs represent the range of possibilities if only mean changes or uncertainty changes are considered. The richness of shapes stems from the interaction of changing uncertainty and mean.*

The third set of graphs, III, show the effects of mean changes and variance changes in opposite directions. Note that the first graph, the classic diffusion S-shaped curve, can only be generated by allowing increasing variance, that is, by relaxing the known variance assumption. In this graph, $\sigma_X^2 > \sigma_\mu^2(0)$ and $\mu > \mu(0)$. Early low penetration and variability of word of mouth slows the diffusion effect.

In the second graph, $\sigma_X^2 << \sigma^2(0)$ and $\mu < \hat{\mu}(0)$ so early variance reduction initially moderates the decline.

The third graph of III, which may have an asymptote either higher or lower than initial sales, is a more extreme case of the previous one.

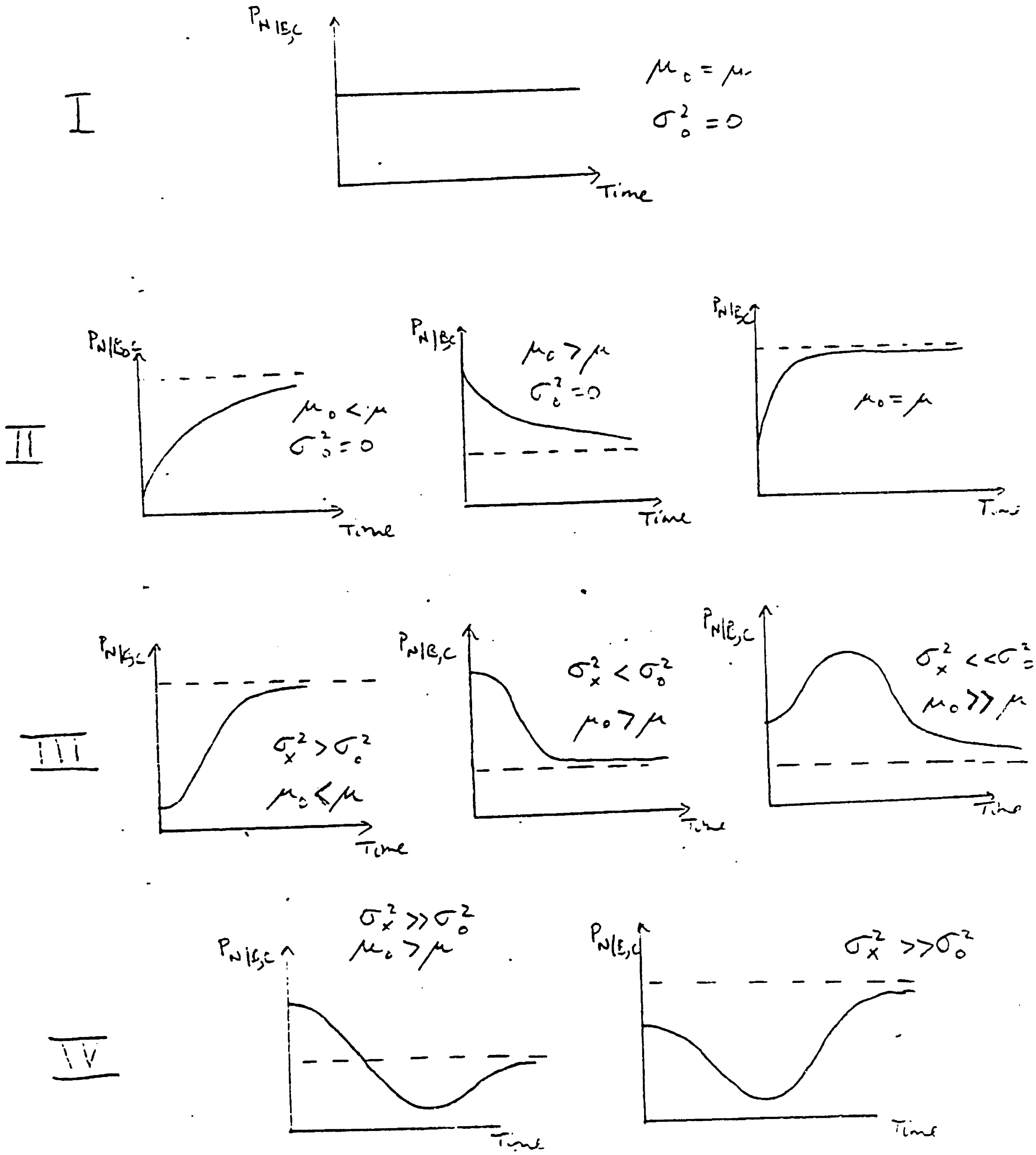


Figure 3.3 Alternative Choice Probability Dynamics Using MAUD

Initial uncertainty about the product is very high and is reduced quickly. As it ceases to be a factor, the declining mean change becomes more apparent. This graph is similar to the trial repeat graph for a frequently purchased product with high trial and low repeat (see Urban and Hauser [1980, p. 40]).

Graphs in IV occur when incoming WOM variance is so high that it causes an increase in the consumers' variance which initially overshadows mean change effects, either positive or negative. This shape corresponds to increasing uncertainty (in the early stages) and thus has no direct interpretation in terms of the Bayesian updating rules which we have developed. It may be possible to generate the same shape by dropping the population homogeneity assumption. Alternatively, the known variance assumption can be dropped.

3.4.3 Overview

In this chapter we have developed a model which is capable of explaining the perceptual position of a new brand in the market and which can handle a flexible range of growth patterns over time.

Chapter 4 moves from the general consideration of prelaunch durable forecasting to a speacific application of the model to a new auto brand. This allows a demonstration of how the model may be specified in practice. Measures and stimuli that can be used to calibrate the model, estimation techniques, and results obtained when applying the model are given.

CHAPTER 4: APPLICATION

4.1 Introduction

The multiattribute utility diffusion model, MAUD, developed in Chapter 3, was applied to the prelaunch forecasting of the brand share of a 1985 new car, planned by one of the major domestic auto manufacturers, MMC.[1] While the word "model" is frequently used for a specific car line within the automobile industry, the term "brand" is continued in this chapter to avoid confusion with the word "model" used in its mathematical sense.

The auto industry was chosen for the application for the following reasons:

- -- The extended problem-solving nature of auto purchase suggests that risk is an important factor (Pras and Summers [1979]).
- -- Data are available in considerable detail on the numbers and ages of different auto brands currently in operation, thus allowing a stratified sample to be extrapolated to the population as a whole.
- -- The industry has high fixed tooling costs and prototypes of new brands available years in advance, mentioned in Chapter 1 as typical of industries producing durable goods.

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1. Throughout the application, Michigan Motor Company (MMC) is used as a disguised name for the sponsoring company. Regada is used as a disguised name for the concept brand tested.

-- Evidence of brand life cycle effects has been presented for the auto industry by Silverman [1982], suggesting that diffusion is an important phenomenon for this category.

-- The well-developed second-hand market allows other components of the model to be fit (for example of the existing stock model, see Section 4.5).

The specific application reported in this chapter involved the substantial redesign and downsizing of an existing car line MMC's Regada. The structure of the chapter is outlined briefly below. Section 4.2 discusses the specific form of the multiattribute diffusion model used and some further assumptions necessary in this application. After a discussion of conditioning brand choice on purchase and consideration, the consumer behavior model used is outlined. This model, a modification of Tybout and Hauser's [1981] integrated model of consumer choice, suggests that attribute perceptions are reduced to factor perceptions which influence total preference. Total preference is discounted for price and risk, as outlined in Chapter 3, to obtain estimated risk adjusted net preference. This variable is transformed to choice using a logit model.

Details of the strategy used to fit the model are included in Section 4.3. The section starts with a description of the experimental design for data collection including testing, logistics, and stimuli used. This is followed in subsection 4.3.2 by an overview of measurement and estimation to give the reader a sense of which variables in the model are measured directly and which are computed. A game plan for fitting the model is also included in this subsection. The measures (subsection 4.3.3) and specific estimation techniques used (subsection 4.3.4) flow naturally from this overview.

Results of the application are included as Section 4.4. The model is fit in two stages. First, an analysis of the experimental effects of giving consumers information about the car are analyzed. Then, second, this is related to physical sales in the marketplace. A correspondence is achieved by comparing experimental results for the 1983 Regada with historical sales after its last major redesign.

The chapter ends with a discussion as to how this brand preference component of the new product forecasting system fits in with other components: purchase incidence, new brand consideration, and competitive entry (Section 4.5).

4.2 The Specific Model

4.2.1 Conditioning on Purchase and Consideration

The modeling framework developed in Section 1.2 posited that the probability of purchasing the brand under investigation (the stimulus brand) consisted of three components. Specifically, equation (1.1) stated:

$$P_N = P_{CBN} = P_C \cdot P_{B|C} \cdot P_{N|C,B} \qquad (1.1)^1$$

where

P_N = Probability of buying brand N for an individual,

P_{CBN} = Joint probability of considering brand N, buying within the category, and choosing brand N.

P_C = Probability of considering brand N.

$P_{B|C}$ = Conditional probability of buying within the category for those consumers who consider brand N.

$P_{N|C,B}$ = Conditional probability of choosing brand N, given that it is considered, and a category purchase is made.

It is this last probability, $P_{N|C,B}$, which the multiattribute utility diffusion model addresses. Thus, measurements are conditioned on consideration of N and a durable purchase. This consideration will be thought of as a dealer visit. Measures of the probability of meeting

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1 Notation for Chapter 3 carries through. This notation and new notation introduced specifically for Chapter 4 is summarized in Appendix A.

this condition are taken as part of fitting the other two elements, P_C and $P_{B|C}$.

4.2.2 The Consumer Behavior Model

Respondents in the survey were asked to evaluate markets under various scenarios. For example, one scenario was the auto market as it existed when the research was conducted. Another was that market after the entry of the stimulus brand. The final one was the market after the stimulus brand had become better known.

An adaption of Tybout and Hauser's integrated model of consumer choice was used to examine perceptions, preference, and choice under each of these conditions (Tybout and Hauser [1981]). Tybout and Hauser cite theoretical and behavioral evidence to suggest that physical characteristics are abstracted to perceptions (e.g., Brunswik's lens model), that perceptions jointly combine to form preferences (e.g., the Fishbein and Rosenberg models), and that preference mediated by environmental constraints determines choice. Individual and situational differences mediate both the attribute-to- perceptions transformation and the perceptions-to-preference transformation. Their model is illustrated in Figure 4.1.

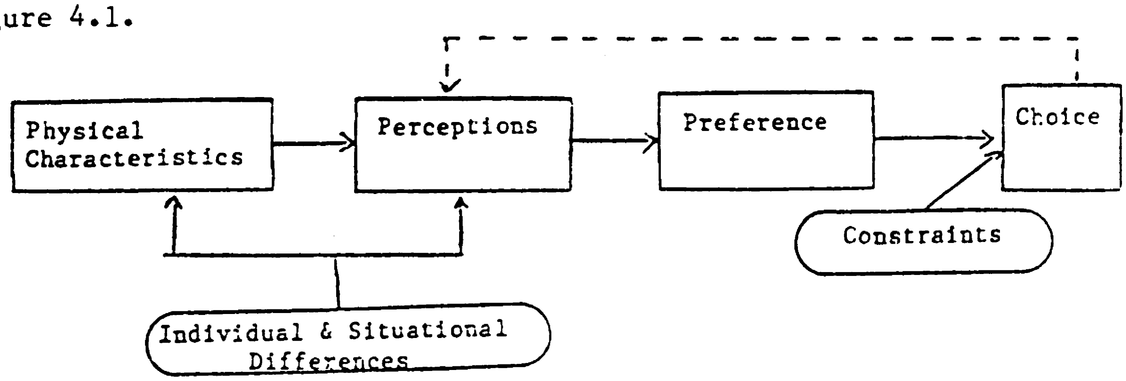

Figure 4.1 Tybout and Hauser's Integrated Model of Consumer Choice.

Tybout and Hauser point out that perceptual measures are particularly important for image-laden products. Dichter [1964] and Levy [1978] argue that the auto is just such a product.

This thesis is not concerned with the attribute-to-perception transformation; data were collected directly on perceptions. However, the perceptions-to-preference stage is modeled and estimated. The relation of choice to preference is also considered. Preference, v_j, defined in Chapter 3 by equation 3.1, was postulated to be discounted by price to get net preference (equation 3.2) and by risk (equation 3.8) to get risk-adjusted net preference as the determinant of choice.

There are arguments both in favor of and against looking at a reduced space of perceptual dimensions. Hauser and Simmie [1981] claim that in practice the number of dimensions which consumers use is small, suggesting that reduced spaces should be able to capture most important elements of the influence of perceptions on preference. In an empirical test, Hauser and Koppelman [1979] show that little information is lost by the use of a reduced space (derived by factor analysis) rather than using the full set of attributes and it increases managerial interpretability. Shocker and Srinivasan [1979] point out the likely problems with multicollinearity when using a full attribute set in statistical analyses, and the advantage of parsimony achieved by the use of reduced spaces.

Against this, reasons for using a full set of attributes might include a lack of interpretability of factors, and problems with "technological correlations." A technological correlation occurs if two variables move together in practice (e.g., operating costs and size) and thus are likely to have a spurious positive correlation, causing them to load together positively on the same factor. Like multicollinearity, such a correlation will be problematical if the variables cease to move together.

A number of these arguments favor a reduced-space approach so factor analysis was conducted.[1] However, estimation of preference directly on all attribute perceptions was also undertaken (see Table 4.5 in Section 4.4).

A diagram of the model used, together with the source of variables in the model is included as Figure 4.2.[2]

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1 These arguments relate primarily to convenience and simplicity of data analysis. Care should be taken when drawing normative implications from such reduced spaces since they do not necessarily represent the way in which consumers process information. For a discussion of a more process-oriented and more general approach to these problems, see Bagozzi [1983]. A discussion of extending the results contained in this thesis to encompass such issues is discussed in Chapter 5 under Future Research.

2 The algebraic formulation corresponding to this diagram is given in Section 4.3.2.

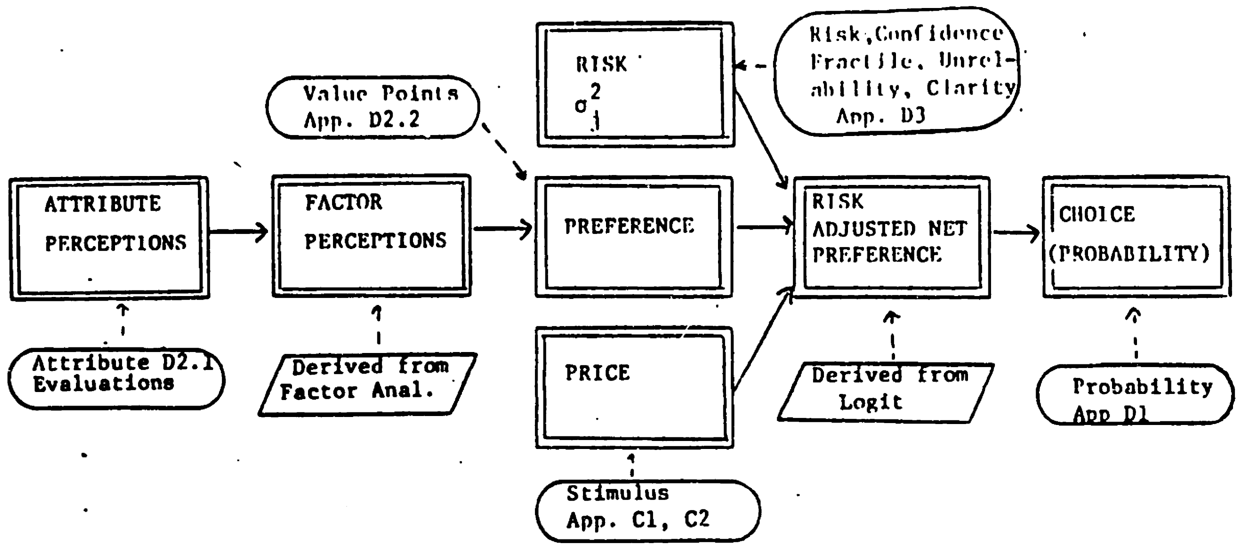

Figure 4.2 Consumer Behavior Model Used to Represent Dynamic Multiattribute Evaluations in this Research

4.2.3 The Multiattribute Model and Updating in Practice

Equation 3.8 implies that the consumer will buy the stimulus brand, N, given that he considers and buys within the category, if

$$X_N - \frac{r}{2}\sigma_N^2 > X_j - \frac{r}{2}\sigma_j^2 \qquad j \epsilon C \qquad (3.25)$$

$$\text{i.e.,} \quad \chi_N > \chi_j \qquad j \epsilon C$$

where X_j is the consumers' estimated net preference, σ_j^2 is the total uncertainty, and χ_j is the risk adjusted net preference.

X_j is measured with error as detailed in Equation 3.2.5. In fact,

$$X_j - \frac{r}{2}\sigma_j^2 + e_j \sim N(\mu_j - \frac{r}{2}\sigma_j^2 , \sigma_e^2)$$

Using the logit approximation outlined in Section 3.3, the probability of choosing brand N may be written:

$$P_N = \frac{e^{\beta(X_N - \frac{r}{2}\sigma_N^2)}}{\sum_{j\varepsilon C} e^{\beta(X_j - \frac{r}{2}\sigma_j^2)}} \qquad \frac{e^{\beta X_N}}{\sum_{j\varepsilon C} e^{\beta X_j}} \tag{3.35}$$[1]

At any point in time, t, the expected net preference and the uncertainty associated with each brand may be written as variants of equations (3.28), (3.12), and (3.26), respectively:

$$X_j(t) = \frac{\tau X_j(0) + n\bar{x}}{\tau+n} = \frac{\tau X_j(0) + n\mu_j}{\tau+n} + \begin{array}{l}\text{Normally}\\ \text{Distributed}\\ \text{Error}\end{array} \tag{4.1}$$

$$\sigma_j^2(t) = \sigma_{\hat{\mu}_j}^2(t) + \sigma_{\varepsilon_j}^2 \tag{4.2}$$

$$\sigma_{\hat{\mu}_j}^2(t) = [(\frac{\tau}{\tau+n})^2 \sigma_{\hat{\mu}_j}^2(0) + (\frac{n}{\tau+n})^2 \frac{\sigma_{\bar{x}}^2}{n}] \tag{4.3}$$

where $X_j(0)$ and $\sigma_{\hat{\mu}}^2(0)$ are the estimated mean and the information uncertainty at some reference point time, time 0. The role of error in equations (4.1) - (4.3) may be seem from remembering that in Chapter 3 we assumed that all variances were known (but not necessarily constant). Thus, (4.2) and (4.3) have no error associated with them. $\bar{x}$ was assumed to come from a normal distribution, as was $X_j(0)$. Therefore, $\tilde{X}_j(t)$

---

1 The logit equation was actually estimated on total value (v), price and risk (σ^2) since a direct measure for risk adjusted net value was not available.

is normal. The risk-adjusted net preference, $\tilde{X}_j(t) = X_j(t) - \frac{r}{2} \cdot \sigma_j^2 + e_j$, is also normal because of assumptions about measurement error. Similar measurement errors must be assumed to be inherent in other brands before the logit approximation (3.37), above, may be applied.

These updating formulae may be substituted in the probability expression, equation (3.37), to allow the recursive calculation of brand choice over time once initial and true values of μ_j and σ_X^2 are established and the relation of n to cumulative sales is given.

Two further assumptions are applied at this stage. First, only the top three choices in the consideration set are included in the model (in addition to the stimulus brand). This is consistent with constraints imposed by the independence of irrelevant alternatives of the logit model. An estimate is available for the probability of other than the top three choices to allow appropriate adjustment of the probabilities.

The second assumption is that there are no dynamic effects in the utilities of the top three choice brands over time. While that assumption will be relaxed in future research, particularly when the competitive entry model is fit, it is not as great a violation of the process as it at first appears. There is no a priori reason to expect systematic bias in the estimate of mean preference for the other brands. While the uncertainty of other brands may decrease with search and further diffusion, that factor will also be present for the stimulus brand as a result of how we defined inherent product variability for it. This definition is spelled out in the results section.

With these assumptions, the full model becomes:

$$P_N(t) = \frac{e^{\beta[(\frac{\tau}{\tau+n})X_o + (\frac{n}{\tau+n})\mu - \frac{r}{2}\{(\frac{\tau}{\tau+n})^2 \sigma_o^2 + (\frac{n}{\tau+n})^2 \sigma_x^2 + \sigma_\varepsilon^2\}]}}{\sum_{1}^{3} e^{\beta(X_j - \frac{r}{2}\sigma_j^2)} + e^{\beta[(\frac{\tau}{\tau+n})X_o + (\frac{n}{\tau+n})\mu - \frac{r}{2}\{(\frac{\tau}{\tau+n})^2 \sigma_o^2 (\frac{n}{\tau+n})^2 \sigma_x^2 + \sigma_\varepsilon^2\}]}} \qquad (4.4)$$

where $n = k.y(t)$, a constant proportion of cumulative sales. Equation 4.4 is obtained by substituting the updating formulae (4.1)-(4.3) in the logit equation (3.35), using these two additional assumptions.

To forecast the evolution of the probability of an individual preferring the stimulus brand, we need estimates of the following variables:

X_o, σ_o^2	Initial perceptions of the stimulus brand;
μ, σ_X^2, σ_ε^2	Levels of the true mean, heterogeneity of perception and inherent variability of the stimulus brand;
X_j, σ_j^2	Perceptions of the top three brands in the consumers' consideration set (assumed constant over time).

A discussion of measures of these variables is included in Section 4.3.3, following. Specific measures used are in Appendix D.

Estimates of the following parameters are also required.

- τ: Initial strength of beliefs about the stimulus brand (or in some sense, a brand loyalty carry-over effect),
- k: Proportion of the cumulative owners from whom a consumer will obtain information,
- β: Logit value parameter
- r: Logit risk aversion parameter,
- λ: Logit price parameter.

4.3 Measures and Estimation Methods Used in the Application

4.3.1 Experimental Design

Instrument Development. The questionnaire used in this application was developed after substantial pretesting. An initial version of the questionnaire, jointly developed by Hauser, Roberts, and Urban, was pre-tested in Troy, Michigan, on 30 respondents in June, 1982. The objective of this pretest was to determine the feasibility of the overall approach and the meaning and reliability of the initial measures. Although the approach proved feasible, extensive revisions to questions on utility and confidence in choice proved necessary.

A full field trial with 80 respondents was undertaken in Phoenix, Arizona, in January, 1983, to tighten up on questionnaire wording and to test the rather complex logistics of the research. The field trial went smoothly requiring only minor modifications to the survey so that the full experiment was able to be conducted in Cincinnati, Ohio, in February-March, 1983 with 336 respondents.

Sample. The target sample size was 320. 336 usable interview records were obtained. Two respondents did not complete the survey. The figure of 320 was chosen to allow two complete replications of the competitive entry conjoint analysis included in the survey (Hauser, Roberts, and Urban [1983]), and to ensure sufficient sample size to obtain statistically significant results.

The major part of the sample was stratified according to current brand switching patterns to the stimulus brand. Lists available from R.L. Polk and Company allowed the direct selection of a target sample. These lists showed the brand being replaced for all MMC Regada purchasers on a historical basis. Strata quotas for current ownership strata were selected in proportion to the number of each brand replaced by new purchasers using most recently available historical data. No attempt was made to forecast this change in draw over time or to adjust for a different draw due to downsizing. Because switching patterns to the new brand may be different to those of the old one, 100 respondents were selected randomly to allow some inference to be made about brand preference in new segments.

A check of the car which respondents said that they would replace next showed a reasonable correspondence between the quota specifications and the auto owners obtained, with some undersampling on the stimulus brand (33 obtained against 61 specified).

Married respondents were asked to bring their spouse and joint responses were collected. 89% of interviews were scheduled outside of working hours to avoid a bias against employed respondents. 83/336 (=24.7%) couples were interviewed and of the respondents who were not accompanied, 162 (64.0%) were male and 91 (36.0%) were female.

Recruitment was by telephone followed by a letter. An incentive of $25 was offered for participation. A survey of non-response due to non-contact or refusal was not undertaken.

Structure of the Interview. Information was collected during a one and one-half to two hour face-to-face interview. As was suggested in Chapter 3.3, the brand preference data formed just one part of the survey.

The modules contained in the survey are detailed in Table 4.1.

	Durable Purchase Study
	Economic Scenario Analysis
+	Inventories of Currently Owned Cars
+	Auto Buying Process
	Consideration Set and Top Choice Evaluation
	Competitive Conjoint Analysis
	Post Test Drive Evaluation
	Post Videotape and Safety Report Evaluation
+	Innovativeness and Demographics
	Task Evaluation

Table 4.1 Measurement Task Modules in Auto Buying Experiment

The large amount of information to be collected in the survey necessitated splitting the sample so that approximately one-half of the sample (174/336) had an abridged version of the sections marked + in Table 4.1, while the remainder (162) omitted the durable evaluation and economic scenario section.

The interviews consisted of a variety of tasks for the respondent, including card sorts, answering questions, a test drive, filling out response sheets, observing a videotape, and reading information and reports. This prevented boredom on the part of either the interviewers or respondents.

<u>Experimental Stimulus</u>. After data were gathered on respondents' evaluation of the current marketplace, including their top choices, information was given to them about the stimulus brand.

Respondents were given data about the brand in three stages in order to simulate the purchasing process as closely as possible and the diffusion effects of increasing information over time. Detailed evaluations were solicited at each stage.

In the first stage, the respondent viewed a line drawing of the auto together with a set of specifications: maker, price, miles per gallon, engine size, resale value, maintenance, financing, and features. This is a similar approach to most conjoint analyses (see Shocker and Srinivasan [1979]).

In the second stage, respondents actually examined and test drove the car, a technique proposed by Hauser and Urban [1982].

In the final stage, respondents viewed a videotape of three "consumers" who had been given the opportunity to test drive the cars for six months, and a "Laboratory Report" of it. The "consumers" in the videotape were, in fact, professional actors and the text of their evaluations was based on focus groups previously held about the brand, with input from the auto company and its advertising agency.

The laboratory maintenance and safety report was simulated to look like those currently on the market (e.g., <u>Consumer Reports</u>, <u>Car and</u>

Driver, etc.). Again, the auto company was given the opportunity to suggest levels for the report.

Positive and negative versions of both the videotape and the safety report were prepared to enable their effect to be evaluated. Respondents were randomly allocated to either a positive group or a negative one.

Examples of the stimuli are included as Appendix C.

Use of Control Brand. In order to allow an estimate of the methods effect of placing a respondent in a new car and then asking him or her to evaluate it, a control brand was used for one-third of the respondents (108/336). The control car was the 1983 version of the 1985 prototype brand that was being tested. Both cars were masked and only one respondent is reported to have commented on recognizing the 1983 version.

In addition to providing a measure for the methods effect, the control car also provided a way of relating the experimental effect of sequential information exposure to the sales of the new brand in practice.

Logistics. The complexity of the interview necessitated props which would minimize interviewer difficulty. Thus, information was filled out on 3x5" printed cards for auto brands evaluated, and on 8.5 x 11" sheets for attribute evaluations and other detailed responses. Each respondent had his or her own 9x11" envelope so that correct safety reports and conjoint concepts were given to each respondent and information about one respondent could not be mixed up with that of another (a problem in the pretest).

3x5" cards, lists of current autos on the market with their prices and other details, safety reports, conjoint concepts, response sheets, and labelled envelopes were produced professionally under supervision from M.I.T. Every envelope was checked by a member of the project team.

Professional interviewers were trained intensively by Professor Urban and the author before the survey began. Additionally, two field supervisors attended the Phoenix pretest and took interviewers through a training videotape prepared in Phoenix. An MIT project team member was in attendance for almost all of the interviews and editing of responses was performed straight after interview completion.

The interviews were carried out in a hotel conference facility which enabled the cars to be parked behind the interview rooms.

4.3.2 Measurement and Estimation Overview

The analysis of the data collected in the application is divided into two sections. The first is an analysis of the experimental effect of the videotape and safety report treatments. This looks at the dynamics of beliefs in the laboratory and their effect on stated probability of purchase.

The second section interprets these results in relation to the expected marketplace diffusion of the stimulus brand. It does this by examining sales of the Regada since its relaunch in October 1976 in an attempt to establish a transformation between the experimental effect and the brand's sales history.

The procedure used at each stage can be best represented in the form of two flow charts, Figures 4.3 and 4.4.

The perceptions/preference/choice model outlined in Section 4.2.2 is estimated in each of the three scenarios; the current market, the current market just after entry, and the current market after entry and some word of mouth diffusion (boxes 1-3 in Figure 4.3).

For each of these markets, reduction to the perceptual space (factor analysis), relation of perceptual dimensions to preference, and estimation of choice based on risk-adjusted expected net preference is undertaken.

Analysis of Experimental Effects

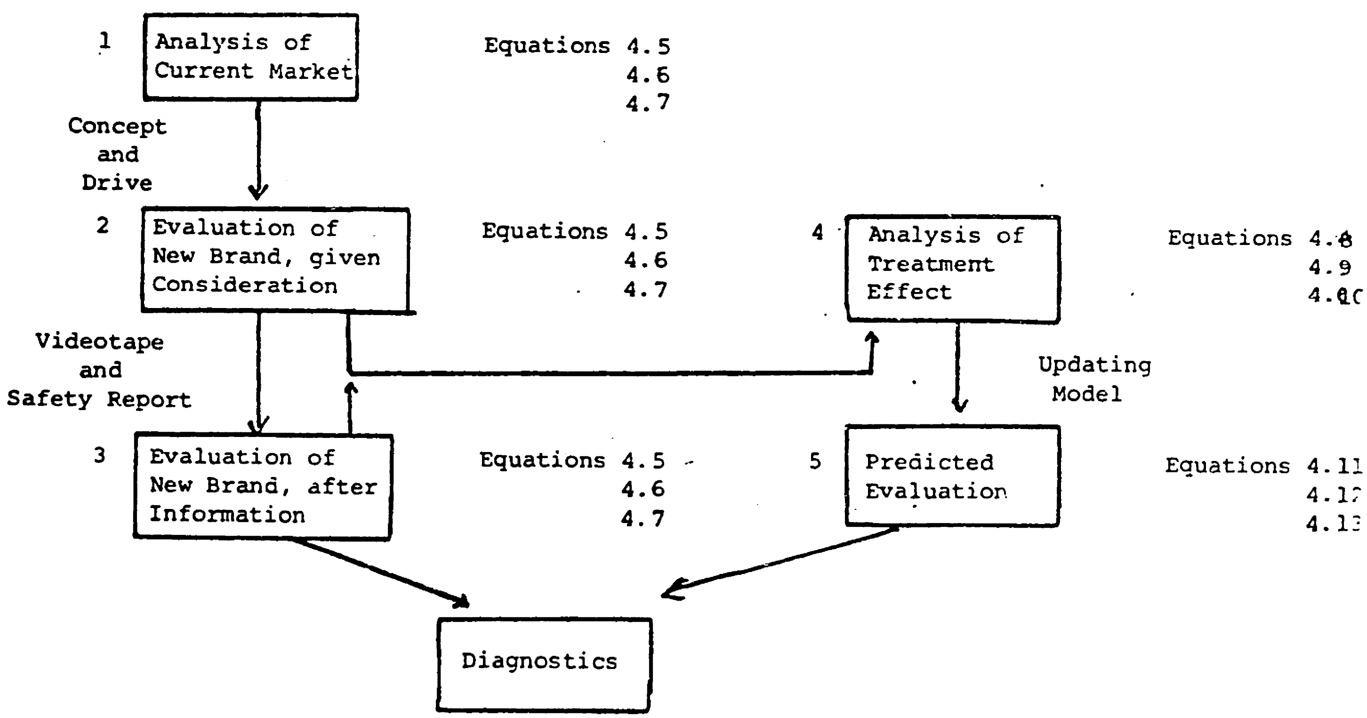

Figure 4.3. Estimation Structure for Evaluating Experimental Effects of Information Acquisition.

Algebraically it may be described:

Reduction of attribute perceptions to underlying factors:

$$z_{j\ell} = \sum_{k \in K} b_{\ell k} y_{jk} \tag{4.5}$$

where

y_{jk} = kth attribute perception of brand j

$b_{\ell k}$ = factor loading coefficient of factor ℓ on attribute k

$z_{j\ell}$ = factor score of the ℓth factor for brand j.

Transformation of perceptions to preference:

$$v_j = \sum_{\ell \in L} a_\ell z_{j\ell} \tag{4.6}$$

where

a_ℓ = importance weight of ℓth factor

v_j = estimated mean total preference for brand j.

Transformation of preference to choice

$$P_j = \frac{e^{\beta(X_j - \frac{r}{2}\sigma_j^2)}}{\sum\limits_{j' \in C} e^{\beta(X_{j'} - \frac{r}{2}\sigma_{j'}^2)}} = \frac{e^{\beta(v_j - \lambda p_j - \frac{r}{2}\sigma_j^2)}}{\sum\limits_{j' \in C} e^{\beta(v_{j'} - \lambda p_{j'} - \frac{r}{2}\sigma_{j'}^2)}} \tag{4.7}$$

The analysis of the treatment effect in box 4 (Figure 4.3) is obtained by looking at the recommendation which the respondent gave the brand before seeing the videotape and safety report (R'), the recommendation he gave it afterwards (R"), and the perceived recommendations which he felt the videotape and safety report were giving R_T.[1]

1 Note a double prime (") is used for post treatment measures in the experiment and a single (') is used for pretreatment measures. Refer to Appendix A.

The Bayesian updating formula for the mean suggests that

$$
\begin{aligned}
R'' &= \frac{\tau}{\tau+n} R' + \frac{n}{\tau+n} R_T \\
&= R' + \frac{n}{\tau+n} (R_T - R') \\
&= R' + \frac{1}{(\tau/n)+1} (R_T - R')
\end{aligned}
\tag{4.8}
$$

$$
\Rightarrow \frac{\tau}{n} + 1 = \frac{R_T - R'}{R'' - R} \quad \Rightarrow \frac{\tau}{n} = \frac{R_T - R'}{R'' - R'} -1
$$

The reader may see that our ability to measure τ/n depends heavily on our ability to measure recommendation levels accurately. The error structure of τ/n is complex. It is not symetric and an examination of its properties is suggested under Future Research in Chapter 5.

Given the above computation of τ/n, estimates of the true mean and word-of-mouth variance may be obtained by the rearrangement of the Bayesian updating formula:

$$
\begin{aligned}
&X'' = \frac{\tau}{\tau+n} X' + \frac{n}{\tau+n} \mu_T \\
&\Rightarrow \hat{\mu}_T = X'' + \frac{\tau}{n} (X'' - X') + \text{error}
\end{aligned}
\tag{4.9}
$$

If we assume a normally distributed error structure or recommendations (R', R'', R_T) and continue that through to equation 4.8, the distribution error of our estimate of μ becomes extremely complex (and is not symetric). For simplicity, we have chosen to approximate by adding error only at this stage. If μ is provided by management judgment, rather than being estimated from the sample, then equation (4.9) does not have to be used and the problem of multiplicative asymetric errors does not arise.

One further problem of estimating μ_T in this way is that if there is a methods effect in measuring X" and X', this will not cancel out in our estimate of μ_T, as may be seen from equation 4.9. We cannot rely on the methods effect parameter, K, in fitting marketplace diffusion to totally remove this problem because the importance of μ_T will vary as the product diffuses (e.g., see equation 4.11).

The variance of the evaluation associated with the stimulus can be imputed in a similar way to the mean:

$$\sigma''^2 = \left(\frac{\tau}{\tau+n}\right)^2 \sigma'^2 + \left(\frac{n}{\tau+n}\right)^2 \sigma_x^2$$

$$\Rightarrow \sigma_x^2 = \left(1 + \frac{\tau}{n}\right)^2 \sigma''^2 - \left(\frac{\tau}{n}\right)^2 \sigma'^2 \qquad (4.10)$$

Estimates of τ/n, μ_T, $\sigma_{\bar{x}}^2$ from box 4 of Figure 4.3 and estimates of β, $r/2$, and λ from the logit estimation of pre-videotape preference and probability, allow prediction of the post-videotape risk-adjusted net preference. From this, post-video choice probabilities may be estimated using individual pre-video utilities and strength of prior beliefs:

$$\hat{P}''(1)\ \frac{e^{\beta[(\frac{\tau}{\tau+n})V' + (\frac{n}{\tau+n})\mu_T - \lambda p - \frac{r}{2}\{(\frac{\tau}{\tau+n})^2 \sigma'^2 + (\frac{n}{\tau+n})^2 \sigma_x^2 + \sigma_\varepsilon^2\}]}}{\sum_1^3 e^{\beta(V_j - \lambda p_j - \frac{r}{2}\sigma_j^2)} + e^{\beta[(\frac{\tau}{\tau+n})V' + (\frac{n}{\tau+n})\mu_T - \lambda p - \frac{r}{2}\{(\frac{\tau}{\tau+n})^2 \sigma'^2 + (\frac{n}{\tau+n})^2 \sigma_x^2\ \sigma_\varepsilon^2\}]}} \qquad (4.11)$$

where

$\hat{P}''(1)$ = predicted probability of stimulus brand preference post-video, given stimulus brand utility, pre-video.

$\hat{P}''(1)$ may also be adjusted to reflect errors in fitting the pre-video data. The rationale for this adjustment stems from the fact that our errors in forecasting an individual's probability of stimulus brand post-video choice may be related to errors in forecasting pre-video probabilities using the logit model. So, as a heuristic, we try adjusting $\hat{P}''(1)$ for individual pre-video errors, both additively and multiplicatively. Note that these errors are known prior to the video. Thus, estimates $\hat{P}''(2)$ and $\hat{P}''(3)$ may be obtained by

$$\hat{P}''(2) = \hat{P}''(1) + (P' - \hat{P}') \tag{4.12}$$

and

$$\hat{P}''(3) = \hat{P}''(1) \cdot \frac{P'}{\hat{P}'} \tag{4.13}$$

where

P' = stated probability of stimulus brand preference pre-video.

$\hat{P}'$ = fitted probability of stimulus brand preference by logit model in box 2, Figure 4.3.[1]

---

1 The rationale for assuming that we will obtain an improvement using $\hat{P}''(2)$ depends on the hypothesis that there are two sources of error in our fitting of the logit model to the concept. One of these is random, as suggested by the respondent x car logits that have been estimated (e_1); the other is a systematic individual bias in estimating the concept which we postulate will remain as information levels increase (e_2).

Thus we assume:

$$\hat{P}' = P' + e'_1 + e_2$$

$$\hat{P}'' = P'' + e''_1 + e_2$$

Therefore, $\hat{P}''(1) + (P' - \hat{P}') = P'' + (e''_1 - e'_1)$.

By the use of this heuristic we are invesigating whether $\mathrm{var}\,(e''_1 - e'_1) \gtrless \mathrm{var}\,(e''_1 + e_2)$. A similar rationale could be advanced for using P"(3), assuming multiplicative errors.

Forecasting Preference Changes in the Marketplace

Figure 4.3 outlines the analysis of the experimental situation. In contrast, Figure 4.4 describes the relation of the parameters derived in the study to actual marketplace reaction. Box 1 in Figure 4.4 represents the results from the experimental treatment which we use to forecast choice dynamics of the new brand.

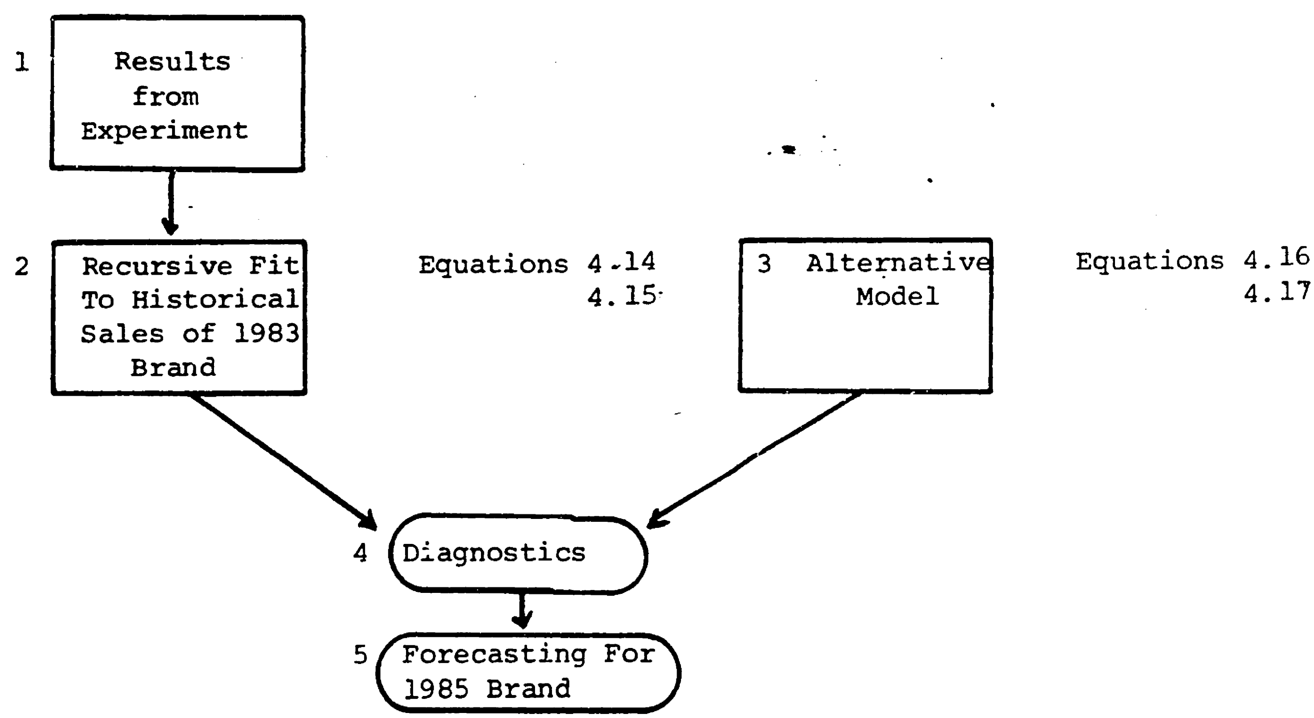

Figure 4.4. Estimation Structure for Forecasting Diffusion of Preference for 1985 Brand.

Equation (4.4) in Section 4.2.3 provides the specific updating formula which is used to update the probability of brand preference in box 2 (Figure 4.4). Some estimates obtained from the analysis of experimental effects are carried over at this stage. These include initial beliefs (X_o and σ_o^2), true levels of μ and σ^2, beliefs concerning other brands (μ_j and σ_j^2), and the model parameters β, r, and λ.

This leaves a requirement to estimate τ and n (which is assumed a constant proportion, k, of cumulative sales). In addition, because the methods effect of allowing a consumer to drive the stimulus brand and not his other top choices will be likely to affect his judgment process, it is desirable to multiply $\hat{P}_N$ by a constant K to determine the extent of this effect.[1] Thus, equation (4.0) becomes

$$\hat{P}_N(t) = \frac{Ke^{\beta[(\frac{\tau}{\tau+n})X_o + (\frac{n}{\tau+n})\mu - \frac{r}{2}\{(\frac{\tau}{\tau+n})^2 \sigma_o^2 + (\frac{n}{\tau+n})^2 \sigma_x^2 + \sigma_\varepsilon^2\}]}}{\sum_1^3 e^{\beta(X_j - \frac{r}{2}\sigma_j^2)} + e^{\beta[(\frac{\tau}{\tau+n})X_o + (\frac{n}{\tau+n})\mu - \frac{r}{2}\{(\frac{\tau}{\tau+n})^2 \sigma^2 (\frac{n}{\tau+n})^2 \sigma_x^2 \sigma_\varepsilon^2\}]}} \tag{4.14}$$

and $$n = kY_t \tag{4.15}$$

where at this stage of estimation τ, K, and k are unknown.

---

1 In a slightly different form,

$$\hat{P}_N = \frac{K e^{\beta X_N}}{\sum_1^3 e^{\beta X_j} + Ke^{\beta X_N}} = \frac{e^{\beta X_N + \ln K}}{\sum_1^3 e^{\beta X_j} + e^{\beta X_N + \ln K}}$$

we can estimate ln k as a parameter in the logit model. It takes the form of an dummy variable for the concept car.

Note that the τ/n in the experimental stage cannot be used here because the information stimulus of the experiment and the marketplace are different.

Given these estimates and also consideration and category purchase probabilities, $\hat{P}_N(t)$, the probability of brand purchase, may be generated.

Historical sales of the 1983 Regada allow us to estimate the remaining parameters τ, k, and K and determine the fit of our model. The criterion used is the minimization of the residual sum of squares between historical sales of the 1983 version and the fitted population sales. Fitted population sales are obtained from summing adoption probabilities of the sample after making assumptions about industry sales and consideration. As a null model, against which to test the fit, Bass' logistic model was used (Bass [1969]). That model is described in some detail in Chapter 2. Its algebraic form is:

$$P_N(t) = (a + bY_t) \tag{4.16}$$

with the assumption of a fixed population, m. Thus,

$$\text{Sales}_t = (a + bY_t)(m - Y_t) \tag{4.17}$$

After comparing the models in a diagnostic phase, the multiattribute utility diffusion model is used to predict sales of the 1985 brand, according to equation (4.14), the logit equation containing the Bayesian updating formulae.

Summary of Measurement and Estimation Overview

The sequential nature of estimation of the model and the variety of measures used may make it difficult for the reader to work out which variables and parameters are estimated and which are measured. In an effort to clarify the sources of variables and parameters in the model, Table 4.2 attempts to summarize how each equation in the model is quantified.

Equation Number, Page Number, and Title	Variable	Measured	Estimated/ Computed	Comments
4.5 $z_{\ell j} = \sum_k b_{\ell k} y_{jk}$	$z_{\ell j}, b_{\ell j}$		✓	Factor Scores and Loadings.
	y_{jk}	✓		Attribute Ratings
4.6 $v_j = \sum_\ell a_\ell z_{\ell j}$	v_j	✓		Preference (Value Points)
	a_ℓ		✓	Factor Importance Weights
4.7 Logit	P_j	✓		Stated Probability of Brand Choice
	p_j	✓		Price of Brand
	σ_j^2	✓		Risk
	β, λ, r		✓	Logit Parameters
4.8 τ/n Estimates	τ/n		✓	Relative Strength of Beliefs
	R', R''	✓		Pre and Post Recommendation
	R_T	✓		Perceived videotape recommendations
4.9 True Mean	μ_T		✓	Imputed true expected value
	X', X''	✓		Pre and Post value points
4.10 Stimulus Variance	σ_x^2		✓	Imputed variance of videotape
	σ'^2, σ''^2	✓		Pre and post Uncertainty
Analysis of Sales 4.14 Probability of Choice	β, r, λ		✓	Carried over from 4.3
	σ_j^2, X_j	✓		Top 3 Brands' risk and value (same measure as for concepts)
	σ_x^2,		✓	Carried over from 4.5
	μ_T		✓	(σ_ε^2 assumed = σ_j^2 for j=1)
	K, τ, k		✓	Estimated by Grid Search
	μ_o, σ_o^2	✓		Initial estimates (post drive)

Table. 4.2 Summary of Parameters and Variables in the Model and Their Sources.

4.3.3 Measures Used in the Experiment

Table 4.2 outlines those measures which were obtained directly from the survey and those which were derived. Direct measures used in the model fitting are basically of four types: probability, utility (including value and preference), risk and uncertainty, and perceived recommendation variables. A general description was given in Section 3.2. Details specific to this application are provided below. Examples of the measures are given in Appendix D.

In addition to data from the survey, monthly sales of the 1983 Regada and auto industry sales were provided by MMC.

Probability. The primary probability or intent measure used was an 11-point Juster scale in which probability on a 0 to 10 basis was accompanied by verbal descriptions ranging from "no chance, almost no chance" to "certain, almost certain" (Juster [1966]). This scale has had substantial empirical validation (e.g., see Kalwani and Silk [1983]). The complete scale is contained in Appendix D.

A number of respondents used the verbal anchors for their probabilities and so did not find it inconsistent to give "a good possibility" (6/10) as being the probability of buying each of their top three choices. Thus, a complementary probability, the probability of buying other than their top three choices was also solicited to allow renormalization.

As a convergent test of the probability measure, as suggested by Hauser and Urban [1982], respondents were also asked to rank their top three choices and to insert the concept in the ranking, both pre-videotape and post-videotape viewing. Under the assumption that respondents would choose their top-ranked brand, we obtain an alternative estimate of choice.

Perceptions and Preference. Perceptions on nine attributes were collected on a five-point scale ranging from extremely poor to excellent. These attributes were selected by combining open-ended interviews prior to the Troy feasibility test (Bertran and Hauser [1982]) with a review of the marketing literature, internal company research studies, and management judgment. The attribute list was refined between the three stages of the research. Final attributes chosen were: luxury and comfort, style and design, reliability, fuel economy, safety, maintenance costs, quality, durability and resale value, and road performance. Attribute evaluations were only taken from one-half of the sample (162/336).

A number of different preference measures were tested. Some measures of preference were after allowing for price and some were not. Measures also varied in the nature of the metric. Constant sum chip allocations using physical counters proved too complex a task over the whole of the consideration set. Although the task was easier if the total number of chips allocated was allowed to be variable, the task still caused difficulty. Constant sum paired comparisons were also pretested. They were found to be easier for respondents but more time consuming.

The reservation price of a brand as a measure of utility caused pretest respondents some confusion because the availability of close substitutes made it difficult to work out what the alternatives to non-purchase would be. If the price of a Chevrolet Caprice went up by 20%, what does that imply about other brands?

The measure adopted was a thermometer scale with the preference for the most preferred auto from those currently available being given 100 points and indifference about ownership being given 0 points. Pretesting measures of total preference (before allowance for price) suggested that high price-high preference cars were not being given as many value points as one might expect, suggesting some price discounting of preference. Therefore an attempt was made to measure preference after removing price. This was done according to the utility/dollar brand choice criterion (see Section 3.1.1). That is, consumers were asked to allocate points on a usefulness-per-dollar basis. (See Appendix D for the exact wording of the question.)

Like probability, value points were also normalized to sum to one, increasing the interpretability of the first choice value points across respondents.

Risk and Uncertainty. A number of measures of risk and uncertainty were used in the survey. These included;

-- Risk -- A direct question of how much risk was associated with the purchase of the car, measured on all top three choices and the concept at both stages (five-point scale).

— Confidence in choice -- A measure of how sure the consumer was of his or her judgment of the brand, given imperfect information, measured on top choice only and concept at both stages (five-point scale).

— Reliability — Perceived reliability of the brand was solicited for the top three choices and the concept at both stages (five-point scale).

-- Fractile Measure -- The probability of a brand being worse than the second choice (or better than it if it was currently ranked worse) was obtained using a Juster scale. After retransformation,[1] a measure of variance is available. This measure was collected for the top choice and the concept, pre- and post-video.

---

1. $\hat{\mu}_1 \sim N(\mu_1, \sigma_1^2)$ and $\hat{\mu}_2 \sim N(\mu_2, \sigma_2^2)$

$$\Rightarrow \quad \hat{\mu}_1 - \hat{\mu}_2 \sim N(\mu_1 - \mu_2, \sigma^2_{\hat{\mu}_1 - \hat{\mu}_2})$$

$$\Rightarrow \quad P_r[\mu_2 > \mu_1] = Pr[\frac{\mu_2 - \mu_1}{\sigma_{\hat{\mu}_2 - \hat{\mu}_1}} > 0] = Pr[\frac{\hat{\mu}_2 - \hat{\mu}_1}{\sigma_{\hat{\mu}_2 - \hat{\mu}_1}} > \frac{e_2 - e_1}{\sigma_{\hat{\mu}_2 - \hat{\mu}_1}}]$$

$$= P^+ \quad \text{where } \hat{\mu}_1 = \mu_1 + e_1, \ \hat{\mu}_2 + \mu_2 + e_2$$

$$\therefore \quad \sigma_{\hat{\mu}_2 - \hat{\mu}_1} = \frac{\hat{\mu}_1 - \hat{\mu}_2}{\Phi^{-1}(P^+)}$$

where $\Phi^{-1}(P^+)$ is the inverse cumulative normal distribution of the stated probability of car 1 being worse than car 2.

$$\sigma^2_{\hat{\mu}_2 - \hat{\mu}_1} = \sigma^2_{\hat{\mu}_1} + \sigma^2_{\hat{\mu}_2} - 2\,\sigma_{\hat{\mu}_1, \hat{\mu}_2}$$

and thus this measure is not a pure measure of σ^2_{μ}. It will be reasonable measure of $\rho_{12} = 0$ or $\rho_{12} = 1$. The measure could poteutially have problems if ρ_{12} is very different from ρ_{c2}, where ρ_{c2} is the correlation between the concept mean and the mean of the second choice auto. Given the data, this could be calculated and adjusted. However $\sigma_{\hat{\mu}_2 - \hat{\mu}_1}$ gave a reasonable fit to the data.

-- Pessemier's index of perceptual clarity -- Wilton and Pessemier [1981] suggest that as more information about the brand becomes known, the brand will be perceived more uniformly across the population. Therefore, as a measure of perceptual clarity, they suggest using the population variance of the utility rating. That derived measure was calculated for each of the top three autos and the concept pre- and post-video for twelve segments. These segments were (MMC, Other U.S., Foreign car replacers) x (1983 control group, 1985 test group) x (saw positive videotape, negative videotape).

These risk measures were available for 162 respondents in the sample, except for the derived Pessemier measure which was available for the whole sample. The first, fourth, and fifth risk measures (risk, fractile, and perceptual clarity) are expected to largely capture total risk (σ_j^2). Confidence in choice is expected to be more related to information uncertainty, while unreliability is thought to be a measure of perceived inherent product variability.

Other risk measures which were tried in pre-test, but found too complex for respondents, included attribute-specific confidence in choice and the probability of a car being 10 points worse than its evaluation. The first measure proved too long, since it involved (9x5) = 45 additional risk judgments. The second task had a dual difficulty. Because the 0-100 point scale is not a natural one to respondents, it is difficult for them to estimate the probability of a brand falling somewhere else on the scale. Additionally, many respondents found it counter-intuitive that more confidence in their choice suggested a lower probability (of the car being ten points worse).

Perceived Recommendation. In order to impute the strength of beliefs (τ) prior to the videotape, relative to the effect of the videotape and safety report stimuli (n) according to equation (4.8), it was necessary to have measures of the preference prior to the videotape, the preference after the videotape, and the perceived level of preference being conveyed by the informants in the videotape.

The measure used for this purpose was a five-point recommendation scale from very positive to very negative (see Appendix D). Respondents were asked the recommendation which they would give to the brand both before and after seeing the videotape. They were also asked the level of recommendation which they felt that the videotape and safety report were conveying.

Other Measures in the Interview. A considerable number of other measures were collected in both versions of the questionnaire. Some of these were used to fit other components in the forecasting system. Data to estimate Hauser and Urban's [1982] value priority model are an example of this. Other information was gathered to allow further hypotheses on the data to be tested. For example, scales of innovativeness, sociodemographic information, and precipitants of purchase were all solicited. Hauser, Roberts, and Urban [1983] provide a preliminary review of these measures and analysis of them. However, analysis on other components of the model is part of future research.

<u>Secondary Data</u>. The above data were used to fit the model in the experimental setting. When we came to forecasting actual sales of the new brand in the marketplace (see Figure 4.4), we fit historical sales of the 1983 Regada. Monthly sales data for the Regada since 1959 and for the industry since 1974 were provided by MMC.

4.3.4. Estimation Techniques

As described in Section 4.3.2, the Measurement and Estimation Overview, the model is estimated in two stages: an analysis of experimental effects, and the establishment of a relationship to historical sales and preference forecasting.

Analysis of Experimental Effects. Figure 4.3 showed the structure used to estimate the model. There are three distinct types of analysis in this stage. They are, first, calibration of the attributes-factor perceptions-preference-choice model for the current market, after entry, and after videotape (Boxes 1, 2, and 3). The second type of analysis is fitting the updating model, including estimation of strengths of beliefs and true values (Box 4). The final phase consists of using the model to predict post-videotape choice using pre-videotape data (Box 5).

The first type of analysis, fitting the consumer model depicted in Figure 4.2, consists of the three relationships: perceptual mapping (factor analysis), relating underlying perceptual dimensions to preference (preference regression), and relating preference, price and uncertainty to the probability of choice (logit estimation).

Factor analysis was performed using both common and principal components factor analysis, as suggested by Urban and Hauser [1980]. This corresponds to the estimation of equation 4.5 in Section 4.2.2.

Relating the underlying perceptual dimensions to preference was performed using linear regression since a linear relationship was suggested in Chapter 3 and 4. This corresponds to the estimation of equation (4.6). Regressions of preference directly on attributes were also undertaken.

Relating preference, price, and risk to choice was undertaken using a logit estimation procedure described in Section 3.3. This corresponds to the estimation of equation (4.7) in Section 4.2.2. The alternative pricing formulation of preference/price and risk/price, outlined in Chapter 3.1, was also estimated.

The second type of analysis, estimating τ/n and true means and variances for the videotape, consisted of substituting values in equations (4.8), (4.9), and (4.10) for τ/n, μ_T, and $\sigma^2_{\bar{x}}$ and averaging across segments of the population. Segments were defined by maker of vehicle being traded in. True attribute scores and factor scores for the test and control autos under positive and negative word of mouth were also calculated.

The final type of first-stage analysis consisted of generating predicted values of the post-video probabilities of choosing the stimulus brand. This phase consisted of substituting estimated values of parameters and variables in equations (4.11), (4.12), and (4.13), and calculating goodness-of-fit statistics described in the Results section, Section 4.3.

<u>Analysis of Diffusion of Preference in the Marketplace.</u>

Equation (4.14) gives the probability of preferring brand N at time t, and it can be applied to forecast preference dynamics for both the 1983 Regada (which was launched in 1977) and the 1985 version.

Rewriting equation (4.14) slightly:

$$P_N(t) = \frac{K e^{\beta[(\frac{\tau}{\tau+n})X_o + (\frac{n}{\tau+r})\mu_T - \frac{r}{2}\{(\frac{\tau}{\tau+n})^2 \sigma_o^2 + (\frac{n}{\tau+n})^2 \sigma_x^2 + \sigma_\varepsilon^2\}]}}{\sum_1^3 e^{\beta(X_j - \frac{r}{2}\sigma_j^2)} + e^{\beta[(\frac{\tau}{\tau+n})X_o + (\frac{n}{\tau+n})\mu_T - \frac{r}{2}\{(\frac{\tau}{\tau+n})^2 \sigma_o^2 (\frac{n}{\tau+n})^2 \sigma_x^2 + \sigma_\varepsilon^2\}]}} \tag{4.18}$$

allows an examination of the variables which are known and of the parameters which need estimation. Section 4.3.2 showed these to be τ, n, and K. n is actually function of time and so will be written n_t. n_t, the cumulative sample of owners who will be contacted by time t, was posited to be a linear function of cumulative sales Y_t (equation 4.15);

$$\text{i.e.} \qquad n_t = kY_t \tag{4.19}$$

k is a parameter to be estimated, while Y_t may be calculated recursively, given other elements in the model (probability of consideration and category purchase). Thus, returning to the modeling framework, an aggregation of equation (1.1) gives:

$$\text{Sales}_t = \Delta Y_t = \sum_{\text{Popul.}} P_C(t-1) \cdot P_{B|C}(t-1) \cdot P_{N|B,C}(t-1) \tag{4.20}$$

where

P_C = Probability of N being considered;

$P_{B|C}$ = Cond'tional Probability of Brand Purchase; and

$P_{N|B,C}$ = Conditional probability of Brand Choice given consideration and category purchase, the modeling objective this this thesis.[1]

Therefore, combining (4.19) and (4.20), the change in n_t over time can be incorporated in the model:

$$n_t = kY_t = \sum_{t'=1}^{t} \sum_{popul} P_C(t'-1) \cdot P_{B|C}(t'-1) \cdot P_{N|B,C}(t'-1) \qquad (4.21)$$

Because other components of the model have not yet been developed, "naive" methods of generating P_C and $P_{B|C}$ were used. These are described in the next section.

Values of τ, k, and K in equations (4.10) and (4.15) were found using a grid search over parameter values using the residual sum of squares surface as an objective function. Ideally a hill-climbing program would have been desirable but the recursive nature of the estimation precluded the use of standard non-linear, least-squares packages. The sum of squares surfaces were generally well-behaved (see Section 4.4).

After fitting τ, k, and K for the 1983 version, diagnostics were calculated, including a test of fit against the Bass model. The values of τ, k, and K for 1983 were then used with the parameters from the experimental analysis of the 1985 brand to generate preference forecasts.

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1 Problems of using observations at discrete periods of time rather than continuously, are discussed in Chapter 5 under Future Research.

4.4 Results

Results are presented in the same framework as the measurement and estimation overview. First, the data from the experiment are analyzed according to Figure 4.3. Results from fitting the Perception/Preference/Choice model to the market at each of its stages (before entry, immediately after entry, and post diffusion) are presented in Section 4.4.1. This is followed by Section 4.4.2 which gives imputed strengths of beliefs and true values of the new brand parameters. The final section on the experiment uses the updating model for the prediction of post-video probabilities, tested against predictions based on the post-video logit.

The second phase of results, relating the experiment to sales in the marketplace, starts with fits of the model to the historical sales of the 1983 brand in Section 4.4.4. This allows the estimation of τ, k, and K in the marketplace as well as an adjustment factor to account for the methods effect. Diagnostic tests of the model applied to historical data are also possible at this stage. The application of these results to the forecasting of the 1985 brand is presented in Section 4.4.5.

The chapter ends with a discussion of the internal consistency of the analysis. This is divided into a review of the difficulty, interest, and realism respondents experienced with the survey, a survey of interviewer reactions by a member of the team, convergence tests on the multiple measures used, and a discussion of methods of determining validity.

4.4.1 Analysis of Perception, Preference, and Choice

This section starts off by comparing the factor analyses, preference regressions, and logit runs in each of the three market scenarios to ensure that the same framework fits each one, and to examine the stability of parameters.

The effect of the new brand's entry is calculated in terms of the perception of its attributes, factor scores, relative utilities, and the share which it is forecast to obtain. This exercise is repeated for the post-video evaluation, with attention being given to changes in factor scores, utility, and share relative to the prevideo level.

Factor Analysis. The first analysis attempted was factor analysis to see how many underlying dimensions the nine-item list of attributes represented. Results are given in Tables 4.3a and 4.3b. Correlation matrices of the attribute ratings were used as the data input.

Both common and principal components factor analyses were performed for the top three choice brands and concepts and the results are very close. Initial communalities for the common factor analysis were squared multiple correlations. A varimax rotation was used to increase interpretability. The eigen value cutoff of 1.0 suggests two factors in each case.

The screen test to find when additional factors stop adding substantial explanatory power by examining the eigen values also suggested two factors. Figure 4.5 shows an "elbow" at the second

Attribute	Top 3 Choices & N Pre & Post		Top 3 Choices		Top 3 Choices & N prevideo		Top 3 Choices & N postvideo	
	Factor Loading Matrix							
	Appeal	Sense	Appeal	Sense	Appeal	Sense	Appeal	Sense
Luxury	0.892	0.083	0.884	-0.051	0.887	-0.069	0.891	-0.071
Style	0.740	0.229	0.748	0.153	0.742	0.197	0.741	0.213
Reliable	0.372	0.722	0.396	0.691	0.365	0.692	0.39[illegible]	0.742
MPG	-0.139	0.808	-0.202	0.786	-0.180	0.805	-0.146	0.794
Safety	0.710	0.210	0.720	0.172	0.730	0.189	0.697	0.204
Maintain	0.167	0.771	0.149	0.756	0.167	0.755	0.149	0.779
Quality	0.531	0.658	0.501	0.650	0.549	0.616	0.487	0.696
Durable	0.421	0.693	0.386	0.677	0.409	0.680	0.402	0.698
Perform	0.749	0.369	0.686	0.391	0.746	0.332	0.719	0.407
Cum Exp 1	49.3%		46.3		47.1		48.8	
2	66.4%		63.4		64.7		66.0	
Eigenvalue 1	4.43		4.16		4.24		4.39	
2	1.54		1.54		1.58		1.55	

Table 4.3A. Factor analysis of attribute ratings for the current top three brand choices, plus the new brand, pre- and post-diffusion, principal components.[1]

---

1. Because it was hypothesized that reliability, or (6.0-Reliability) would be a measure of inherent product variability, these factor analyses and subsequent analysis were also repeated without the attribute, reliability. Results in all cases are extremely similar. For example, a factor analysis on the eight remaining attributes gives factor loadings of .889, .749, NA, -.105, .719, .199, .555, .447, and .762, for Appeal, and -.112, .208, NA, .832, .186, .781, .629, .693, and .355 for sense cumulative explanation of 67.5% and eigen values of 3.92 and 1.47.

Attribute	Principal Components Top 3 Choices & N Pre & Post				Common Top 3 Choices & N Pre & Post			
			Factor Loading Matrix					
			Communalities				Communalities	
	Appeal	Sense	Initial	Final	Appeal	Sense	Initial	Final
Luxury	0.892	0.083	1.0	0.803	0.912	-0.080	0.558	0.838
Style	0.740	0.229	1.0	0.600	0.641	0.266	0.455	0.481
Reliable	0.372	0.722	1.0	0.660	0.352	0.687	0.529	0.596
MPG	-0.139	0.808	1.0	0.672	-0.058	0.656	-0.354	0.434
Safety	0.710	0.210	1.0	0.548	0.598	0.249	0.408	0.419
Maintain	0.167	0.771	1.0	0.622	0.186	0.677	0.427	0.493
Quality	0.531	0.658	1.0	0.715	0.498	0.661	0.622	0.684
Durable	0.421	0.693	1.0	0.657	0.393	0.667	0.548	0.600
Perform	0.749	0.369	1.0	0.697	0.689	0.393	0.582	0.629
Cum Exp 1	49.3%				77.8%			
2	66.4%				100%			
Eigenvalue 1	4.43							
2	1.54							

Table 4.3B. Factor analysis of attribute ratings for the current top three brand choices and the new brand pre- and post-diffusion. Comparison of Principal Component and Common Factor Analysis.

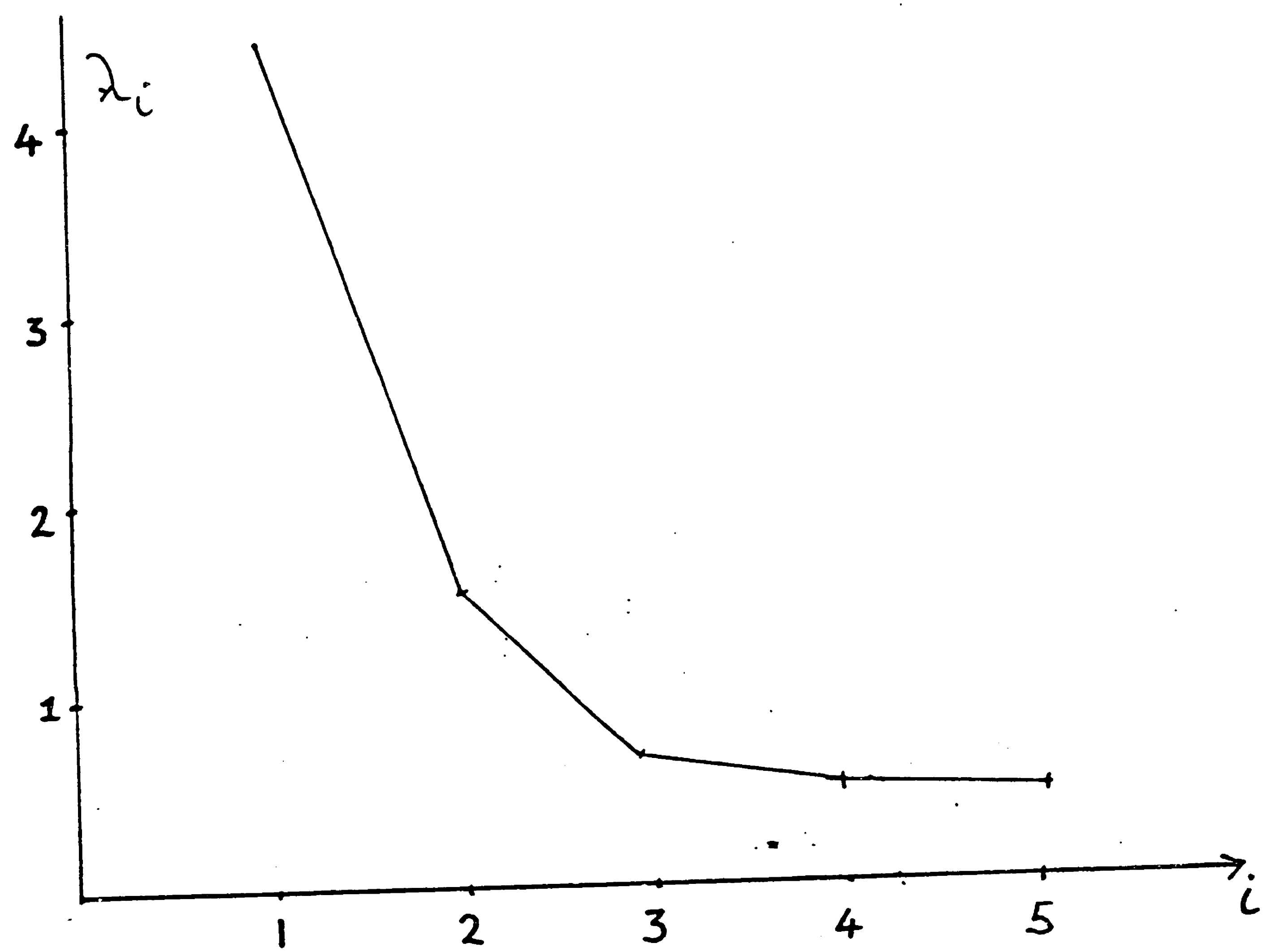

Figure 4.5. Eigen Values for Factor Analysis of Attribute Ratings: Principal Components on Top 3 Choices, Concept Pre-Videotape and Concept Post-Videotape.

factor. The finding of two factors is consistent with a number of other researchers who have looked at reduced space perceptions of autos (e.g., Green and Tull [1978], Moore and James [1978], and MMC proprietary studies).

The factor loadings in Table 4.3 are very similar, suggesting that the same perceptual dimensions are being used to evaluate each of the markets. The proportion of the variance explained, between 63% and 66%, is satisfactory for this number of attributes.

With the first factor loading heavily on luxury, style, safety, and road performance, "appeal" seems to be an appropriate name for this factor. The second factor loads heavily on reliability, miles per gallon, maintenance, quality, and durability, suggesting "sensible", or "good sense" as a name.

Preference Regressions. Given the factor analysis, preference (operationalized by number of value points on a scale 1-100+) was regressed on both factor scores and directly on attributes.

The results of these regressions are presented as Tables 4.4 and 4.5.

Note that the fits on the factors are almost as good as those on the attributes despite seven less degrees of freedom used in the fitting (R^2's of .31 vs. .33). Note also that many attributes are not significant in each of the three markets and safety is of the opposite sign to that expected in two. Finally, note that the factor score coefficients are very stable from one regression to the next while those of the attribute regressions move substantially for a number of attributes, suggesting multicollinearity.

All of these observations suggest the use of the factor scores to model preference. The factor score regressions show that "appealing" is given slightly less weight than "sensible" in the preference regression. As a test of the consumer behavior model (outlined in Figure 4.2), price was included in the preference regressions on factors and attributes. As postulated, it was not significant.

	Top 3 Choices	Top 3 Choices Plus Prevideo	Top 3 Choices Plus Postvideo
Intercept	.250 (113.59)	.251 (128.87)	.254 (128.54)
Appealing	.020 (8.90)	.020 (10.55)	.020 (10.03)
Sensible	.026 (11.55)	.028 (13.67)	.028 (14.00)
$\bar{R}^2$	.3022	.3083	.3190
Condition No.	4.18	3.75	3.85

Table 4.4. Regressions of Value Points on Factor Scores for Top 3 Current Choices, after New Brand Entry, and After New New Brand Diffusion.[1]

	Top 3 Choices		Top 3 Plus Entrant		Top 3 Plus Entrant Postvideo	
Intercept	-.06	(-2.56)	-.03	(01.92)	-.02	(-1.03)
Luxury	.181	(1.67)	.224	(2.71)	.231	(2.77)
Style	.124	(1.28)	.175	(2.27)	.072	(.89)
Reliability	.495	(4.93)	.301	(3.78)	.423	(5.03)
Fuel Economy	.204	(2.69)	.243	(4.02)	.178	(2.77)
Safety	.094	(.95)	-.158	(-2.03)	-.114	(-1.43)
Maintenance	.159	(1.86)	.189	(2.92)	.114	(1.62)
Quality	.122	(1.07)	.141	(1.54)	.174	(1.80)
Durability	.156	(1.73)	.047	(.63)	.121	(1.56)
$\bar{R}^2$	.3302		.3238		.3300	
Condition No.	31.2		31.1		28.75	

Table 4.5. Regressions of Value Points on Attribute Ratings for Top 3 Current Choices, After New Brand Entry, and After New Brand Diffusion.

1 Figures in brackets are t-statistics.

Logit Models. Logit models presented below are estimated using a multiple regression approximation to the maximum likelihood solution.[1] The reliability measure of risk, was chosen, but all five measures gave significant fits of the expected sign, as described in Section 4.3.6.

Results obtained from fitting the logit approximation to variables using preference additively discounted by price are given in Table 4.6. Results consistent with the preference per dollar formulation are given in Table 4.7.

Both formulations give highly significant explanatory variables with the exception of price in the second regression. The price variable has been included to "clean" the value measure of any residual price connotations and thus its coefficient is not readily open to interpretation. The new brand was generally more expensive than those evoked by respondents which may lead to the instability of price.

---

1. This method is based on

$$P_j = \frac{e^{\beta \chi_j}}{\sum_{j' \epsilon C} e^{\beta \chi_{j'}}} \Rightarrow \ln \left(\frac{P_j}{P_1}\right) = \beta(\chi_j - \chi_1)$$

The approach was adopted because of problems in applying the maximum likelihood logit estimation algorithms to a continuous dependent variable. Maximum likelihood logit programs which allow the input of continuous data assume a different data generation mechanism (basically they assume that choice probabilities are the aggregation of discrete choices across a population). In a private conversation with Professor Daniel McFadden, he suggested that for data collected using a Juster scale, the multiple regression estimation technique is more appropriate than his program, QUAIL, and standard errors from the regression were correct. The reference choice used (subscript 1) was the top choice auto from those currently available.

	Top Choice Brands	Top Choice Brands Post Entry	Top Choice Brands Post Diffusion
Value Points	2.20	2.47	2.63
	(6.22)	(10.76)	(7.69)
Price	-2.6×10^{-5}	-3.2×10^{-7}	-3.6×10^{-5}
	(-5.77)	(-0.07)	(-8.82)
Risk	-0.207	-0.162	-0.230
	(-5.40)	(-5.39)	(-6.81)
$\bar{R}^2$	0.0798	0.1503	0.1365
Condition Number	2.24	3.56	2.55

Table 4.6. Multiple Regression Logit Approximations to Choice Probabilities Modeled on Preference, Price, and Risk (Consumer Surplus Formulation)[1]

	Top Choice Brands	Top Choice Brands Post Entry	Top Choice Brands Post Diffusion
Value/Price	2.48	2.99	3.12
	(10.24)	(17.10)	(16.45)
Risk/Price	- 0.111	- 0.103	-0.105
	(-4.53)	(-4.78)	(-4.42)
$\bar{R}^2$	0.0690	0.1415	0.1421
Condition Number	1.21	1.17	1.21

Table 4.7 Multiple Regression Logit Approximations to Choice Probabilities Modeled on Preference Per Dollar and Risk Per Dollar.[1]

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1 Figures in brackets are t-statistics.

Similarly, the intercept might be expected to be insignificant (see previous footnote).

The risk and preference coefficients in Table 4.6 are reasonably stable after entry which suggests that these variables are being evaluated in the same way in each of the three markets. The risk per dollar variable is reasonably stable in the regressions in Table 4.7, but the preference per dollar coefficient changes considerably between regressions.

The R^2's are not easily interpreted given the transformation of the dependent variable. However, the regressions indicate a significant relation between choice probability and the preference and risk variables, of the expected sign, as postulated by the model.

Examination of the Market Consisting of Top Three Choices. Factor scores were calculated for the top three choices for each respondent and then these were averaged by brand.[1] That is, the average factor score for each brand considered in the top three was calculated. These were plotted on a perceptual map, included below as Figure 4.6.

1. The issue of the meaning that can be attached to such maps, averaged across respondents, is discussed in Chapter 5 under Future Research.

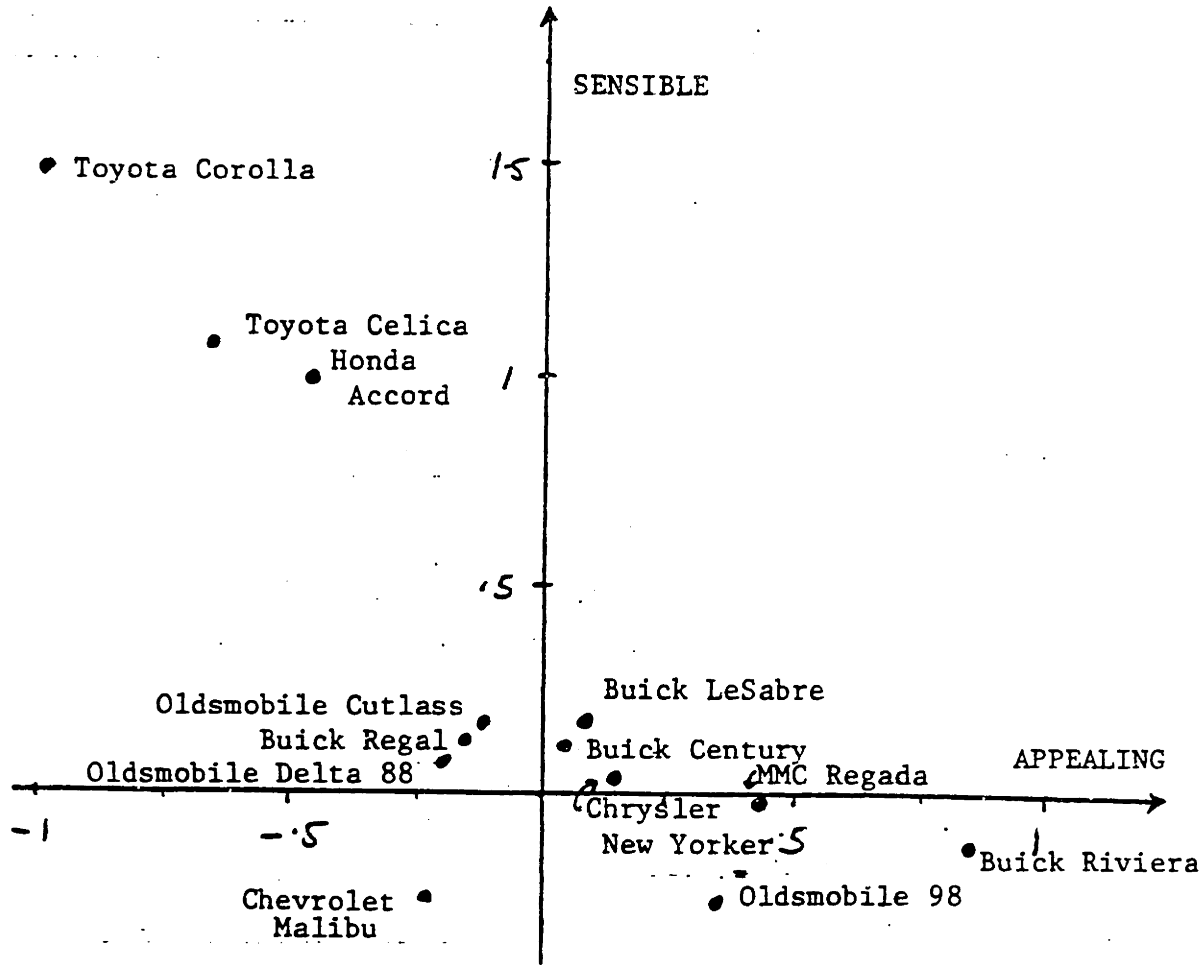


Figure 4.6 Perceptual Map of Average Positions of Brands Considered by More than 10 Respondents.

The map has not been scaled by price so the larger, more expensive brands such as the Riviera may not have as great an advantage over brands such as the Century as initially appears. The ratio of the appeal factor coefficient to that of good sense in the preference regression reported in Table 4.4 was approximately equal. That suggests that for this sample, putting price to one side, the Buick Riviera and MMC Regada are reasonably attractive, relative to their Japanese competitors; the Honda Accord, Toyota Celica, and Toyota Corolla.

Entry of New Brand, 1985 Test and 1983 Control. The entry of the new brand may be examined in terms of attributes, factor scores, preference, and choice. At each level managerial implications may be drawn. For example, Figure 4.7 shows the attribute perceptions and position on the perceptual map of the 1983 brand and the 1985 brand. While the 1985 Regada appears not to be perceived as being as heavy on fuel consumption as the 1983, it is considerably below what respondents expect to get on average from their current first choice.[1] The position of both the new brands after entry on the perceptual map is a strong one, and it is encouraging to see that the test brand is seen as more sensible than the brand it will replace, without losing very much of its appeal as the brand is downsized.[1] The difference between the 1983 Regada evaluated by those who evoked it (1) and when viewed as a masked concept (2 and 3) is not large and may be ascribed to a methods effect. Points 2 and 3 in Figure 4.7 show the average positions of the 1983 and 1985 Regada conditioned by those who put it in their top three choices, while points 4 and 5 show the average positions for the whole sample.

Figure 4.8 shows that post entry, the average number of value points and probability for the 1985 brand lies just above that for the 1983. In terms of value points, both are around the second choice brand, but in terms of probability, they fall below it. This is consistent with the model since risk may be seen to be higher with the test and control

1 Some caution should be used in placing too much emphasis on these observations which are intended to be illustrative. Statistical tests were not performed. For the testing of differences in attributes, multivariate profile analysis should be undertaken to allow a level of significance to be attached to these observations.

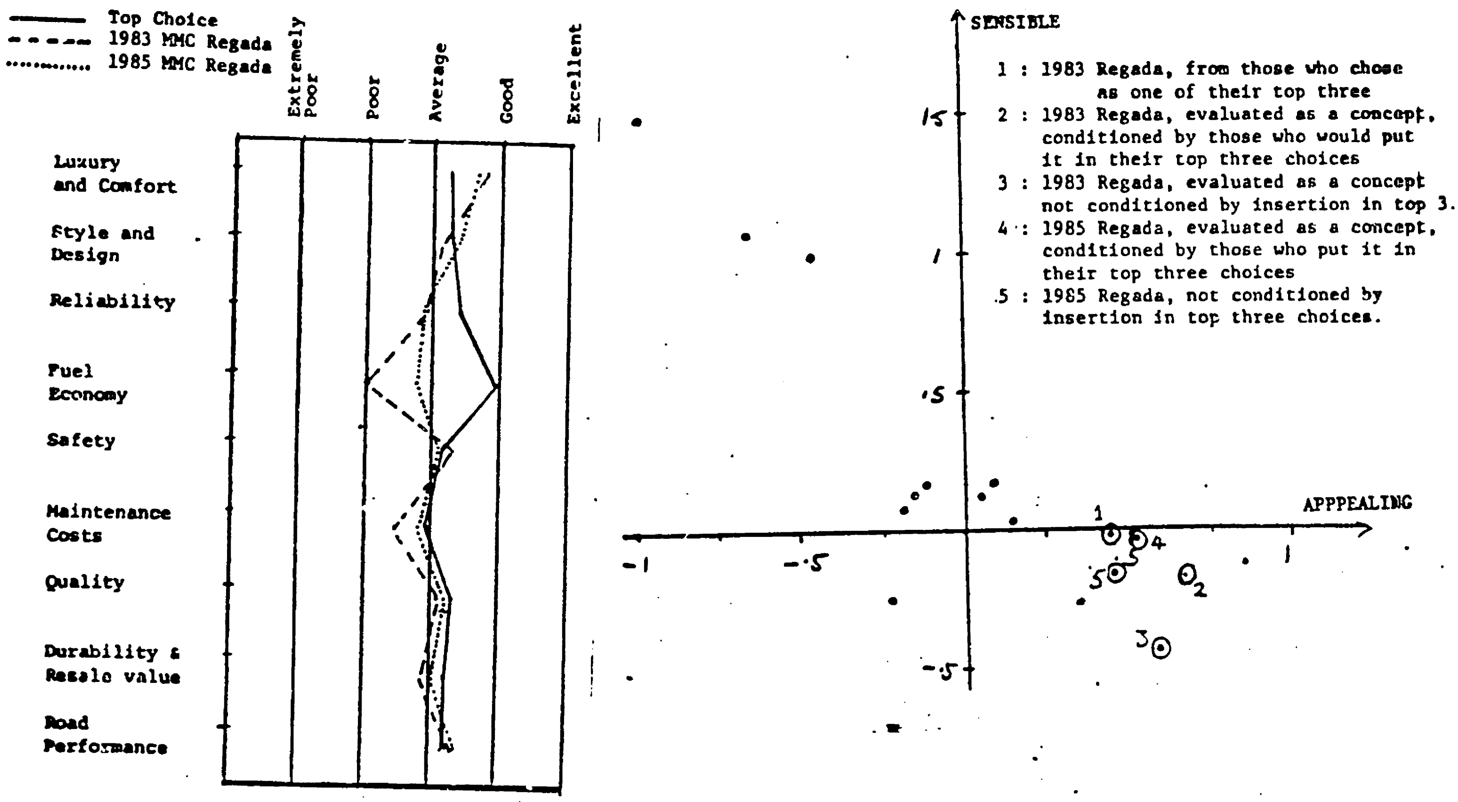


Figure 4.7. Attribute Ratings and Perceptual Positions of Test Brand and Control Brand After Entry (Post Drive).

brands and also its average price of over $14,000 is substantially greater than that of the average second choice, which is $10,500.

<u>1985 Test and 1983 Control Post Diffusion.</u> Figure 4.8 shows the change in the positions of both the 1985 and 1983 brands after positive and negative word of mouth. The negative word of mouth substantially damages both vehicles' positions with respect to appeal and good sense. The positive word- of-mouth videotape improves both vehicles' position with respect to good sense slightly but slightly detracts from the appeal. Value points and probability both tell the same story; that the

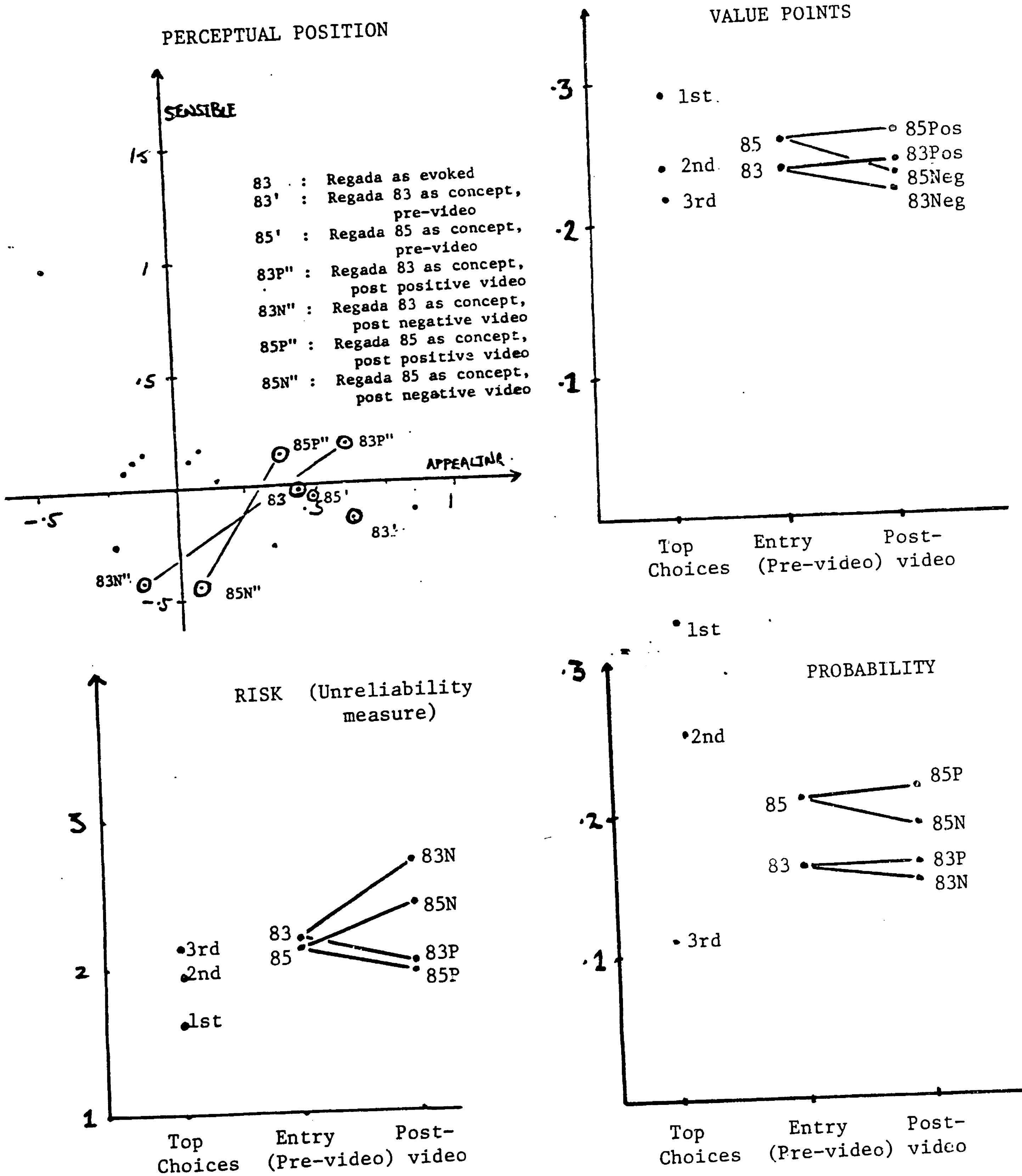


Figure 4.8. Effect of Videotape and Safety Report Treatment on Factor Scores, Preference, Risk, and Probability.

negative word-of-mouth effect is severe, while the positive videotape has a very small positive effect. It is interesting that average risk increased substantially with negative word of mouth. Of the five risk measures, four increased on average for both the 1985 and the 1983 negative video viewers, while the converse was true for the positive video viewers.

This increase in risk (in Figure 4.8) may be due to the mean square error term which simplified out of equation 3.20 when the variance was assumed to be known. If such dissonant reports are commonplace, then this assumption of known variance may not be justified. Relaxing the known variance assumption would not substantially affect updating or the expected utility calculations. What it would do is introduce an intractable distribution for risk-adjusted net preference, $X_j - \frac{r}{2} \sigma_j^2$. An alternative explanation of the increase in risk is that respondents are using the term in a different manner to its use in the model. A more rigorous definition and measurement of the risk construct is proposed in Chapter 5.

To establish the "true" (long-term) levels of risk, value, attributes, and factor scores, it is necessary to be able to work out how representative the positive and the negative videotapes are of what owners and others will say about the brand in practice. That question is considered in the next section, 4.4.2.

The above examination of the differential effects of the positive and negative stimulus is on an aggregate basis. A feel for movements at the individual level may be gained by examining scatter plots of value points assigned to the concept prior to the video and value points assigned after the video. These are presented as Figure 4.9.

The 45° line represents no change in value points assigned to the brand post-video. Points above the 45° line represent an increase in points, while those below represent a decrease. The predominance of points above the 45° line for the positive graphs and below the 45° line for the negative graphs indicates the differential effects of the two treatments.

4.4.2 Analysis of Treatment Effects

Equation 4.8 in Section 4.3.2 shows how the ratio of prior strength of beliefs to stimulus effect can be calculated. τ/n was imputed from how much the respondent updated his recommendation of the stimulus brand relative to the difference between what he perceived the videotape saying about it and his prior beliefs. A higher τ/n means a greater strength in prior beliefs and so less updating will occur. τ/n was estimated on segments based on the car that respondents planned to replace next. Brands were divided into MMC, Other U.S., and Foreign. Because separate questions were asked about the perceived recommendation in the videotape and the perceived recommendation in the safety report, separate τ/n's were able to be calculated for both of these.

These estimates are contained in Table 4.8.

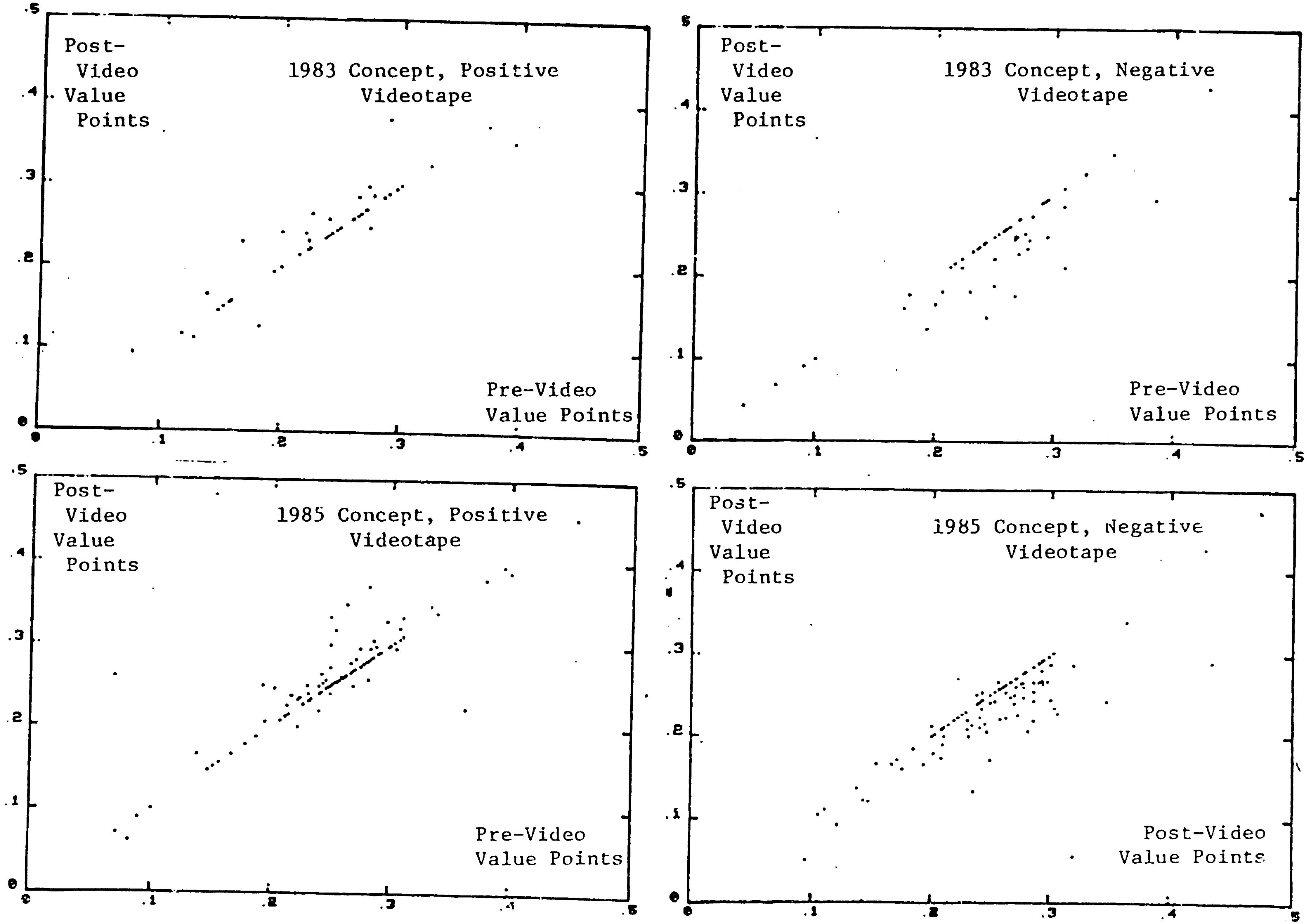


Figure 4.9 Trends in Value Points After Videotape and Safety Report Exposure

	Will Replace	τ/n Video	τ/n Safety Report	Average
Drove 1985 Test Car	MMC	1.444	1.444	1.444
	Other US	.706	.559	.632
	Foreign	.100	.200	.150
	All Cars	.823	.823	.823
Drove 1983 Control Car	MMC	1.36	.667	1.013
	Other US	.952	.905	.929
	Foreign	1.25	.375	.250
	All Cars	.923	.834	.879
Full Sample	All Cars	.889	.858	.874

Table 4.8 Experimental Data: Relative Strength in Prior Beliefs, τ/n[1]

1. Note that τ/n is computed using equation 4.8,

$$\tau/n = \frac{R_T - R'}{R'' - R'} ,$$

there R stands for recommendation (see Appendix D4 for the wording of the question). Value points were not used for this calculation.

The result that respondents who would be replacing an MMC car had the greatest strength of belief in their priors is an intuitive one, since those respondents could be expected to have a greater prior knowledge of MMC brands and thus a larger "equivalent sample size."[1] Similarly, the lowest confidence in their priors belonging to foreign brand replacers is appealing. There are no obvious differences between those who drove the 1983 control car and those who drove the 1985 version.

1 Note that "prior" is prior to viewing the videotape and seeing the Maintenance and Safety Report. However, it is after the test drive.

From these τ/n estimates, it was possible to estimate respondents' true means of concept car mediated by the videotape which they saw according to equation (4.9). These means were calculated for the same segments as τ/n. They were also estimated separately for those who saw the positive videotape and safety report and those who saw the negative one.

As can be seen from Table 4.10, our estimates of μ_T vary by whether a respondent saw the positive or negative videotape. This is to be expected because if negative information is circulating about the car, it is reasonable for respondents to infer a low true mean value. Conversely, if positive information is circulating, a high value would be inferred. However, it does require that we are able to say which videotape is more representative of what owners will actually say about the car.

Equation (4.9) suggests that the true value of the mean for an individual (μ_T) is given by his post-video value (X") plus the amount that he did not update:

$$\mu_T = X'' + \tau/n(X'' - X') \qquad (4.9)$$

That is, μ_T is set so that X", updated beliefs, will fall a τ/n distance between the prior beliefs, X', and the true μ_T. Errors in X', X", and τ/n will be magnified in this calculation of μ_T. While this would be a substantial problem if individual μ_T's were calculated, on a segment basis these errors should not be as serious.

	Will Replace	True Mean	True σ^2 with No Inherent Unreliability	True σ^2 with Inherent Unreliability
Drove 1985 Test Car	MMC	92.78	8.09	2.55
	Other US	83.80	4.91	0.97
	Foreign	71.28	3.22	1.39
	All Cars	84.29	5.80	1.65
Drove 1983 Control Car	MMC	87.72	6.49	1.25
	Other US	80.06	6.87	1.96
	Foreign	68.14	3.62	1.25
	All Cars	78.40	6.46	1.76
Full Sample	All Cars	82.21	6.24	1.75

Table 4.9. Estimates of True Mean and Variance for Different Segments in the Population

	Car Driven	True Mean[1]
Saw Positive Tape	1983	85.50
	1985	95.38
	All RSP	91.99
Saw Negative Tape	1983	70.86
	1985	72.91
	All RSP	72.45

Table 4.10. Estimates of True Mean Classified by Concept Driven and Videotape/Safety Report Viewed

1 The different "true" mean between those who saw the positive videotape and those who saw the negative one has the following interpretation. If the 1985 Regada performs according to the concept description, if the test drive is representative, and if word of mouth corresponding to the positive videotape circulates about it, then the "true" mean of what owners wil say will be 95.38 value points. However, if the negative videotape is representative of what owners will say, then the mean will be only 72.91.

The true inherent risk of incoming word of mouth was estimated using equation (4.10) and is given in the second column of Table 4.9. However, because inherent product variability suggests that risk will not go to zero and because we have measured total risk rather than information uncertainty, allowance was made for this in column 3.

From equation (3.22)

$$\sigma_\mu^2 = \sigma^2 - \sigma_\varepsilon^2 \qquad (4.22)$$

Information Uncertainty = Total Uncertainty - Inherent Product Variability

The respondent's reported risk of the first choice auto was used as an estimate of σ_ε^2 in the third column. This estimate of σ_ε^2 is likely to overstate inherent product variability and in practice the true variance of incoming word of mouth is likely to fall somewhere between these two estimates. To find the sensitivity to measures of inherent product variability, both extremes were tried in fitting historical sales of 1983 Regada in Section 4.4.3.

The higher ranking of the true mean position by MMC replacers relative to that of other U.S. manufactured cars or foreign cars is intuitively appealing. Owners of MMC cars would be expected to feel more favorably about them than other car owners. The higher estimated true risk is somewhat counterintuitive.

It is possible to use the recommendation given prior to the videotape and the average perceived recommendation of the positive and negative videotapes to estimate how realistic the videotapes and safety reports were in simulating what the sample would say about the autos.

This information is given in Table 4.11.[1]

	Recommendation Prevideo (R')	Perceived Recom. (R_T) of Negative Tape	Perceived Recom. (R_T) of Positive Tape
Drove '85	1.79	2.31	1.81
Drove '83	1.80	2.23	2.00
Total Sample	1.79	2.27	1.87

Table 4.11 Recommendation given to the Concept by Respondents (pre-video) compard to the Recommendation Respondents Perceived the Negative and Positive Videotape were given the Concept.

1. Scales for recommendations from 1 (very positive) to 5 (very negative). See Appendix D4 for details.

In column 1, the recommendation that all respondents would give the concept (pre-video) is included. Columns 2 and 3 show the recommendations that negative and positive videotape viewers, respectively, thought that the videotape and safety report were giving the concept.

The table shows that for both the test and control car, respondents' reactions were more favorable than even the positive videotape and safety report. That does not necessarily mean that even the positive videotape was too negative a stimulus. It is quite possible for respondents' post-drive opinions to be highly complimentary but for the long term word-of-mouth about the brand to be unfavorable. However, MMC management judgment was that long-term experience with the car would be extremely favorable and so it was decided to use the positive videotape and safety and maintenance report as the true mean level of information that would circulate about the brand. This information can be monitored post-launch and parameters may be updated if required.

Table 4.10, which gave the imputed means and variances for the test and control cars, may be expanded to include the pre-video beliefs. By doing so, data are provided in the form necessary to estimate the probability updating equation 4.11. This may then be used for the test of the updating formula on the experimental data, fitting the history of the 1983 brand, and forecasting the preference dynamics of the 1985 brand.

Note that value points have been given as a proportion of total value points in this table (normalized value points). Although averages are presented in the table, the model was fit on an individual basis.

	τ/n	v' [1]	v'' [1]	μ_v	σ'^2	σ''^2	σ_x^2 [2]	σ_x^2 [2]	Price
1983 Positive	.8789	.2360	.2418	.2469	1.923	1.962	5.283	.510	14160
1983 Negative	.8789	.2452	.2274	.2118	2.250	2.643	7.592	2.963	14160
1983 All	.8789	.2405	.2348	.2293	2.104	2.291	6.458	1.760	14160
1985 Positive	.8226	.2542	.2609	.2663	2.148	1.981	5.129	.720	14925
1985 Negative	.8226	.2599	.2384	.2221	2.094	2.385	6.504	2.611	14925
1985 All	.8226	.2574	.2497	.2440	2.121	2.179	5.804	1.650	14925

Table 4.12 Average levels of Normalized Value Points, Price, and Risk: Prior, Post-Video and True

1. Since the logit was estimated using net value, v, rather than total value, X, $v = \mu + \lambda p$ has been included.

2. Column 7 gives variance using equation (4.10) with no allowance for inherent product variability. Column 8 uses equation (4.10) after adjusting for inherent product variability using equation (4.22)

True values imputed from the positive videotape were those used for fitting; that is, those in the first and fourth rows of table 4.11.

4.4.3 Using the Updating Model

With estimates of τ/n, true means and variances, and prior means and variances, as well as the logit parameter estimates, it is now possible to use the updating model to predict post-video value and risk and thus post-video probability of purchase, as explained in Section 4.3.2.

Equation 4.11 gave the estimate of post-videotape information probabilities ($\hat{P}''(1)$), based on pre-video information measures and segment estimates of true levels.

$$\hat{P}''(1) = \frac{e^{\beta[(\frac{\tau}{\tau+n})V' + (\frac{n}{\tau+n})\mu_T - \lambda p - \frac{r}{2}\{(\frac{\tau}{\tau+n})^2 (\sigma'^2) + (\frac{n}{\tau+N})^2 \sigma_{\bar{x}}^2 \}]}}{\sum_1^3 e^{\beta(V_j - \lambda p_j - \frac{r}{2}\sigma_j^2)} + e^{\beta[(\frac{t}{\tau+n})V' + (\frac{n}{\tau+n})\mu_T - \lambda p - \frac{r}{2}\{(\frac{t}{\tau+n})^2 \sigma'^2 + (\frac{n}{\tau+n})^2 \sigma_{\bar{x}}^2\}]}} \tag{4.11}$$

Results of fitting the updating model and comparisons to fitting the post-video logit model are given in Table 4.13. The updating formula and use of the pre-video logit coefficients only provide a marginally higher sum of squares than direct use of the post-video logit.

Estimation of Post Video Probability	Sum of Squares	Results	"R^2"	Aggregate Share
$\hat{P}''(1)$, Pre-video logit and updating	$\Sigma(\hat{P}''(1)-P'')^2$	2.442	negative	.2220
$\hat{P}''(2) = \hat{P}''(1)-(\hat{P}'- P')$	$\Sigma(\hat{P}''(2)-P'')^2$	.913	.5730	.1750
$\hat{P}''(3) = \hat{P}''(1) \cdot P'/\hat{P}'$	$\Sigma(\hat{P}''(3)-P'')^2$	.794	.6286	.1790
$\hat{P}''(4)$, Post video logit and measures	$\Sigma(\hat{P}''(4)-P'')^2$	2.125	.0061	.1905
Variance* n (Residual SS)	$\Sigma(\bar{P}''-P'')^2$	2.138	0.00	.1833

Table 4.13. Sum of Squares of Estimators of the Post-Video Probabilities.

If a correction is made for the error in fitting the pre-video logit on an individual basis (estimators 2 and 3 in Table 4.13), then the sum of squares of the estimators using the updating rule begin to look very attractive. The updating formula combined with the logit model does not perform well on an individual basis without adjustment, with a sum of squares higher than the sum of squares around the mean. However, after adjustment for pre-video logit errors ($\hat{P}''(2)$ and $\hat{P}''(3)$), up to 63% of the variation is explained. Much of this difference may be attributable to the weak explanatory power of the logit models. For example, Table 4.13 shows that the post-video logit only had an R^2 of 0.0061 for the post-video concept.

On an aggregate basis, the predictions of new brand choice appear close. Some caution should be used in interpreting these shares since post-video recommendations were used in the computation of the true value of the Regada. Thus, they are not totally pre-video estimates.

4.4.4 Fitting the Model to the Lifecycle of the 1983 Version.

Examining how well the control car experimental results can fit the historical sales pattern of the 1983 version has two purposes. First, we hope to estimate three parameters, τ, n (or k in $n = ky_t$), and a methods effect parameter, K, outlined in Section 4.3.2. Second, we expect to get an estimate of how well the model fits the actual evolution of a brand's sales.

The MMC Regada has been on the market since 1959, but underwent major modification in "model year" 1977 and emerged as "an all new car" in

October 1976, to quote the sponsoring company. The brand was downsized and had major structural and peripheral changes made to it. The monthly sales history of the brand since that time is given in Figure 4.10, together with data seasonally adjusted using the U.S. Bureau of the Census X-11 program.

In order to remove distortions due to industry sales from our brand share model, brand sales divided by industry sales is given in Figure 4.11.

The data in Silverman's thesis [1982] suggest that life-cycle effects at the brand level for the auto industry are felt in the first two to three years of the product's life. By that stage, other effects not currently handled by the model (such as competitive entry) become dominant. By initially restricting our attention to the first twelve months of the brand's life, we are largely able to avoid these problems since new auto brand launches follow a twelve-month cycle.

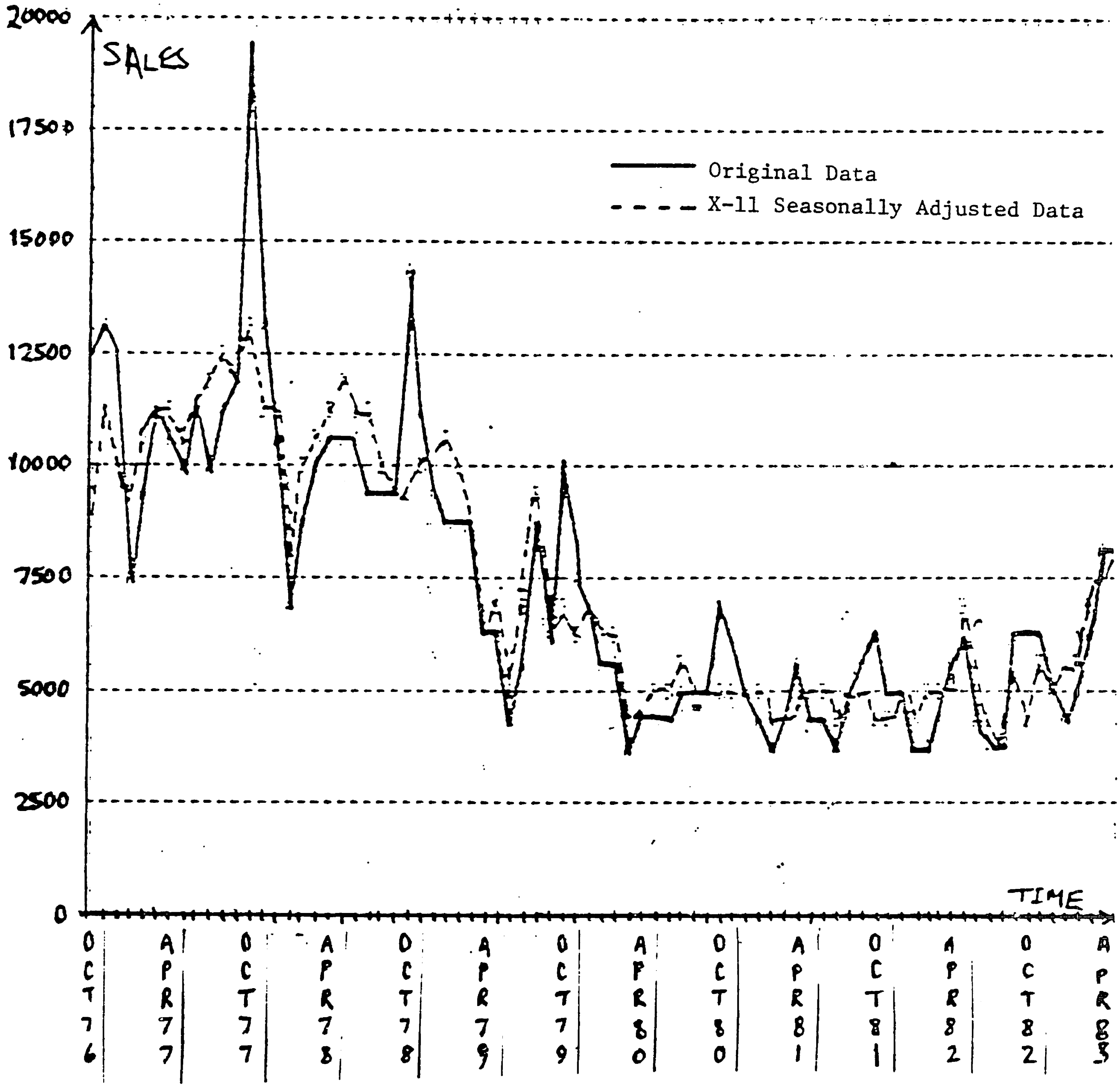


Figure 4.10. Monthly Sales of 1983 Regada from its Relaunch October 1976 to May 1983.

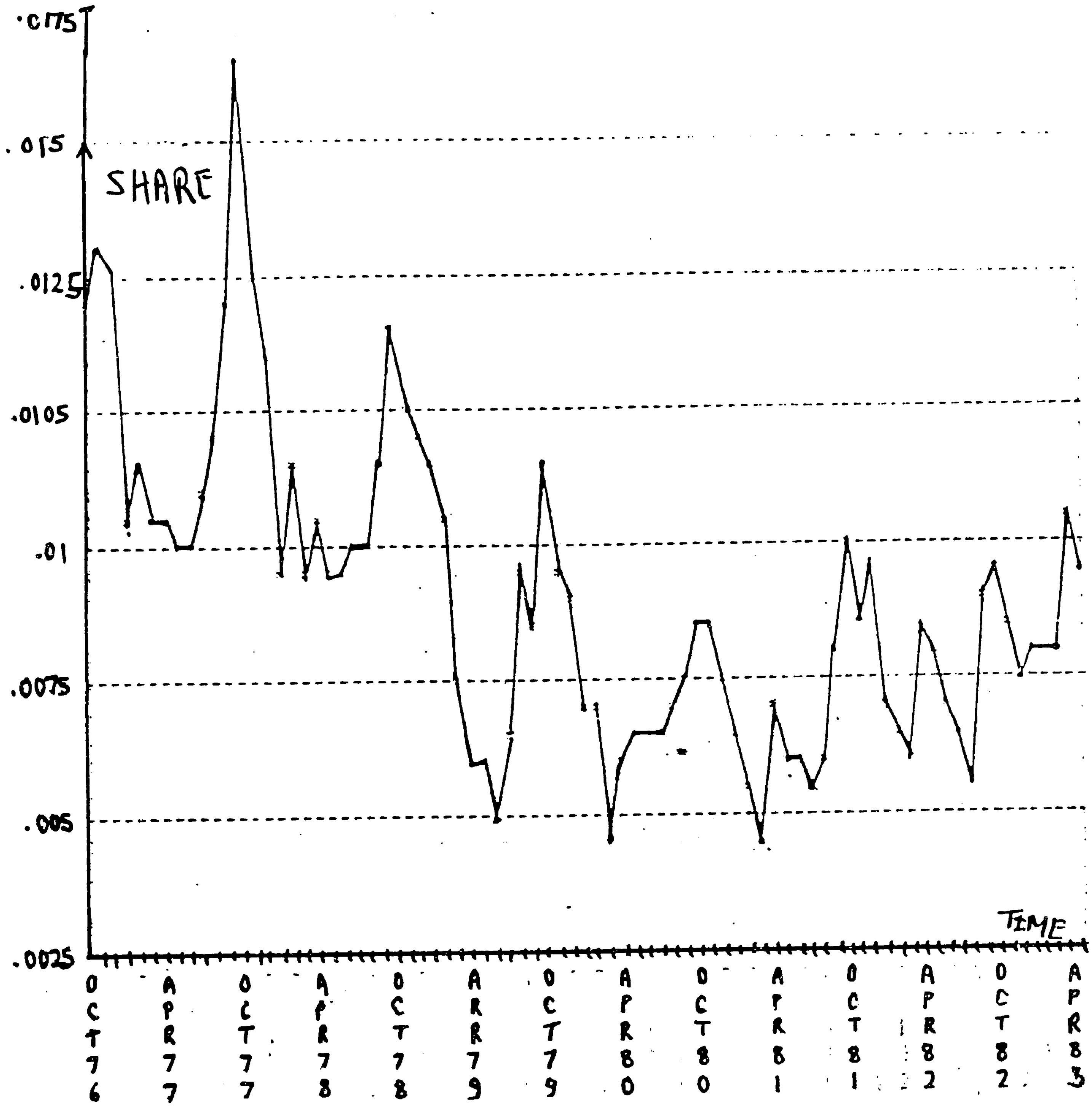


Figure 4.11. Monthly Sales of 1983 Version/Total Industry Sales October 1977 to May 1983.

Relation of Preference to Brand Purchase: Assumptions About P_C, $P_{B|C}$

The recursive nature of the brand choice model (given conditioning) makes it dependent on estimates of previous cumulative sales, which in turn make it dependent on estimates of industry sales and consideration.

From equation (1.1)

$$P_N = P_C \cdot P_{B|C} \cdot P_{N|B,C}$$

or

$$\frac{P_N}{P_{B|C}} = P_C \cdot P_{N|B,C} \tag{4.23}$$

If we assume that $P_{B|C}$ is the same across considerers and non-considerers, within the luxury market or in the auto buying population as a whole, we can write:

$$\frac{P_N}{P_{B|C}} = \frac{\text{Number of Sales of N/Number of Potential Auto Buyers}}{\text{Number of auto sales/Number of Potential Auto Buyers}} = \frac{\text{Sales N}}{\text{Industry Sales}}$$

Given the growth pattern in sales in Figures 4.10 and 4.11, it seems unlikely that consideration will have increased substantially over the period. If we assume constant consideration over time and a constant probability of category purchase across the population, Equation (4.23) simplifies to

$$\frac{\text{Sales}_N(t)}{\text{Industry Sales}(t)} = P_C \cdot P_{N|B,C}(t) \tag{4.24}$$

where $P_C(t) = P_C$ is constant.

Individual estimates of $P_{N|B,C}$ for the sample were estimated by taking the logit parameters from the previous section, together with the estimates of v_o, σ_o^2, μ_T, σ_x^2. Values of the parameters τ and k in the probability updating formula 4.18 were searched over a grid. For each (τ,k) pair, $P_{N|B,C}(t)$ was generated for the first twelve months and then an estimate of P_C was obtained by regression through the origin of Sales 1983/Industry Sales on $P_{N|BC}$, as indicated by equation 4.24.

A sum of squared residuals surface was calculated and the (τ,k,P_C) triplet corresponding to the minimum sum of squares was selected. A coarse grid search was followed by a finer grid search.

Consideration and the Methods Factor

If an independent assessment of consideration of the 1983 Regada can be obtained, then an estimate of K, the methods factor in Equation (4.18) may be made by comparing this to the estimate using the regression implied by equation (4.24). Until other elements of the model are estimated, consideration was set at the level of those who currently placed the 1983 Regada in their consideration sets in the survey (when they originally looked at a list of brands currently available). This proportion was 55/336 = 16.3%.

Brand preference in the sample has to be adjusted for the fact that a sample purposely oriented towards potential buyers of the brand was chosen before we can generalize to the population as a whole. That is, a member of our sample has a greater chance of buying the 1983 Regada than an average member of the auto buying community. This sample bias may be calculated by reference to switching data published by R. L. Polk and Company. A weighting by the replacements that respondents will trade in suggests that historically approximately 4.15% of them would buy a Regada, compared to 0.7% for the population as a whole. Therefore one would expect the constant of proportionality in Equation (4.24) to be

$$P_C \cdot \frac{.7}{4.15} = .1637 \cdot \frac{.7}{4.15} = .0276.$$

This can be compared to the constant of proportionality in the analysis which follows to determine the methods effect parameter, K.

Fitting the First 12 Months: Original Data

The first thing that is apparent from an examination of the sales pattern in Figure 4.10 and 4.11 is that the customary upward S-shape, usually associated with diffusion models is absent. The MAUD model is capable of explaining a decline in brand share in terms of initial mean being higher than the product's true performance or if the variance of the incoming word-of-mouth is much greater than the variance of initial perceptions. As discussed in Chapter 3, the assumption of known variances which we made during the derivation of the model implies that uncertainty should decrease. The model is still capable of fitting increasing variance, it is just not possible to interpret it within the framework we have developed.

Table 4.12 indicates that the true mean is slightly higher than the prior mean, apparently ruling out the explanation of a decline in expected value. However, if no allowance is made for inherent product variability (column 7 in Table 4.12), the imputed variance of incoming word-of-mouth about the brand is considerably higher than the prior reported variance (column 5).

A fit of the model to the first twelve months of original share data indeed does indicate a decline in fitted share and this is due to initially increasing variance.

The sum of squared residual surface for the (τ,k) pair, together with the implied P_C (slope of the regression on historical share) are presented in Table 4.14. Fitted and actual values of share tabulated in Table 4.15 and plotted in Figure 4.12.

The parameters $\tau = 0.4$ and $k = 8.0\text{x}10^{-6}$ give a fit of $\bar{R}^2 = 0.432$ when historical share is regressed on forecasts from the MAUD model. The implied consideration proportion, P_C, = 0.0602.

The final τ/n ratio varies from infinity at launch (when there is assumed to be no word-of-mouth from owners) to 0.16 after twelve months when word-of-mouth exposure to those who are considering N and will buy an auto is dominant over prelaunch priors. The effect of new sales WOM relative to priors reaches the same level as simulated in the experiment in period three.

Slope Parameter:

τ =	$kx10^6$ = 5.0	6.0	7.0	8.0	9.0
.2	0.0717	.0796	.0829	.0838	.0834
.4	.0552	.0582	.0596	.0602	.0603
.6	.0513	.0527	.0535	.0538	.0539

Residual Sum of Squares x 10^5

τ =	kx10 = 5.0	6.0	7.0	8.0	9.0
.2	4.84	6.12	6.82	7.31	7.78
.4	3.81	3.28	3.07	3.05	3.18
.6	4.57	4.17	3.97	3.90	3.92

Table 4.14. Estimates of Regression Coefficients and Residual Sum of Squares for 1983 Actual Penetration on Fitted Preference, First 12 Months, Grid Search for Minimum.

PERIOD	SHARE			SALES			% ERROR
	Actual	Forecast	Error	Actual	Forecast	Error	
Oct76	.0147	.0150	-.00029	12782	13036	-254	-1.99
Nov76	.0157	.0133	.00232	13179	11224	1954	14.82
Dec76	.0151	.0125	.00260	12001	10105	2095	17.17
Jan77	.0106	.0120	-.00143	7705	8742	-1037	-13.46
Feb77	.0114	.0118	-.00031	9299	9550	-251	-2.70
Mar77	.0103	.0116	-.00132	11186	12624	-1438	-12.83
Apr77	.0105	.0115	-.00105	10807	11891	-1084	-10.07
May77	.0097	.0115	-.00177	10302	12168	-1866	-18.11
Jun77	.0099	.0115	-.00165	11074	12923	-1849	-16.70
Jul77	.0110	.0116	-.00059	10047	10587	-540	-5.37
Aug77	.0121	.0116	.00044	11255	10841	413	3.67
Sep77	.0143	.0117	.00260	11871	9712	2158	18.18

Table 4.15 Forecasts of Share and Sales of 1983 Regada in First 12 Months of its Life Cycle Compared to Actual Sales: Original Data.

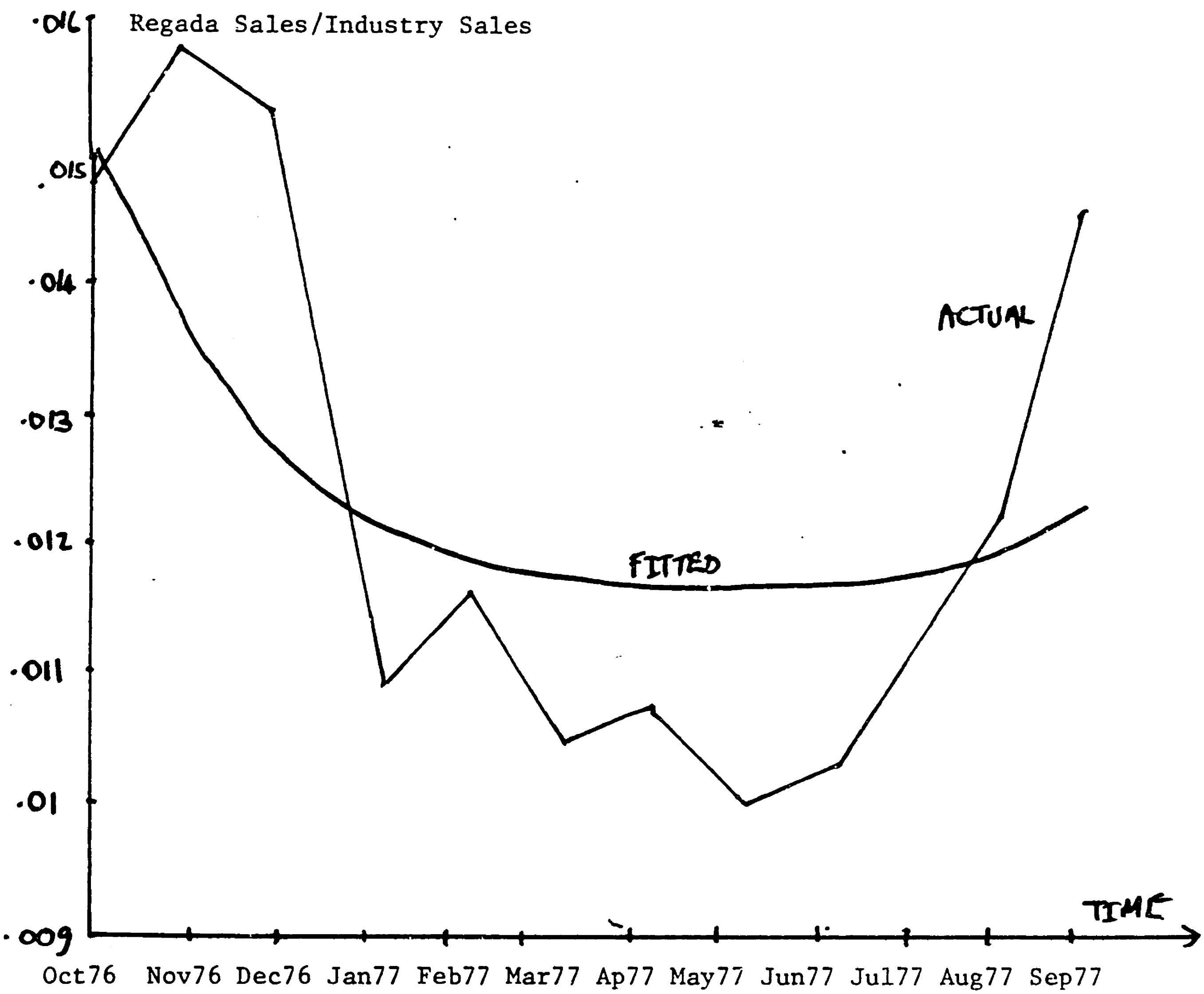


Figure 4.12. Actual and Fitted Share of 1983 Regada in First 12 Months: Original Data.

The parameter values imply that on average after twelve months just over half a person is spoken to by considerers of the new brand. This is low for two reasons. Firstly, if only every second considerer speaks to an owner on average, this does not sit well with the mechanics of updating. Second, the low n, particularly at low levels of penetration, combined with the high σ_x^2, is driving the whole model. Increasing variance is not consistent with the model, as derived.

Fitting the First 12 Months: Seasonally Adjusted Data

Historical brand share of the MMC Regada will be seasonal if the seasonal pattern of Regada sales is different to that of the industry as a whole. An examination of share in Figure 4.11 suggests that this indeed might be the case. Regada share is high around October, the month of new auto launches, and it is intuitive that luxury car purchasers would be more sensitive to new brand launches than the auto buying population as a whole.

In an effort to investigate the inconsistent parameters obtained when fitting original share, seasonally adjusted share was also examined. This was done in two ways. First, X-11 seasonal adjustment was used. This is a very sensitive and complex filter but has the disadvantage that, by not being a pure algebraic manipulator, its effect on structure and error distributions is not always clear. Therefore, a seasonal adjustment using eleven seasonal dummies on nine years of data was also undertaken. In contrast to X-11 this is a fairly coarse adjustment but has relatively easily understood properties. Seasonally adjusted share data for the first twelve months are presented as Figure 4.13.

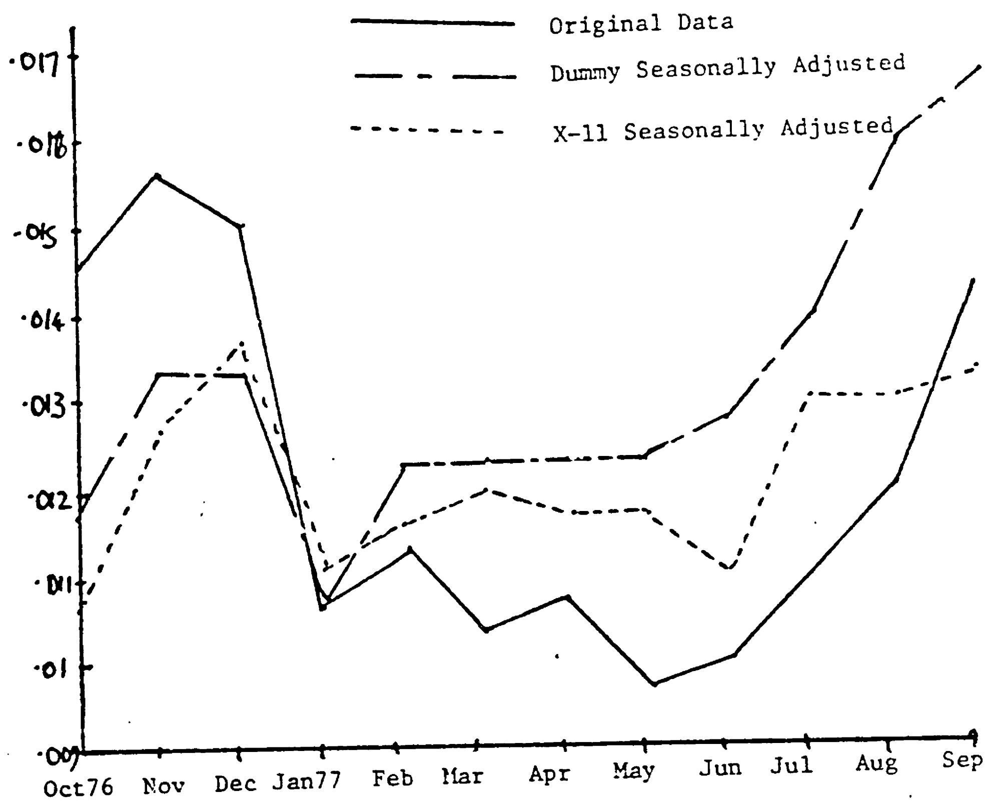


Figure 4.13. First 12 Months of 1983 Regada Share Data: Original, X-11 Seasonally Adjusted, and Dummy Seasonally Adjusted.

Using X-11 there is very little signal in the data. Two minima occur. One with low τ/n corresponds to the first point being well fit then almost total updating so subsequent fitted points are close to the mean (see Figure 4.14). $\bar{R}^2$ was 0.103, τ was 0.7, and k was $2\text{x}10^{-5}$. The second minimum considered of a slight positive trend corresponding to slow updating (high τ/n)(see Figure 4.14). This had an $\bar{R}^2$ of 0.112 and τ=25, k=$2\text{x}10^{-6}$. The first of these fits is not satisfactory because it is all being driven by one point and it does not seem reasonable that all consumers almost totally update in the first month after a new brand's launch. The second fit suffers the same problem of implicit samples of less than one which occurred with original data.

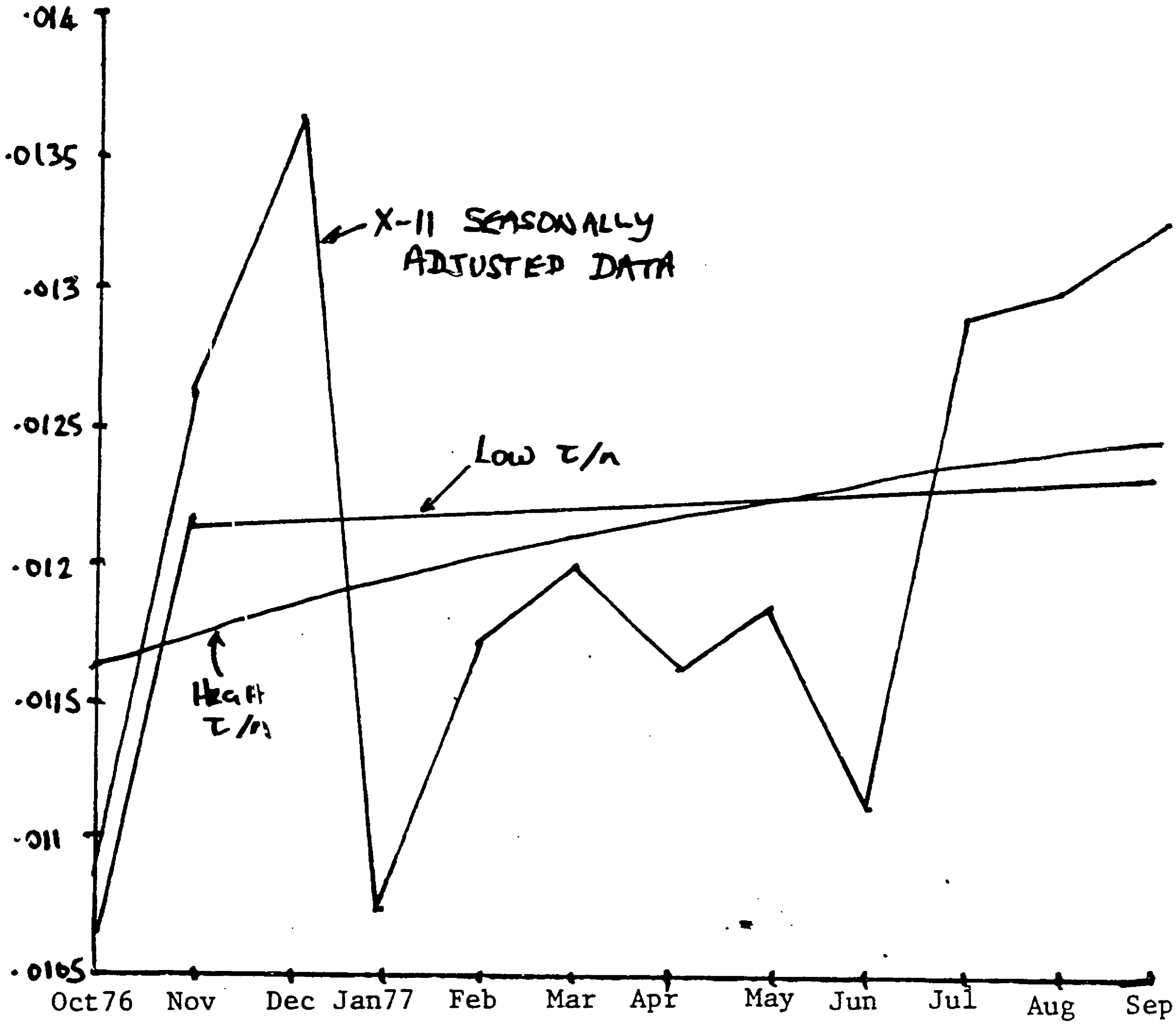


Figure 4.14 Actual and 2 Fits to 1983 Brand Share, X-11 Seasonally Adjusted: First 12 Months.

For those reasons, the use of seasonal dummies was also tried. The significance of seasonality in Regada's brand share is shown in the regression of monthly share on seasonal dummies, presented as Table 4.16.

Figure 4.13 shows that share data seasonally adjusted using dummies generally increased. The fit of MAUD to this data gave more interpretable results. τ was 32 and k was 1.60×10^{-4}, suggesting that in the first month 2.05 owners would be spoken to by a considerer (or 2.05 pieces of uncorrelated information were available). This increases to 27 by the end of twelve months suggesting that at that time prior

Variable	Value	t-Statistic	Variable	Value	t-Statistic
Intercept	.0114	13.12	January	-.0020	-1.64
February	-.0022	-1.82	March	-.0034	-2.72
April	-.0024	-2.03	May	-.0030	-2.41
June	-.0028	-2.30	July	-.0028	-2.30
August	-.0032	-2.62	September	-.0010	-0.83
October	.0015	1.21	November	.0006	0.47
$\bar{R}^2$	.2026		DW	0.29	
N	108				

Table 4.16 Regada Share Regressed on Seasonal Dummies: October 1976-September 1981.

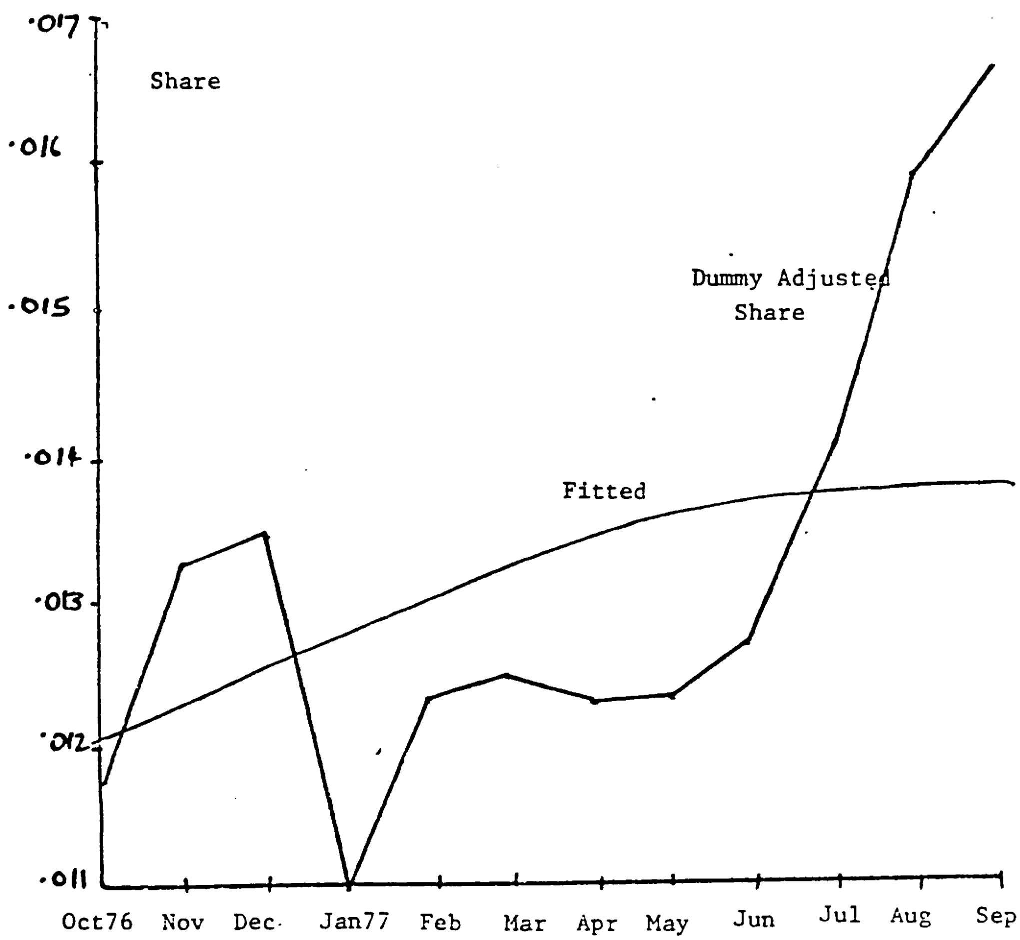


Figure 4.15. Actual and Fitted 1983 Brand Share, Dummy Seasonally Adjusted: First 12 Months.

information is given a weighting of 32/(32+27) = 54% relative to new information gained since launch. $\bar{R}^2$ of the fit was 0.279, better than X-11. The fit, together with data and extrapolated model results are given as Figure 4.15.

Note that in the second year forecast new share continues to increase to its asymptote of 20% (level with no information uncertainty). The reason for the decline in the actual data is addressed in the discussion section which follows.

The slope of the regression of $\hat{P}_{N|B,C}$ on Regada Sales/Industry sales was 0.04697. As shown previously, this is an estimate of consideration (after adjustment for the bias of the sample). On the basis of consideration of the 1983 Regada in the sample, we expected this to be 0.0276. This suggests that our independent consideration estimate is underrated or that the methods effect K is 0.04697/0.0276 = 1.70. That is, respondents underrated the 1983 Regada relative to actual buying behavior. A combination of both effects is also possible.

<u>Forecasting Sales of the 1985 Version</u>

The share data for the 1983 Regada adjusted by seasonal dummies was used to forecast sales of the 1985 version because of its fit and interpretability.

The prior levels of the value, risk, and price in table 4.12, the logit parameters for the choice regression, and the values of τ, n, and K from fitting the 1983 Regada can now be used to forecast the diffusion of the 1985 version. That has been done in Table 4.17 assuming constant consideration. That assumption is a strong one for the 1985 version since the value from concept statement to post drive in the experiment went up by a greater percentage than that of the 1983 version and started higher. The similarity of the diffusion shape of the 1985 version to that of 1983 is a function not only of the use of 1983 historical sales to estimate t, k, and K, but also the similarity of reactions to treatment by respondents driving the concept and the control (see Figure 4.7). The 1985 brand forecasts are plotted in Figure (4.16) and tabulated in Table (4.17).

PERIOD:	1985 $P_{N\|B,C}$ Forecast	1983 $P_{N\|B,C}$ Fitted
1	.203	.165
2	.209	.170
3	.213	.175
4	.217	.178
5	.221	.181
6	.224	.184
7	.226	.186
8	.228	.188
9	.230	.189
10	.232	.190
11	.234	.192
12	.235	.193
13	.236	.193
14	.237	.194
15	.238	.195
16	.239	.195
17	.240	.196
18	.240	.196
19	.241	.197
20	.242	.199
21	.242	.197
22	.243	.198
23	.243	.198
24	.243	.198

Table 4.17 Forecast Raw Choice Share, Conditioned by Consideration and Auto Purchase: 1985 Version Forecast and 1983 Version Fitted

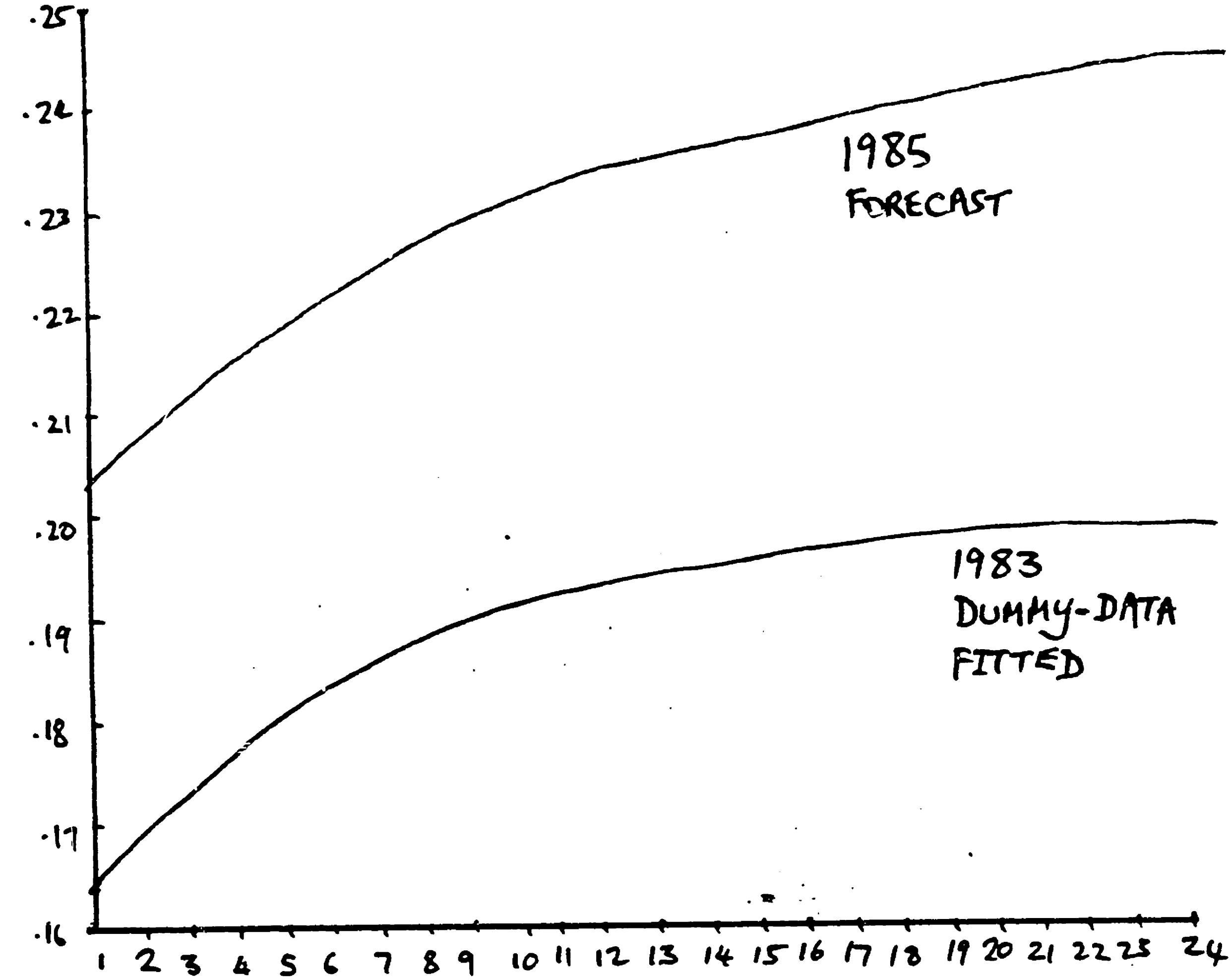


Figure 4.16 Forecast Evolution of 1985 Regada Brand Share vs. Fit to Dummy-Adjusted Actual 1983.

Comparison to Bass's Model

Bass' model (Bass [1969]) was fit on the first twelve months to original brand sales, X-11 seasonally adjusted brand sales, and brand sales adjusted by seasonal dummies. The results are reported in Table 4.18 below. Only the regression on original data is significant and that has the opposite sign for the quadratic cumulative sales term to that which was expected.

	Original Data	X-11 Seasonally Adjusted	Adjusted Using Seasonal Dummies
Intercept	14242 (9.39)	9930 (9.67)	13834 (13.17)
Cumulative Sales	-.108 (-2.29)	.018 (0.55)	-.005 (-.17)
Cumulative Sales **2	$6.96\text{x}10^{-7}$ (2.20)	$-2.10\text{x}10^{-8}$ (0.09)	$7.19\text{x}10^{-8}$ (.51)
$\bar{R}^2$	.23	.14	.01

Table 4.18 Bass Fitted to First 12 Months of 1983 MMC Regada Sales.

Bass' model does, however, perform considerably better over longer time periods, as shown in the discussion section following.[1]

4.4.5 Discussion

Fitting the historical sales of the 1983 Regada has raised a number of critical issues. For example, it has highlighted the importance of the control car in the relationship of experimental results to the

---

1 Note that MAUD was applied to Regada share data, while Bass was applied to actual sales, in keeping with both models' derivation. A graph of actual sales was given as Figure 4.10.

marketplace. Widely varying results are obtained depending on the adjustments which are done to brand share. This sensitivity not only to the choice of the control car, but also to how historical sales of the control car are treated is a fundamental issue with the application of the methodology and is discussed at greater length in Chapter 5 under Future Research.

The other major issue raised is the time horizon of forecasts. While Bass did not perform well for the first twelve months of the 1983 Regada historical sales, if the fitting period is extended to 60 months, the model gives an excellent fit (as shown in Table 4.19). This is consistent with Heeler and Hustad's [1981] finding that Bass tended to perform poorly on early sales data, but well if sufficient data were available.

BASS FIT TO FIRST:

	8 months	12 months	24 months	60 months
Intercept	15493 (5.97)	14242 (9.39)	10894 (6.55)	11451 (12.74)
Cumulative Sales	-.177 (-1.55)	-.108 (-2.29)	-.011 (0.41)	.003 (0.39)
Cumulative Sales **2	1.4×10^{-6} (1.28)	6.96×10^{-7} (2.20)	-0 (-0.64)	-4.00×10^{-8} (-2.74)
$\bar{R}^2$	.184	.230	-.028	.649

Table 4.19. Bass Fitted to Original Data: Different Time Horizons.

The early peak of Bass' curve for the 60-month fit may be interpreted in terms of carry-over diffusion effects from the previous year's model (as suggested by Lawrence and Lawton [1981]). See Figure 4.17.

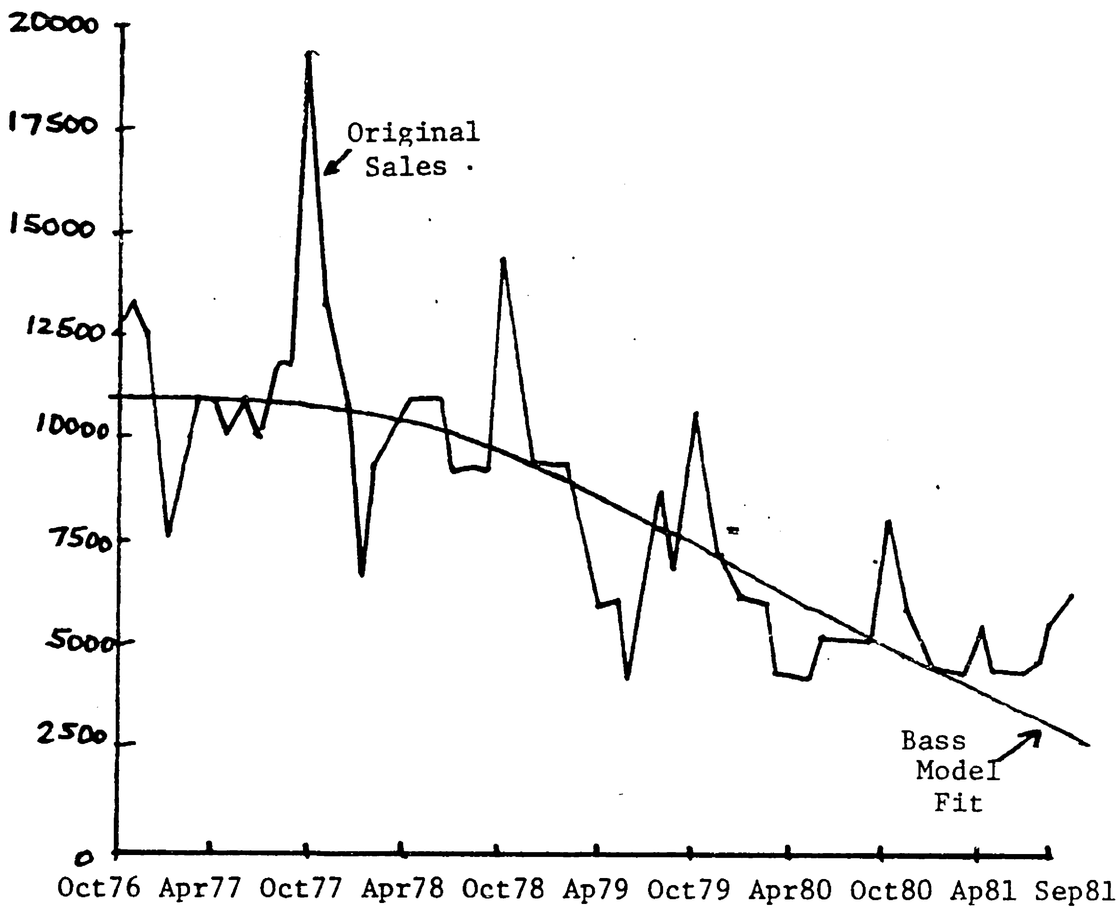


Figure 4.17 Bass Model Fit to Regada Sales, Oct. 1976-Sept. 1981.

A lead time of twelve months was chosen for fitting the MAUD model to avoid effects not included in the model (for example, competition). It turns out to be fortuitous because given that the "true" mean for the 1983 Regada was estimated to be approximately equal to the prior mean, MAUD cannot fit the share decline of the Regada over the 5 years in a way consistent with the model's derivation. (See Figure 4.11 for a graph of Regada share over 60 months.) Two explanations of the decline are possible. First, it should be emphasized that MAUD is only a model for brand choice given purchase and consideration. As applied, it also assumes static competition. One explanation is that tahe 1983 Regada Brand Choice declined because of competitive entry, not currently included in the model but proposed in Section 4.5 and Chapter 5.

An alternative explanation is that measuring the 1983 version among likely considerers seven years after its launch gives us a "prior" which is in fact based on fairly good information about what type of car would be like. MMC management's view is that the 1977 downsizing of the Regada was rejected by consumers at the time. That is, consumers had higher priors about the brand before its introduction than those that they had after experience with it. A combination of the two effects is also possible. The implications of this hypothesis to the application of this model are discussed in Chapter 5.

A higher prior mean would allow the slight downward sloping curve of the 1983 Regada to be fit (see Graphs II.2 and III.2 of Figure 3.3).

4.4.6 Convergence of Measures and Validity

The five operationalizations of risk, described in Chapter 3.3, were tested for convergence by examining the joint correlation matrix, Table 4.20.

	Confidence in Choice	Risk	Unreliability	Fractile	Perceptual Clarity
Confidence in Choice	1.000				
Risk	0.290	1.000			
Unreliability	0.342	0.231	1.000		
Fractile Risk	-0.041	0.041	-0.067	1.000	
Perceptual Clarity	0.104	0.116	0.327	0.031	1.000

Table 4.20. Correlation Matrix of Different Risk Measures.

While all of the correlations in the matrix are significant and of the expected sign, except for those with the fractile risk measure, correlations are very low.

These low intercorrelations and the fact that each risk was significant when regressed on normalized probability suggested including all of the measures into a regression together. The result was surprisingly strong, suggesting that more effort could be put into the development of a composite risk measure.

$$P_j = .22+.86v_j-2.5\times10^{-6}p_j-.012\sigma_1^2-.016\sigma_2^2-.024\sigma_3^2-.0004\sigma_4^2-.0027\sigma_5^2$$

$$(7.24)\ (-1.94)\quad (-1.68)\ (-2.46)\ (02.41)\ (-2.57)\ (-5.51)$$

$R^2 = .4950$ Condition number = 19.9

where

σ_1^2 = Confidence in choice σ_2^2 = Risk

σ_3^2 = Unreliability σ_4^2 = Fractile measures, and

σ_5^2 = Perceptual clarity

It would appear that each of these measures is capturing a different facet of the uncertainty/risk construct.

The other multiple measure used was rank of brand within top three choices and concept, used as a convergent measure for probability. Regressions of rank on utility and risk are not directly comparable to those of probability because of different scaling. However, they were significant and fits were similar.

A comparison of predicted shares of the test and control cars pre- and post-video is interesting. The predicted percentages of trial are quite close, except for an anomolously small 7.1% for respondents seeing the positive videotape and driving the 1983 car who preferred it. Results are given in Table 4.21.

	Probabilities		Ranking	
	1983	1985	1983	1985
Post Drive	16.5%	20.5%	14/109=12.8%	43/224 = 19.2%
Post Video +ve	15.7%	20.9%	4/56= 7.1%	23/108 = 21.3%
-ve	14.6%	18.4%	9/53 =17.0%	17/114 = 14.7%
Post Video All	15.1%	19.6%	13/109=11.9%	40/224 = 17.9%

Table 4.21. Comparison of Probabilities and First-Order Ranking of Test and Control Cars.

Respondent's Perceptions of the Questionnaire. Respondents were asked to evaluate the questionnaire from the perspectives of difficulty, interest, and realism using four-point scales for the first two measures and a three-point scale for the third. These results actually refer to the Phoenix Pretest, however the tasks in the full field trial in Cincinnati were almost identical. Table 4.22 shows that respondents found it slightly more interesting, but marginally more difficult and unrealistic to evaluate the concepts relative to brands currently available. For details of measures, see Appendix D.

	Details of Autos Owned	Evaluating Current Mkt	Evaluating Concept
Difficulty (1 Not difficult at all 4 Extremely difficult)	1.36	1.78	1.94
Interest (1 Very interesting 4 Not at all interesting)	1.86	1.72	1.61
Realism (1...relevant... 3...little meaning...	1.41	1.67	1.75

(n = 40)

Table 4.22. Difficulty, Interest, and Realism Involved in Evaluating Current Holdings, Those Currently Available, and Those Which Might Become Available.

A survey of interviewers by Young Sohn, a member of the Project team, gave only three poors (the bottom on a three-point scale) out of eleven responses for length of the questionnaire and one poor for the overall questionnaire. Observation by members of the team suggest that it was a very involving process for both the respondent and the interviewer.

Validation. In addition to the tests for convergent validity of measures and internal consistency within the model, a complete validation study is planned as future research and is described in Chapter 5. That validation will attempt not only to verify forecasts made by the model, but also the specific components and measures in the model.

4.5 INTERFACE BETWEEN THE MAUD MODEL AND THE FORECASTING SYSTEM

The recursive nature of forecasting brand choice, given in equations (4.18) and (4.19) requires estimates of the brand's sales over time. To allow this, complementary category purchase and brand consideration forecasts must be made. Additionally, in order to have a complete prelaunch durable forecasting system, not only are category purchase and consideration required, but a model for competitive entry must be developed. Because those models exploit a number of characteristics of the choice hierarchy framework developed in Chapter 1 and the MAUD model, a brief review of them is provided in this section.

The underlying strategy of the forecasting system is to use a number of techniques to forecast each stage as a test of convergent validity. This approach has proven extremely successful for the prelaunch forecasting of frequently purchased goods in ASSESSOR (Silk and Urban [1978]). The elements of the system are outlined in Figure 4.18, a modification of Figure 3 of Hauser, Roberts, and Urban [1983].

One desirable feature of this system is the inclusion of feedback loops so that brand selection and purchase timing are not independent. The diffusion of a particular brand can affect industry sales as well as its consideration, demonstrated later in this section.

This section reviews consideration models, purchase incidence models, alternative brand choice models, and finally, a model of competitive entry.

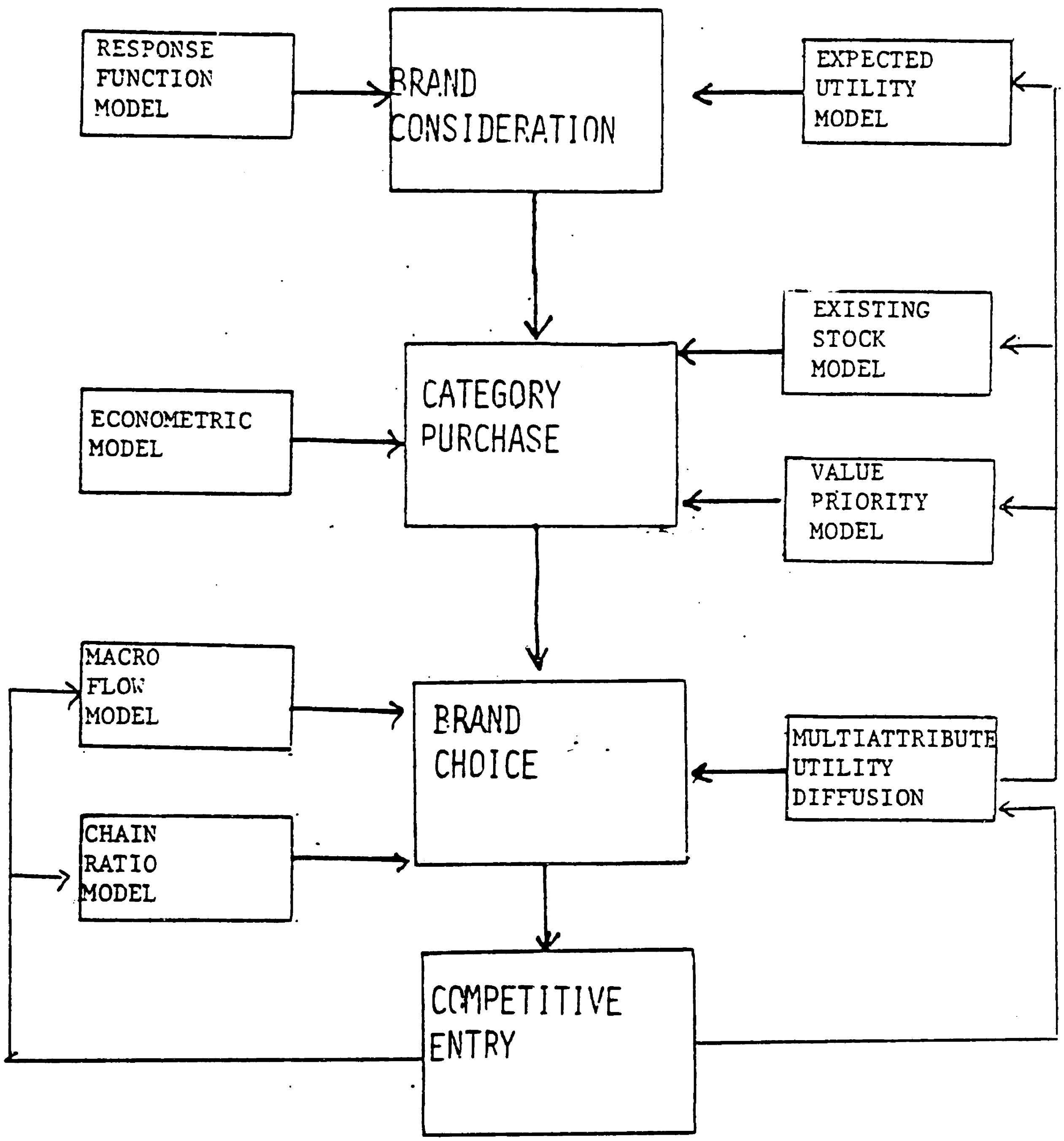


Figure 4.18. Structure of Model Components of Prelaunch Durable Forecasting System.

4.5.1 Consideration Models

Two approaches are suggested for determining consideration of the new brand over time as a function of advertising and word-of-mouth communications. Note that advertising has been incorporated at the consideration stage, but not the brand choice stage. This is consistent with the findings of a number of researchers that advertising is more effective at the awareness stage, particularly for high-involvement decisions (e.g., Rogers and Shoemaker [1971, p. 257]).

The first approach is to use response functions, an adaptation of the BRANDAID approach proposed by Little [1975]. The second approach is to take advantage of our knowledge of the utility of the brand to determine whether it is worthwhile for a rational consumer to include the brand in his or her consideration set.

Response Function Model. A response function relating consideration to advertising may be estimated on past data if it is available, or using management judgment if it is not. Word-of-mouth effects should not be included in such a model because the model is estimated from a different data source from the MAUD model and so we cannot distinguish between word-of-mouth effects at the consideration stage and at the brand choice stage.

Such a model is proposed by Blattberg and Golanty [1978] who use the algebraic form:

$$\log \frac{1-P_C(t)}{1-P_C(t-1)} = \alpha - \beta \, Ad(t) \tag{4.25}$$

where

$P_C(t)$ is probability of consideration in time t, and

Ad(t) is advertising effectiveness in time t.

If such an approach were to be adopted, then a regular survey to establish consideration dynamics could be instituted to track the model and allow more accurate estimates of sales.

While no awareness data were available, a double log regression of sales on advertising for eight brands over three years yielded an R^2 of 0.9657 and an advertising elasticity of 0.390 (t = 4.99). In setting up a decision support system to calibrate the consideration model, one would have to be taken with the direction of causality and the absence of a third variable jointly correlated to advertising and consideration (e.g., the brand's appeal).

Expected Utility Consideration Model. Since the work of Stigler [1961] which pointed out that it was rational for consumers to make less than fully informed decisions when there is a positive cost to information, marketing scientists have been working on optimal and actual search strategies for consumers (e.g., Ratchford [1980], Ratchford [1982], Shugan [1980]). Using this approach, consideration of the new brand may be modeled by comparing the cost of including it in the consideration set (C_N) to the increase in the expected utility of including it in the consideration set. This increase is the expected utility of the consideration set with the inclusion of N minus the expected utility of the consideration set without N.

Ben Akiva and Lerman [1977] give the expression for the expected maximum of the utility of J brands using the logit model ($E(U^C_{max})$).

It is given by:

$$E(U^C_{max}) = E[\max_{j\varepsilon C} U_j] = \ln(\sum_{j\varepsilon C} e^{\beta\chi_j}) \tag{4.26}$$

Therefore, brand N will be included if:

$$E(U^{(CUN)}_{max}) > E(U^C_{max}) + C_N \tag{4.27}$$

i.e.

$$e^{C_N} < \frac{\sum_{j\varepsilon CUN} e^{\beta\chi_j}}{\sum_{j\varepsilon C} e^{\beta\chi_j}} \tag{4.28}$$

$$= \frac{P_{j|C}}{P_{j|CUN}} \tag{4.29}$$

Information is available from the experiment to estimate 4.28 or 4.29 over time.

4.5.2 Purchase Incidence Models

One purchase incidence model at the aggregate level is described below and two at the individual level. The aggregate level model involves classical econometric forecasting, while both of the individual level models, the value priority model and the existing stock model, have the potential to exploit the structure of the choice hierarchy framework, developed in Chapter 1.

Econometric Models. It should be remembered that from equation 1.1, category purchase was conditioned on consideration. While exogenous information is unlikely to be available classified on this basis, demographics, price, and income of buyers are available historically for auto purchasers by brand (from R.L. Polk and Company). Purchase is likely to provide a good surrogate for consideration in determining values of exogenous variables. A number of variables such as gas prices, do not vary by segment. Given these data, a model similar to those described in the literature review under "Aggregate Econometric Models" may be fit.

Value Priority Algorithm. The value priority algorithm developed by Hauser and Urban [1982] was outlined in Section 2.2.2. Its basic objective is to study how consumers make trade-offs between major ticket items in their household planning. Hauser, Roberts, and Urban [1983] describe how data were collected to model consumers' budgets at the individual level by collecting utility and probability estimates for different durable purchases.

Given this utility and probability data a logit model can be estimated to determine probabilities of purchase of a specific durable category (Hauser and Urban [1982]). From these probabilities, individual budgets can be simulated and estimates of the probability of a consumer purchasing an auto can be made. Thus, individual purchase incidence probabilities would be obtained.

One benefit of the nested logit approach (or indeed, a nested probit approach) is that it is possible to calculate how the category purchase probability changes with the insertion of a new brand, using 4.26:

$$E(U_{max}^{C}) = \ln(\sum_{j\varepsilon C} e^{\beta\chi_j}) \quad (4.26)$$

Changes of this new brand's utility over time, estimated by the MAUD model, could then be incorporated into the category purchase probability. If the diffusion effects of other dynamic product classes were able to be calculated (e.g., personal computers) than the effect of their diffusion on auto sales could also be included.

<u>Existing Stock Model</u>. The existing stock model suggests that a consumer will purchase a new durable (U_B) if the expected consumer surplus from a new durable minus transaction and search costs (C_B) exceed the expected consumer surplus of existing stock (U_E).

Equation (1.1) on page 12 suggested that:

$$U_{Bj} = -C_B + U_{j|B} \qquad \text{(for } j\varepsilon C\text{)}$$

where

U_{Bj} = utility gained from buying a durable and choosing brand j

C_B = the utility loss associated with transaction and search

$U_{j|B}$ = the utility of brand j that is bought.

The expected maximum utility over brands was given by equation (4.26):

$$E(U_{max}^{C}) = \ln(\sum_{j\varepsilon C} e^{\beta\chi_j}) \quad (4.26)$$

Upgrading will occur if the expression in (4.26) minus utility lost in the transaction exceeds the utility of existing stock.

$$\ln \sum_{j \in C} e^{\beta X_j} - C_B > U_E \tag{4.30}$$

Under the nested logit assumption, the probability of purchase may be written (Ben Akiva and Lerman [1977]):

$$P_{B|C} = \frac{e^{-\gamma C_B + \gamma \ln[\sum_{j \in C} e^{U_{j|B}}]}}{e^{\gamma E(U_E)} + e^{-\gamma C_B + \gamma \ln(\sum_{j \in C} e^{U_{j|B}})}} \tag{4.31}$$

Probability of category purchase measures were taken in conjunction with the data collection. So too were attribute ratings, value point allocations for existing holdings, and expected trade-in price. Thus, there are enough data to fit the above model as at the time of data collection.

The dynamics of the model may be addressed as follows. Dynamics of the utility of existing brands on the market and their prices stem from the brand choice model, MAUD. Trade-in prices (expected and reservation) were collected and these could be modeled. Alternatively, industry sources provided a reliable guide (e.g., Edmunds, a listing of used car prices). The dynamics of the utility of existing stock as it ages may be modeled as a constant ratio of the trade-in price. Alternatively, cross-sectional analysis of the attribute ratings and value points which respondents gave their current auto may be used to model depreciation in utility to the consumer. An example of the movement of existing stock on the perceptual map demonstrates this effect (Figure 4.19). A similar

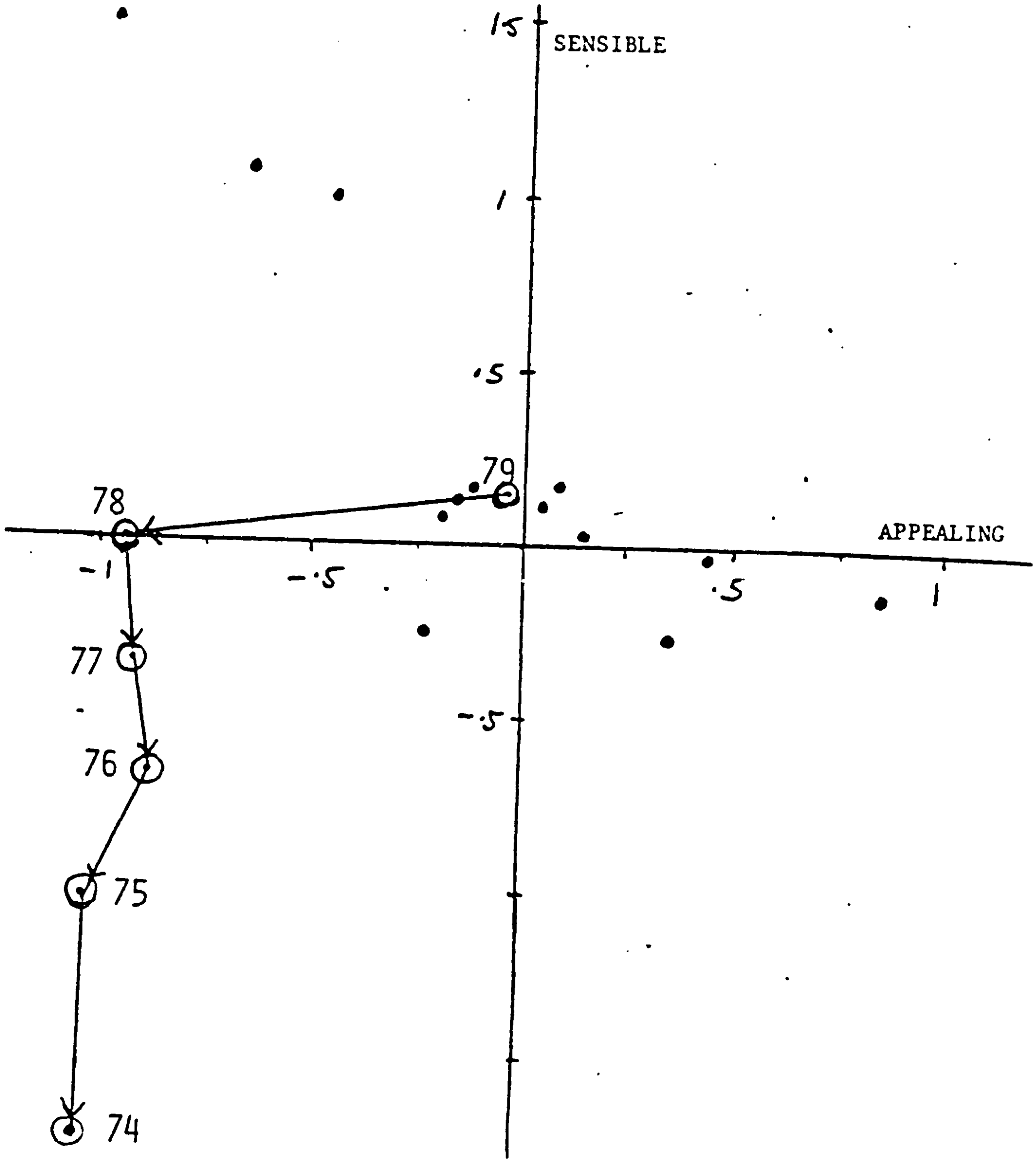


Figure 4.19 Trend in Perceptual Position of Existing Stock with Increasing Vintage.

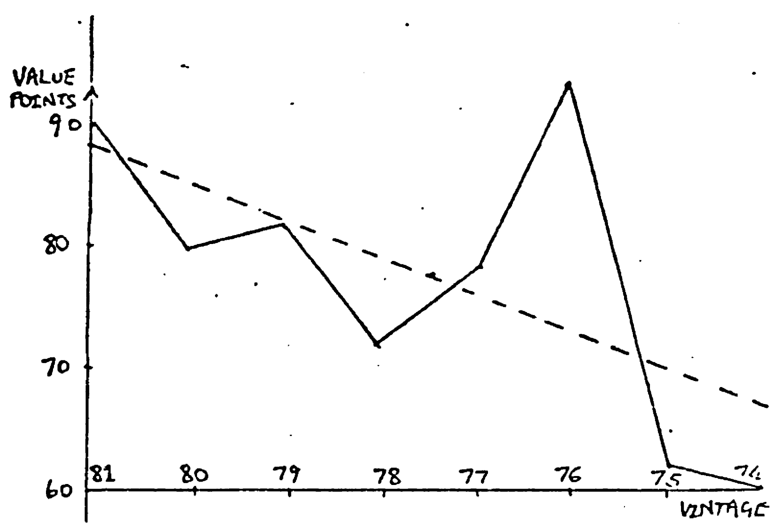


Figure 4.20 Trend in Value Points of Existing Stock with Increasing Vintage.

effect may be seen looking at the decay in value points. The $\bar{R}^2$ of the fitted line in Figure 4.20, showing the depreciation of value points is .2495.

Considering th- these graphs refer to different respondents reporting on different brands of auto, there is a good consistency in the depreciation with vintage (assuming that vintages are approximately homogeneous).

Risk was not measured for existing stock and its effect is likely to be important. Somewhat finer instruments than those outlined in Appendix D may be required since existing stock is likely to be considerably lower than new brands in terms of information uncertainty, but may well be higher in terms of performance risk.

As it stands, the existing stock model is a replacement model and does not say very much about first purchasers. Hauser, Roberts, and Urban [1983] point out that for this group $U_E = 0$ and the model degenerates to the simplest form of the value priority model. However, in more general terms, U_E may be thought of as one measure of an individual's immunity (or lack of susceptibility) to an auto purchase. This idea fits nicely with the epidemiological roots of diffusion theory and provides a rationale for Jeuland's [1981a] development of a diffusion model with individuals having differential probabilities of adoption of an innovation.

Order of acquisition chains provide an obvious source of information on susceptibility for first purchasers. Examining a non-owner's portfolio of durables should give some indication of how likely that person is to acquire the durable in question. Sociodemographic variables may also be used. In addition, a number of indicators of disenchantment with existing stock were collected in this study including: miles on odometer, miles per gallon, condition of current auto, trade-in price minus reservation price, and trade-in price expected in a year's time.

4.5.3 Convergent Models of Brand Choice

In addition to the MAUD model, two alternative brand choice models are suggested in Hauser, Roberts, and Urban [1983]--the Macroflow Model and Chain Ratio Model (Test/Control Model).

Macroflow Model. Macro flow models posit a set of behavioral states which mutually exclusively contain all members of the population. Thus, a population might be divided into the groupings defined in Figure 4.21 below:

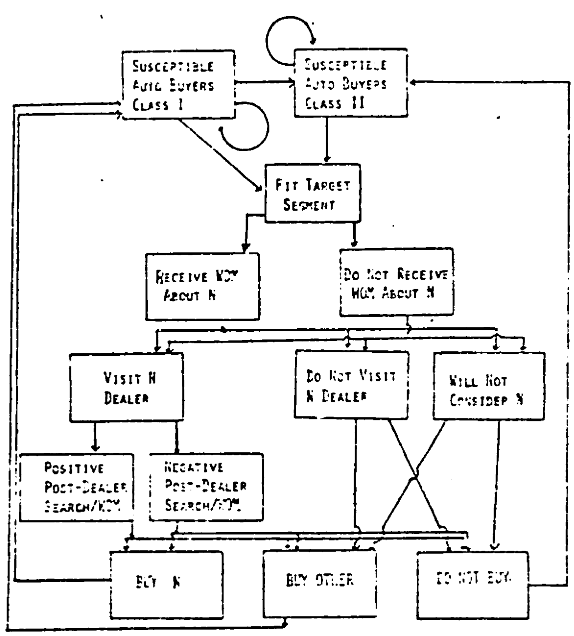


Figure 4.21 Simplified Example of a Macroflow Diagram (Adapted from Hauser, Roberts, and Urban [1983]).

Consumers are assumed to be homogeneous within states and flows from one state to another are modeled. The approach is best illustrated by Urban's [1970] SPRINTER model, described in Section 2.2.1. Urban and Hauser [1980] provide technical details of the measurement and estimation involved.

Note that as illustrated above, the model includes consideration and category purchase. It may be developed as either a brand choice forecasting model or a model of the total forecasting system.

Chain Ratio Method. Kotler [1980] advocates the chain ratio method of breaking a forecast down into components which may be estimated separately.

Thus, we could model $P_{N|BC}(85)$, the brand choice probability of the 1985 version by:

$$\hat{P}^{t}_{N|B,C}(85) = \frac{\hat{P}^{t}_{L}(85)}{\hat{P}^{o}_{L}(83)} \cdot \frac{\hat{P}_{RA}(85)}{\hat{P}_{RA}(83)} \cdot P^{o}_{N|B,C}(83) \qquad (4.32)$$

where

$P^{t}_{L}(85)$: life cycle index for 85 version in time t

$P^{0}_{L}(83)$: life cycle index for 83 version at time of measurement

$P_{RA}(85)$: relative appeal of 85 version (laboratory)

$P_{RA}(83)$: relative appeal of 83 version (laboratory)

$P^{o}_{N|B,C}(83)$: actual share of 83 Regada at time of measurement.

Life cycle indices could be imputed from the data in the experiment, or could be taken from Silverman's analysis of historical brand diffusion effect.

Similar chain ratios may be used to get relative consideration of the 85 version in each period to the 83 version and also industry sales given the new entrant compared to industry sales without it. Thus, the chain ratio method may also be extended to be a simple but robust forecasting system.

4.5.4 Competitive Entry.

Competitive entry may be modeled using the results from a conjoint analysis (Green and Wind [1975]). A double replication of a 320 item set of concepts with attributes similar to those described by Hauser, Roberts, and Urban [1983] were collected in conjunction with the study. The first exposure to the stimulus car, N, or the control car, occurred inserted as one of these concepts. Therefore, a direct comparison of initial appeal of potential entrants relative to the stimulus may be made.

To forecast the preference dynamics for another possible entrant, some assumptions will have to be made about the true levels of the competitor's performance. These assumptions may be made using a combination of historical performance of that manufacturer, the post-diffusion performance of the test car, and an evaluation by the sponsoring auto company's management of the degree to which a competitive entrant will generate favorable word of mouth.

CHAPTER 5: SUMMARY AND DIRECTIONS FOR FUTURE RESEARCH

The multiattribute utility diffusion model, developed in Chapter 3, was operationalized and calibrated in Chapter 4. Chapter 5 gives a brief review of the model and results obtained in fitting it (Section 5.1). It then discusses assumptions made in the model derivation and draws from experience with the model to suggest directions for future research to extend the scope of the model (Section 5.2).

5.1 Summary

The contents of Chapters 3 and 4 are reviewed under three headings: model, experimental design, and results.

5.1.1 Model

Diffusion and Expected Utility Changes. We have introduced a new way of looking at diffusion--in terms of expected utility with a continuous range of possible outcomes. This allows a multiattribute approach to be adopted for new brands so the relative position of the brand in the market can be used for planning the launch.

We have postulated three sources of diffusion: increasing awareness and consideration; changes in the expected level of attributes; and changes in information uncertainty. This formulation allows a variety of growth patterns to be handled as shown in Figure 3.3.

The incorporation of perceived risk into the model in a deductive way ties recent work by researchers in multiattribute utility theory in discounting preference by risk, to an increasing interest in modeling the dynamics of perceived risk in diffusion theory. Using the model, the effect of risk on preference may be studied at the individual level. From this, flow forecasts of changes in adoption probabilities and, when aggregated, the population diffusion process.

Belief Dynamics. We have provided an information and utility updating rule which allows the operationalization of the model prior to launch as long as estimates of true levels of perfect information mean evaluations and their variance can be obtained. Changes in consumer perceptions of mean attribute levels may be studied over time so that the dynamics of perceptual maps and their implications on competitive structure may be considered. Together with the updating of uncertainty, this allows changing preference to be modeled over time and thus changing probability of adoption. We have thus provided a step in showing how integrated models of consumer choice may be adapted to incorporate dynamics.

Choice Hierarchy and Diffusion. We have developed a model which includes diffusion at the brand level, diffusion at the product category level, and a theory-based nexus between the two of them. This has been achieved by use of a choice hierarchy framework of auto purchase/brand choice within which we modeled the effects of changes in brand preference over time.

To examine when the diffusion effects of a specific new innovative brand are likely to have an important influence on category sales, it is useful to return to equation (4.24).

$$P_{B|C} = \frac{e^{-\gamma C_B + \gamma \ln[\sum_{j\varepsilon C} e^{X_{j|B}}]}}{e^{\gamma E(U_E)} + e^{-\gamma C_B + \gamma \ln[\sum_{j\varepsilon C} e^{X_{j|B}}]}} \tag{4.24}$$

The diffusion of N will have an important influence on $P_{B|C}$ when

(1) e^{X_N} is large compared to $\sum_{j\varepsilon C} e^{X_j}$. (For example the consideration set size is small); and

(2) X_N changes dramatically over time.

Condition (1) says that brand N is important in the market and condition (2) says that its diffusion effects are significant. Condition (2) is likely to be met when μ_N at launch is likely to be wrong (for example, a stripped-down brand produced by a manufacturer with a reputation for luxury cars), or σ_N^2 at launch is high, (for example, an unknown manufacturer).

5.1.2 Summary of Experimental Design

Experimental Stimuli. As a part of the research, an experiment was designed, pre-tested, and executed to allow calibration of the model. This was performed by sequential information provision to respondents with detailed measurement at each stage. The treatment was aimed at simulating the consumer's information acquisition path in practice as the new brand diffuses. Information stimuli included a concept description, the test drive of a prototype of the new brand, a word-of-mouth videotape simulation, and an independent laboratory maintenance and safety report (see Appendix C). Advertising copy was also to have been used, but was not available in time. The videotape, safety report, and advertising were an attempt to provide respondents with information about the brand which they would get from other than physical experience with it. They correspond to Cox's [1971] classification of information into consumer-dominated, neutral, and marketer-dominated channels, respectively.

The use of both positive and negative videotapes and safety reports gives a test of the differential effect of content of the stimulus. It also allows a sensitivity analysis to be performed on the forecasts, conditioned by the information which actually does circulate about the product.

The control car also fulfills a double role. First, it allows an experimental effect to be calculated. Evaluation of the test car can be compared to evaluation of the brand by respondents who evoked it in the experiment. Second, in the absence of previous replications of this experiment, the test car provides a benchmark sales history on which to calculate the correspondence between experimental effects and performance in the marketplace.

<u>Measures</u>. A complete set of measures needed to calibrate the model were developed and tested. While it was possible to use validated scales for a number of variables (for example, Juster scale of probability), in others new measures had to be implemented. The thermometer value points

measure, recommendation levels, and the fractile measures of risk are examples of the design of measures specifically tailored for the prelaunch sales forecasting methodology.

Chapter 4 shows that the stimuli did change respondents' perceptions in the directions predicted and that these measures were able to detect such changes. However, refinements to the measures are suggested in Appendix E.

5.1.3 Summary of Results.

The model was implemented using the 1983 and 1985 versions of a domestically produced luxury automobile. Results showed that the calibration of the consumer decision process was stable after insertion of the new brand both prior to the videotape and after it. Factor loadings were similar in each market scenario suggesting that the same perceptual space may be used to represent the way in which the concept brand is evaluated. Preference regression coefficients and logit coefficents were not significantly different, indicating that the abstraction of perceptual factors to preference and from preference to choice are similar for the brands currently ranked in the top three and the concept car.

Attribute evaluations of the concept car seem to show that the 1985 down-sized version has successfully conveyed the perception of good fuel economy without proving worse than the 1983 version on the luxury and styling dimensions. Both versions are positioned close to other luxury domestically produced autos, with the 1985 version having an edge in terms of perceptual position, value points, and probability of brand choice.

The positive and the negative treatments did move respondents in the expected directions in terms of attribute ratings, value points, and probability. The increase in risk caused by the negative videotape is interesting.

The positive treatment did not have as great an effect as the negative on all measures. This may be due to the fact that it confirmed already positive expectations. Alternatively, it may indicate a problem with source credibility for the positive message.

The changes in average recommendations which respondents gave the concept after seeing the videotape and safety report indicate that those treatments were weighted 1.1 times the weighting given to post-drive beliefs. This varied by car being replaced, with Buick replacers being more certain of their prior beliefs than other respondents.

The estimation of relative strength of priors allowed an implicit average true position of the concept and control to be calculated. The updating model applied to pre-video measurements predicted post-video utility and probability fairly well. After adjusting by information available on pre-video forecasting errors, the model explained 63% of the variation of post-video probability reports.

Fitting the lifecycle of the 1983 brand in practice proved more problematical. Using original market share data, the resulting U-shaped curve could be fitted by the model reasonably well ($R^2 = 0.432$), but the implicit number of adoptors spoken to was very low. Employing parameters estimated from this fit for the forecasting of the 1985 version introduces a similar U-shape and the evidence does not seem strong enough to be able to say that this is not an artifact of the noisy 1983 version sales data.

Using X-11 seasonally adjusted data, it was impossible to extract a significant signal from the first twelve months market share either by using the model or even using a time series analysis approach. Therefore, seasonal dummies were used to adjust the market share of the 1983 version. These dummies were statistically significant and the parameters obtained from fitting this data were intuitively appealing. Because of the similarity of changes in preference for the 1983 and 1985 versions with increasing information and because constant consideration was assumed in both cases, the shape of the 1985 version sales evolution follows that of the 1983 closely.

An experiment similar to the one conducted in this study will be undertaken three times in 1984 on three further brands in the same product category. If sufficient data are collected to calibrate this model, a better feel for typical values of τ, n, and k will be gained so that exogenous estimates of them will be available. This approach is analogous to the way in which Lawrence and Lawton [1981] impute Bass' diffusion rate parameter for a new brand from historically based estimates of those of other durables.

5.2 Directions for Future Research

Future research suggested by experience with the model, together with an investigation of how some of the assumptions asociated with it might be relaxed, are discussed in this section. Such research is included under the headings: Further Analysis of Current Experiment; Further Modeling Developments; and Measurement and Application Developments.

5.2.1 Further Analysis of Current Experiment

Development of the Consumer Behavior Model. The components of the consumer behavior model were attribute perceptions, factor perceptions, preference, and choice. Links between them were modeled using traditional tools: factor analysis, preference regressions, and logit models (e.g., see Urban and Hauser [1980]). Recent developments in marketing suggest alternative ways of analyzing the data which are more based on testing or confirming the model and less on exploratory analysis (see Bagozzi [1983]).

In the spirit of such research, it would be valuable to follow a number of Bagozzi's suggestions. A confirmatory factor analysis could be undertaken with a hypothesized structure of the relation between attributes, factors, preference, risk, and price tested. Oblique factors rather than orthogonal should be tested to see if consumer perceptions of auto brands could still be described by only two dimensions.

The relationship between factors and preference (Tables 4.7 and 4.8) is attenuated by measurement error. An errors-in-variables analysis (Johnston [1972]) would be useful to determine the strength of the underlying relationship. Unfortunately, there is currently no theory to allow for adjustment for errors-in-variables with logit models.

The logit model deserves further attention. It would be desirable to fit a probit model to the choice data, even if that involved an approximate assumption about the utility of an "other" (composite) brand and the covariance of its error with the top three choices and the concept. It would also be desirable to write a logit program which allows maximum likelihood estimation with stated probability as the dependent variable.

Finally, significance tests of differences between brand attributes and perceptual positions should be undertaken. The former should be done using multivariate profile analysis, the latter using the natural scaling of the perceptual map (each unit is one standard deviation divided by the number of stimuli evaluated by an individual). The meaning of the perceptual maps, obtained by aggregating across consumers (who are to some extent heterogeneous) should be investigated. One way to do this is to perform a cluster analysis on repondents' ratings of the concept car and then re-factor analyze each cluster of respondents separately.

<u>Fit the Brand Sales Model.</u> In order to fit the complete brand sales model, the consideration models and purchase incidence models outlined in Section 4.5 must be estimated, as well as the convergent methods of forecasting brand choice given purchase and consideration. The structure of the methodology is shown in Figure 4.14.

<u>Secondary Data Collections</u>

Forecasting the dynamic evolution of brand choice and consideration based on an experiment conducted at one point in time suggests that careful monitoring of actual model components should be undertaken to allow validation and parameter updating. MMC currently has an awareness survey for its various brands conducted by telephone on an irregular basis. That survey could be modified and conducted regularly. Early information on brand awareness, perceived acceptability, consideration, and preference could be gathered from it. That would allow tracking of the model and an adaptive forecasting system. In this methodology, we are distinguishing between consideration and awareness. Consideration includes awareness at least to the level of evoking as well as acceptability.

In parallel with that, early adoptors should be monitored by an independent research agency to gain their changing perception of the car and the recommendation they are spreading about it.

Finally, the sample from this experiment should be recontacted to allow a validation of their intention responses and a test-retest reliability study of their other responses.

5.2.2 Further Modeling Developments

In addition to further analysis on the current experiment, a number of aspects of the modeling theory deserve further research.

Other Information Integration Algorithms

Within the Bayesian updating framework, it may be desirable to relax the assumption of known variances. The large increase in four of the five risk measures in reaction to the negative videotape reported in Chapter 4, can only be explained by the model by relaxing this assumption. The algebra necessary to do that was presented in Appendix B. Additional measures of inherent product variability would need to be developed.

No longer assuming variances are known means that the dynamics of perceived inherent product variability (σ_ε^2) become potentially extremely important. If σ_ν^2, the variance of the perceptual bias in word of mouth, is small, the dynamics of inherent product variability will overshadow those of information uncertainty (σ^2) once one or two owners have been consulted. The relaxation of the known variances assumption allows a richer set of brand sales evolutions to be fit consistent with the asumptions of the model. Figure 3.3 and the discussion accompanying it showed that there are a number of shapes which can be fit by the MAUD model, but which cannot be interpreted unless variance is allowed to increase. As shown in Chapter 3, if variances are assumed known, variance (uncertainty) must be monotonically decreasing.

Alternative ways of viewing the updating of beliefs about the brand as diffusion occurs may be classified in three ways. First, Bayesian updating may be generalized to allow for homophily as indicated in Appendix B. Second, the Bayesian updating paradigm may be exchanged for another statistical information integration algorithm. Slovic and Lichenstein [1971] give a detailed review of regression methods and correlational methods as an alternative approach.

The third way of viewing information integration is to construct a new theory based on observed heuristic biases in consumers. For example, the model from such a theory might give less weight to information received later in time by a respondent than it gives to information received earlier.

Incorporation of Price in Purchase Decisions

Two formulations of price in the net preference measure were advanced in Chapter 3. Both are based on maximizing utility subject to a budget constraint or alternatively, consumer surplus. One way to obtain the first, $u-\lambda p$, is to assume that a global maximum is achieved by solving each product category as independent of others and then to maximize within each category. The second, u/p, suggests that a good approximation to the global maximum is to solve a knapsack problem by maximizing u/p within each category. Both can be justified with individual examples of alternative utility-price mixes for different products. Theoretical and empirical research is needed to determine the situations in which the one is preferable to the other.

A less tractable problem concerning the incorporation of price with an exponential risk aversion function revolves around whether it is used to discount preference (as assumed in equation 3.6) or expected utility. Economic theory would suggest the latter and thus discounting value by price ($v_j - \lambda p_j$) can only be justified with exponential utility as a heuristic. Discounting expected utility by price gives (in the additive price formulation):

$$U(\tilde{X}_j) = -e^{-r\tilde{X}_j} - \lambda p_j$$

and

$$E(U(\tilde{X}_j)) = e^{-r(X_j - \frac{r}{2}\sigma_j^2)} - \lambda p_j$$

which is not necessarily monotonic in $X_j - \frac{r}{2}\sigma_j^2 - \lambda p_j$.

One solution to this problem is to assume a linear preference to utility transformation and quadratic marginal value as shown in the footnote of Section 3.11. This formulation is consistent with utility maximization.

Error Structure for Relative Strength of Beliefs and True Value of Mean

As discussed in Section 4.3, the error theory associated with the estimation of μ_T has not been developed. It would be valuable to do so to enable the properties of the estimate to be examined.

If recommendations are assumed to be measured with a normally distributed error, then the error structure of our estimate of (τ/n) from equation 4.4:

$$\tau/n = \frac{R_T - R'}{R'' - R'} - 1$$

will be distributed as the quotient of two normal distributions. The resultant error distribution is neither normally distributed nor symetric. This suggests that our assumption of normal measurement error for means is likely to be at best an approximation. Relaxing this assumption or at least studying its seriousness in the calculation of risk adjusted net preference would be desirable.

True Preference for Concept Brand

Currently the mean level of word-of-mouth preference information which will circulate about the brand (μ_T) is computed from data obtained in the experiment. There are a number of problems with this approach.

The strengths of beliefs are based on the recommendations given to the new brand on a five point scale (equation 4.8). Although these are averaged across segments, a heavy load is placed on the recommendation scale in estimating the amount of updating that is done and how far the true preference is from the post-video level. The other computational problem is that if the preferences pre- and post-drive video have systematic biases due to methods effects, these will not cancel out (equation 4.9).

As formulated, our estimated μ_T depends on both the physical product and the stimulus given (e.g., the videotape). We investigate what happens to preference if the car is as shown and generates the WOM reaction in the positive treatment and what happens to preference if the car is as shown and generates the WOM reaction in the negative treatment. From these, we generate two separate estimates of the true mean and then discuss what combination is the optimal estimate.

It would be desirable to be able to obtain an alternative estimate of μ_T, the mean of word of mouth about preference for the brand, at least as a convergent measure which does not depend on the specific stimulus given. Candidate estimates include a model based on engineering assessment of the new brand's performance (for example, compared to the value and performance characteristics of existing brands), a secondary data collection or experiment to specifically compare the new concept to currently available brands under full information, and further measures in an experiment similar to the current one.

Consideration of the true levels of other top choice autos and their dynamics is also an interesting area for future research. This could be studied by looking at individual brands' positions in the life cycle.

Marketplace Forecasts and Role of the Control Car

This research has identified the critical role of the control car in generating forecasts for the concept. For example, if there is little or no diffusion effect (in terms of either increasing or decreasing historical sales for the concept), it is difficult to calibrate the model. The control brand should be selected with that potential problem in mind.

A further difficulty in fitting the control appears to arise when tastes change between the launch of the control and the conducting of the experiment. In this application, it seemed plausible that evaluation of the control reflected either changed tastes or a high level of information relative launch. Possible ways of tackling this problem include selection of relatively new control brands, mini-experiments to calibrate a series of controls, or fitting the historical sales data of a number of brands, treating μ_T, μ_0, and variances as parameters.

Optimal Discounting of Past Users

If the new year's version of an auto brand varies minimally from the previous year's, it is reasonable to assume that word of mouth from last year's adoptors will be almost as effective in changing the beliefs of a potential customer about the brand as that from this year's. The greater the change in the perceptual position of the new year's version, the greater discounting of past adoptors that must be made. Forgetting and loss of salience with age of auto will also lead to discounting of past adoptors.

Discounting past adoptors is currently dichotomous in the model. No cumulative sales effect is lost until a major redesign of the brand, when it is all lost. This assumption could be relaxed by making discounting of past cumulative sales a function of perceptual similarity to the previous year's version.

In addition, it is currently assumed that only owners spread word of mouth. Information diffusion through non-owners should be incorporated.

Discrete/Continuous Time Periods

Schmittlein and Mahajan [1982] demonstrate the problems of deriving Bass' model for continuous time observation and then approximating it by fitting at discrete intervals. The same approach has been adopted in this thesis. While monthly observation rather than annual observation should decrease the severity of this problem, it is still deserving of further attention.

5.2.3 Measurement and Application Developments

Replication

In applying the model a considerable amount has been learned about the stimuli and measures and the meaning which respondents appear to attach to them. Appendix E outlines changes which should be made in a replication of this study. The most important stimulus changes include rotation of stimuli, use of advertising copy, and inclusion of a dealer module. The most important changes to measures consist of the use of 9-point scales rather than 5-point scales and the replacement of the fractile risk measure with Bettman's [1972] relative risk measure. Further testing of preference points would also seem to be justified.

New Product Categories

Care was taken to point out that the methodology developed by this thesis applies to an existing product class. For totally new product classes, the forecasting problems are somewhat different. The role of the product and how it is perceived are likely to change dramatically as it moves from the novel to the accepted. Stefflre's work [1968] on what the product is perceived to be like may help guide research into how attributes and perceptual dimensions may develop.

Standard marketing practice is to ask consumers to evaluate the new product as it stands (e.g., Green, Caroll, and De Sarbo [1981]). This is likely to offer some insight, but such insight may not totally reflect the long-term position and view of the product. von Hippel [1983] suggests overcoming this by identifying leading edge users who will show the way in how the product will be applied. Unfortunately, such a group is often a biased sample of the population and this bias may be important in adoption and usage patterns. The basic stimulus of field trials, information provision, and sequential measurement appears to offer a natural complement to those two techniques. The current conducting of 23 separate videotext[1] field trials in the United States suggests that this type of approach is already being adopted (Farmer, [1982]).

1 Videotext is a home information service in which a television set is connected to a central computer via telephone lines, allowing personalized information search and display.

5.3 Conclusions

The development of a brand choice model incorporating multiattribute utility and diffusion phenomena in this thesis has been one step in the generalization of diffusion models to handle product positioning and competition. The approach shows considerable promise as a vehicle for combining the two major traditions used in consumer durable forecasting. However, there are a large number of theoretical modeling and measurement questions which require further research. The application of the model deserves some extension and refinement. In particular, the industry sales and consideration models outlined in Section 4.5 need development. We can hope that, given the potential of the approach combined with the obvious issues that need to be resolved before a multiattribute utility diffusion model could be called complete, this research will provoke interest, controversy, and improvements to our understanding of the dynamics of a competitive new durable brand's sales.

APPENDIX A

GLOSSARY OF NOTATION

FRAMEWORK

P_{CBN}	Joint probability of considering brand N, buying within the category, and preferring brand N.
P_N	Unconditional probability of buying brand N.
P_C	Probability of considering brand N (or that proportion of the population that would).
$P_{B\mid C}$	Conditional probability of purchase within category, given C.
$P_{N\mid B,C}$	Conditional probability of purchasing brand N, given category purchase and consideration of N.
N	The stimulus brand (MMC Regada).
j	Brand choice subscript ($j = 1,2,\ldots,J$).
C	Consumer's consideration set ($C = \{1,2,3,\ldots,J\}$).
U_{Bj}	Utility for purchasing brand j, given its consideration.
C_B	Transaction and search cost disutility.
$U_{j\mid B}$	Conditional utility of brand j, given its consideration, exclusive of search and transaction costs.

APPENDIX A (continued)

MULTIATTRIBUTE UTILITY DIFFUSION MODEL

Expected Utility

$\tilde{y}_{kj}$	Random variable representing consumer's beliefs about level of attribute k in brand j (k=1,2,...K). Mean y_{kj}.
$\tilde{v}_j$	Random variable representing consumer's total preference for brand j. Mean v_j.
w_k	Importance weight of kth attribute. $\tilde{v}_j = \sum_k w_k \tilde{y}_{jk}$
$\tilde{X}_j$	Random variable representing consumer's estimate of value of brand j, net of price. Mean X_j, variance σ_j^2 (σ_j^2 = total uncertainty).
p_j	Price of brand j (assumed known to consumer).
λ	Opportunity utility of money (e.g., value per dollar of composite).
U(.)	Utility function.
$\tilde{\chi}_j$	Random variable representing risk adjusted net preference. Mean χ_j (includes measurement error).
r	Relative risk aversion parameter. $\tilde{\chi}_j = X_j - \frac{r}{2}\sigma_j^2 + e_j$.
$\hat{\tilde{\mu}}$	Random variable representing consumer's estimate of mean level of durables of brand j. Mean $\hat{\mu}_j(=X_j)$. Variance $\sigma_{\hat{\mu}_j}^2$ (information uncertainty).
$\tilde{\varepsilon}_j$	Inherent product variability to be realized by consumer. Mean 0. Variance σ_ε^2 (inherent product variability). $\tilde{X}_j = \hat{\tilde{\mu}}_j + \varepsilon_j$.
μ_j	True mean of brand j's net value to consumer.

APPENDIX A (continued)

Dynamics of Expected Utility (Brand j implicit)

$\tilde{h}$	Precision of consumer's estimate of μ, $= 1/\hat{\sigma}_{\mu}^{2}$.
τ	Strength of prior beliefs in mean.
α	Strength of prior beliefs in precision.
$\hat{x}^{i}$	Owner i's estimate of the net value preference of his brand j durable.
ν^{i}	Perceptual error in owner i's estimate (relative to consumer).
ε^{i}	Product variability realized by owner i.
$\bar{x},\sigma_{\bar{x}}^{2}$	Sample mean and variance of sample mean.

Net Preference to Choice and Updating

n_t	Sample size of owners (of brand j) met in time t.
k	Proportion of adoptors that consumer meets.
Y_t	Number of cumulative adoptors. $n_t = k\ Y_t$.
P_j	Probability of brand j choice (implicitly conditioned on consideration set, C, and category purchase).
β	Logit parameter relating risk-adjusted net preference to probability of brand choice, Pj.
X(0)	Net preference for brand j at some reference point in time (t=0).
$\sigma^2(0)$	Total uncertainty attached to brand j at some reference point in time (t=0).

Appendix A (continued)

Application Notation

$\tilde{z}_{jl}$	Consumer's perception of brand j on factor ℓ (mean z_{jl}).
$b_{\ell k}$	Factor loading coefficients. $z_{j\ell} = \Sigma b_{\ell k} y_{jk}$.
a_{ℓ}	Importance weight of ℓth factor; $v_j = \Sigma a_{\ell} z_{j\ell}$.
R"	Recommendation of Regada post videotape (Appendix D4.1).
R'	Recommendation of Regada pre videotape (Appendix D4.1).
R_T	Perceived videotape recommendation (Appendix D4.2).
X"	Estimated mean net value post videotape.
X'	Estimated mean net value pre videotape.
$\sigma''2$	Estimated total uncertainty post videotape.
$\sigma'2$	Estimated total uncertainty pre videotape.
$\hat{P}''(1)$	Estimate of post-video probability, based on pre-video measures and pre-video logit coefficients.
$\hat{P}''(2)$	$\hat{P}''(1)$ additively adjusted for pre-video errors.
$\hat{P}''(3)$	$\hat{P}''(1)$ multiplicatively adjusted for pre-video errors.
$\hat{P}''(4)$	Estimate of post-video probability based on post-video measures and post-video logit.
$\bar{\bar{P}}''$	Post video probability of Regada brand choice.
$\hat{P}'$	Estimate of pre-video probability based on pre-video measures and pre-video logit.
P'	Pre-video probability of Regada brand choice.
K	Bias parameter in logit estimation of Regada choice.

APPENDIX B

ALTERNATIVE METHODS OF INTEGRATING NEW INFORMATION

Exponential Smoothing Model

One of the simplest models for how a decision maker incorporates new information into his belief structure is given by the exponential smoothing model (Brown, [1962]). The model may be written:

$$\tilde{x}_t = \alpha\tilde{x}_{t-1} + (1-\alpha)x_t \tag{B.1}$$

where

$\tilde{x}_t$ = beliefs in time t

x_t = new evidence becoming available in time t, and

α is a weighting constant

$\tilde{x}_{t-1}$ and $\tilde{x}_t$ correspond to the prior and posterior estimates of the mean in Bayesian updating rule, while x_t corresponds to the sample mean.

If $\tilde{x}_{t-1}$ and x_t are uncorrelated (equivalent to the independence of the prior mean and the sample mean in Bayesian updating), then

$$\text{var}\ \tilde{x}_t = \alpha^2\ \text{var}(\tilde{x}_{t-1}) + (1-\alpha)^2\ \text{var}(x_t) \tag{B.2}$$

This is minimized for

$$\frac{\partial}{\partial\alpha}(\text{var}\ \tilde{x}_t) = 0 \tag{B.3}$$

$$\text{i.e.}\quad \alpha = \frac{\text{var}\ x_t}{\text{var}\ x_t + \text{var}\ \tilde{x}_{t-1}} \tag{B.4}$$

At this stage, it is interesting to recall the definition of τ, the strength of prior beliefs in the mean, in the Bayesian updating formulae:

$$\tau = \frac{\sigma_x^2}{\sigma_{\hat{\mu}}^2} = \frac{n\sigma_{\bar{x}}^2}{\sigma_{\hat{\mu}}^2} \qquad (3.15)$$

Therefore, by using the correspondence of the exponential smoothing var x_t and var $\tilde{x}_{t-1}$ to σ_x^2 and $\sigma_{\hat{\mu}}^2$ respectively, (B.4) becomes:

$$\alpha = \frac{\sigma_{\bar{x}}^2}{\frac{n}{\tau}\sigma_{\bar{x}}^2 + \sigma_{\bar{x}}^2} = \frac{\tau}{\tau+n} . \qquad (B.5)$$

and so (B.1) and (B.2) become equivalent to (3.19) and (3.20).

Unlike with Bayesian updating, the weighting parameter does not get updated as more information is fed into the prior. The reason for this is that older information is then discounted.* This discounting is thought to be appropriate for time series with no structurally fixed mean. Currently, no discounting of past owners is included in the Bayesian updating model and the exponential smoothing model suggests that perhaps the updated τ should be somewhere between τ and $(\tau+n)$, perhaps depending on any change of the brand in perceptual space during the period.

Optimal Combination of Forecast

Granger and Newbold [1977] show that if the two sources of information are correlated, the minimum variance linear combination becomes: $\tilde{x}_t = k\tilde{x}_{t-1} + (1-k)x_t$ (B.6) and

$$\mathrm{var}(\tilde{x}_t) = k^2\ \sigma^2_{x_{t-1}} + (1-k)^2\ \sigma^2_{x_t} +\ 2k(1-k)\rho\sigma_{x_t}\sigma_{\tilde{x}_{t-1}} \qquad \text{(B.7)}$$

$$\text{where } k = \frac{\sigma^2_{x_t} - \rho\sigma_{x_t}\sigma_{\tilde{x}_{t-1}}}{\sigma^2_{x_t} + \sigma^2_{\tilde{x}_{t-1}} - 2\rho\sigma_{x_t}\sigma_{\tilde{x}_{t-1}}} \qquad \text{(B.8)}$$

For $\rho=0$, these formulae collapse to those in the exponential smoothing section.

Granger and Newbold (p. 277) extend their results to include the integration of n pieces of information which may have a perfectly general variance-covariance matrix. Thus, any type of homophily in the incoming data may be incorporated into the model. For example, if each owner provided five pieces of information, the variance-covariance matrix could be block diagonal in groups of five.

Partial Adjustment or Habit Persistence Model

While the habit persistence model is normally used in a different context in econometrics to our use of Bayesian updating here, the algebraic correspondence is quite close. Not only are the structure and basic concepts similar, its inclusion of error in the updating rule and the ability to model the new external data incoming during the period in terms of predictor variables suggest ways of extending Bayesian updating to include non- optimality of updating by the consumer on the one hand, and explanatory variables to determine the word of mouth which a given individual will receive on the other.

The basic partial adjustment model is given by:

$$Y_t = Y_{t-1} + \alpha(Y'_t - Y_{t-1}) + \varepsilon_t \qquad 0 \leq \alpha \leq 1 \tag{B.9}$$

where

Y_t is the value of Y_t at t, after adjustment;

Y'_t is the externally provided value of Y_t during the period (normally an ideal level); and

ε_t is an error in the updating.

This formula is the same as the Bayesian updating formula with the exception of the inclusion of error in the updating. The external information Y_t is then modeled in terms of other exogenous data:

$$\text{e.g. } Y'_t = \beta_o + \Sigma\beta_i X_{it} + e_t \tag{B.10}$$

providing another source of error. See, for example, Kmenta [1971].

This approach would allow a prediction for individual consumers of the type of word of mouth which they would receive based on sociodemographic characteristics, innovativeness, and makes and models of currently considered top choice durables.

APPENDIX B.2

BAYESIAN UPDATING WITH UNKNOWN VARIANCES

In Chapter 3, we assume that the following variances were known to the consumer:

-- Variance of his beliefs about the mean value of a durable of brand j (information uncertainty, $\sigma^2_{\hat{\mu}_j}$).

-- Variance of his beliefs about the value he would realize if he bought a brand j durable (total uncertainty, σ^2_j; equals information uncertainty plus inherent product variability, $\sigma^2_{\varepsilon_j}$).

-- Inherent product variability ($\sigma^2_{\varepsilon_j}$).

-- Variance of the word of mouth about the mean value of brand j durables ($\sigma^2_{x_j}$); equals inherent product variability, $\sigma^2_{\varepsilon_j}$, plus the variance of the perceptual bias, $\sigma^2_{\nu_j}$), and thus, by implication,

o Variance of perceptual bias ($\sigma^2_{\nu_j}$)..

In this appendix we assume that none of these variances is known and thus variance estimates, $\hat{\sigma}^2_{\hat{\mu}_j}$ and $\hat{\sigma}_{\varepsilon_j}$, are updated with more information as well as the estimates of the mean. This allows us to investigate when uncertainty will increase with diffusion. It also provides a method of determining when the assumption of known variances is not likely to be a good approximation.

Prior Beliefs of the Consumer

Instead of assuming that beliefs are normally distributed (Section 3.1.1), because the consumer does not know the actual variance of information which he receives about the brand, his distribution of mean estimated value is assumed to be distributed as a Student's t-distribution.

A convenient way to characterize this t- distribution is to assume that the distribution of beliefs for $\hat{\mu}$ for a given variance, $\sigma^2_{\hat{\mu}}$, is distributed normally, i.e.,

$$\hat{\mu} | \sigma^2_{\hat{\mu}} \sim N(\mu, \sigma^2_{\hat{\mu}})$$

Then the distribution of the consumer's estimate of the variance may be more readily defined in terms of the precision, $h = 1/\sigma^2_{\hat{\mu}}$.

If h has a gamma distribution, then $(\hat{\mu}, \hat{\sigma}^2_{\hat{\mu}})$ form a conjugate pair. That is, after updating the distributions of $\hat{\mu}$ and h are still conditional normal and gamma, respectively. Let

$$\tau = \frac{\hat{\sigma}^2_x}{\hat{\sigma}^2_{\hat{\mu}}} \qquad \text{and} \qquad \alpha = \frac{[E(h)]^2}{\hat{\sigma}^2_h} \tag{B.11}$$

where σ^2_x is the variance of word-of-mouth information received about the brand. Then τ may be shown to be a measure of the consumer's strength of beliefs in his prior mean estimate, $\hat{\mu}$, often termed the equivalent sample size. α may be shown to be a measure of the strength of beliefs in the accuracy of the estimate of the precision, h (De Groot [1970], p. 167).

Integration of New Information by Consumer

Given prior beliefs $(\hat{\mu}(t),\ \hat{\sigma}^2_{\hat{\mu}}(t),\ \tau,\ \alpha)$ and the receipt of word of mouth information $(n,\ \bar{x},\ \hat{\sigma}^2_x = \frac{1}{n-1}\Sigma(x^i-\bar{x})^2)$, DeGroot (1970, pp. 169-170) shows that the posterior beliefs have a mean and variance given by the following expressions:

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

$$\hat{\sigma}^2_{\hat{\mu}}(t+1) = \left\{ \frac{\alpha-1}{\alpha-1+\frac{n}{2}}\ \frac{\tau}{\tau+n}\ \hat{\sigma}^2_{\hat{\mu}}(t) + \frac{\frac{n}{2}}{\alpha-1+\frac{n}{2}} \cdot \frac{n-1}{\tau+n}\ \hat{\sigma}^2_{\bar{x}} \right.$$

$$\left. + \frac{1}{\alpha-1+\frac{n}{2}}\ \frac{\tau\, n}{2(\tau+n)^2}\ (\bar{x} - \hat{\mu}(t))^2 \right\} \tag{B.13}$$

Graphically this may be illustrated as shown in Figure B.1.

From these updating formulae, a number of interesting implications may be drawn. First, it can be noted that the posterior mean is a weighted average of the prior mean and the sample mean, hence the term "equivalent sample size" for t. Second, $\hat{\sigma}^2_{\hat{\mu}}$ (t+1) is the sum of three components:

--the prior variance weighted by confidence in the relative strengths of prior beliefs;

--the sample mean variance weighted by the complement of those weights (after the loss of one degree of freedom for estimation of $\bar{x}$); and

--a sample bias effect.

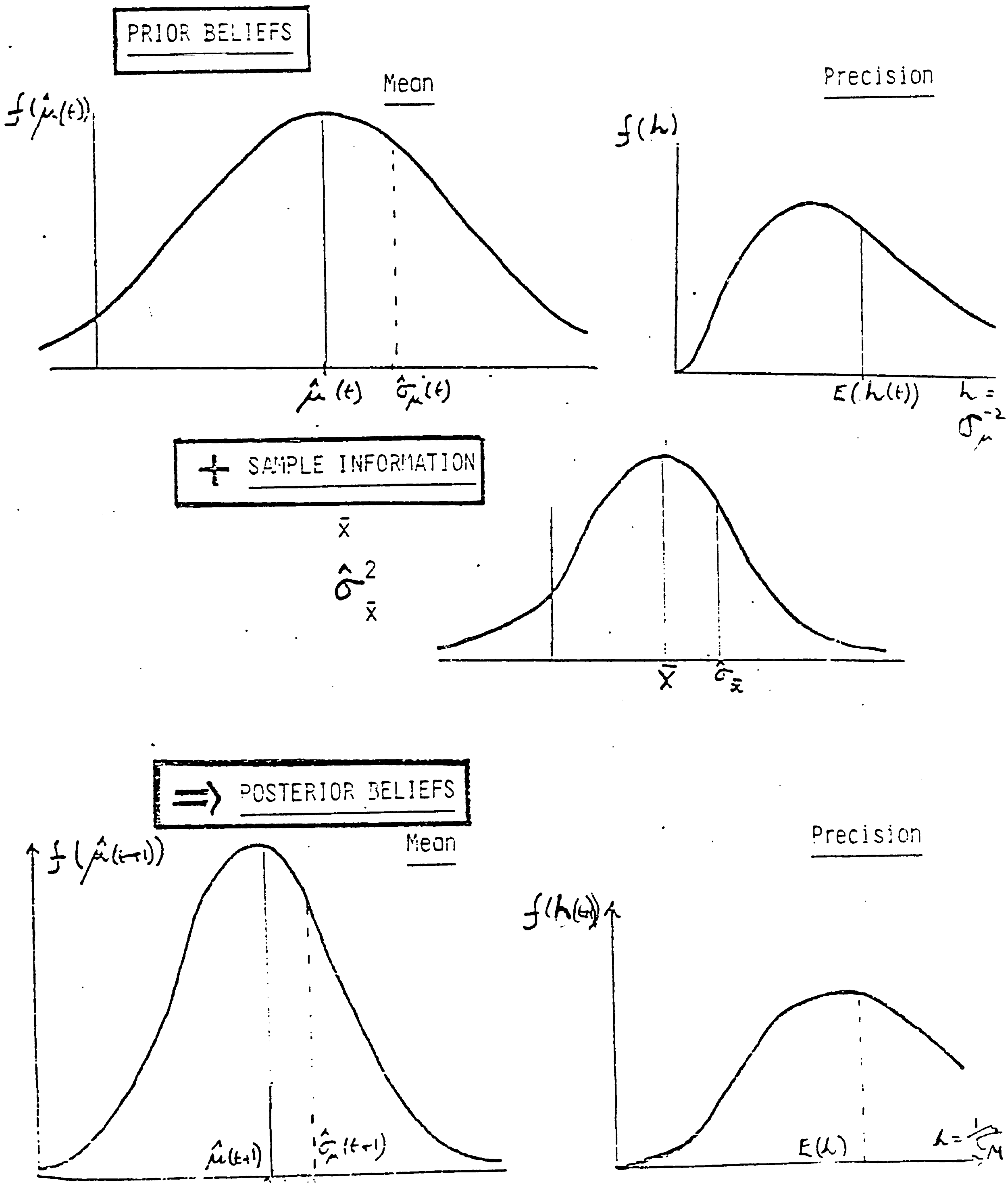


Figure B.1 Illustration of Integration of New Information by Consumers; Unknown Variances

Each of these terms tends to zero as n becomes large since $\sigma_{\bar{x}}^2 = \frac{1}{n}\sigma_x^2$. Thus, the uncertainty about the mean value of the product will decrease toward zero as more information is gained about it. That is not to say that uncertainty about buying a product decreases to zero since the consumer still risks the inherent product variability (see equation (3.12)).

The third interesting aspect of the updating formulae is that equation (B.13) allows us to determine when the uncertainty associated with a product will <u>increase</u> with more information.

Information uncertainty will increase when

$$\hat{\sigma}_{\hat{\mu}}^2(t+1) > \hat{\sigma}_{\hat{\mu}}^2(t)$$

Substituting $\hat{\sigma}_{\hat{\mu}}^2(t+1)$ from equation (B.13) gives:

$$\underbrace{\frac{n}{2}\{(\frac{n-1}{n})\sigma_{\bar{x}}^2 - \hat{\sigma}_{\hat{\mu}}^2(t))\}}_{\text{sample variance effect}} + \underbrace{\frac{\tau n}{2}\{\frac{(\bar{x}-\mu(t))^2}{\tau+n} - \hat{\sigma}_{\hat{\mu}}^2(t)\}}_{\text{sample bias effect}} - \underbrace{\alpha\tau\,\hat{\sigma}_{\hat{\mu}}^2(t)}_{\text{sample size effect}} > 0 \tag{B.14}$$

Perception of the inherent product variability will increase when:

$$\sigma_\varepsilon^2(t+1) > \sigma_\varepsilon^2(t) \tag{B.15}$$

From DeGroot [1970, p. 169]

$$\sigma_\varepsilon^2(t+1) = \frac{\alpha-1}{\alpha-1+\frac{n}{2}}\sigma_\varepsilon^2 + \frac{\frac{1}{2}(n-1)}{\alpha-1+\frac{n}{2}}\sigma_x^2 + \frac{\frac{1}{2}\tau n}{\alpha-1+\frac{n}{2}}\ \frac{(\bar{x}-\hat{\mu}(t))^2}{\tau+n} \tag{B.16}$$

Substituting (B.16) in the inequality (B.15) gives the perceived inherent product variability will increase if

$$(\tau+n)(n-1))\sigma_x^2-\sigma_\varepsilon^2(t)) \quad + \quad \frac{1}{2}\,\tau\,(\frac{1}{n}\,\Sigma(x^i-\hat{\mu}(t))^2 - \sigma_\varepsilon^2) > 0. \qquad \text{(B.17)}$$

sample variance effect — sample bias effect

Instead of σ_x^2 in (B.14) and (B.17), we should use $\sigma_x^2 - \sigma_\nu^2$ from equation (3.14) since this is the inherent variability the sample realized. Using σ_x^2 assumes the consumer makes no allowance for σ_ν^2, the owners' bias variance. (In fact, the consumer has no way of telling what is actual inherent variance in value and what is heterogeneity of perceptions).

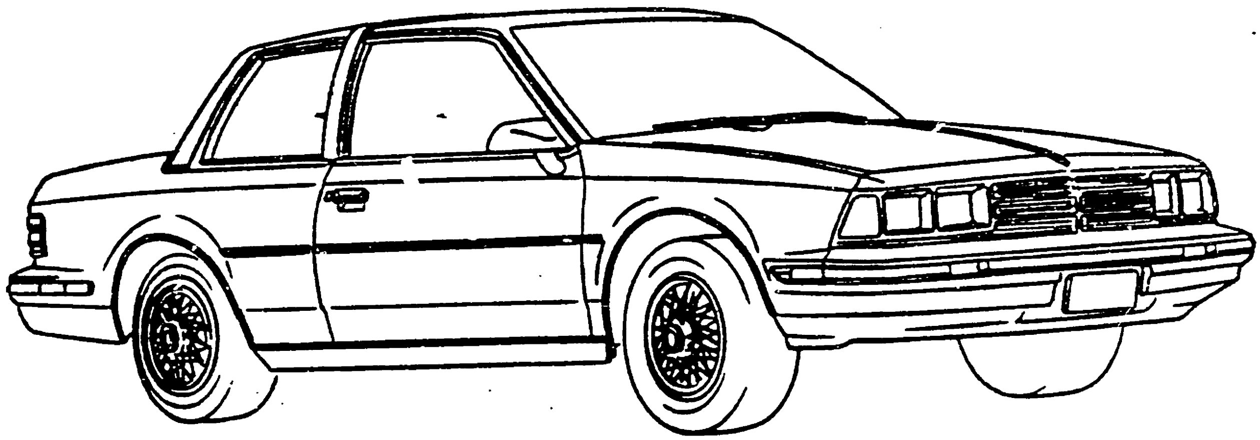
Note that unlike the information uncertainty inequality (B.14), this inequality has no sample size effect. That is as expected. As the sample becomes large, the information uncertainty estimate tends to zero, but the estimate of the inherent product variability does not.

APPENDIX C

EXAMPLES OF STIMULI USED IN THE QUESTIONNAIRE

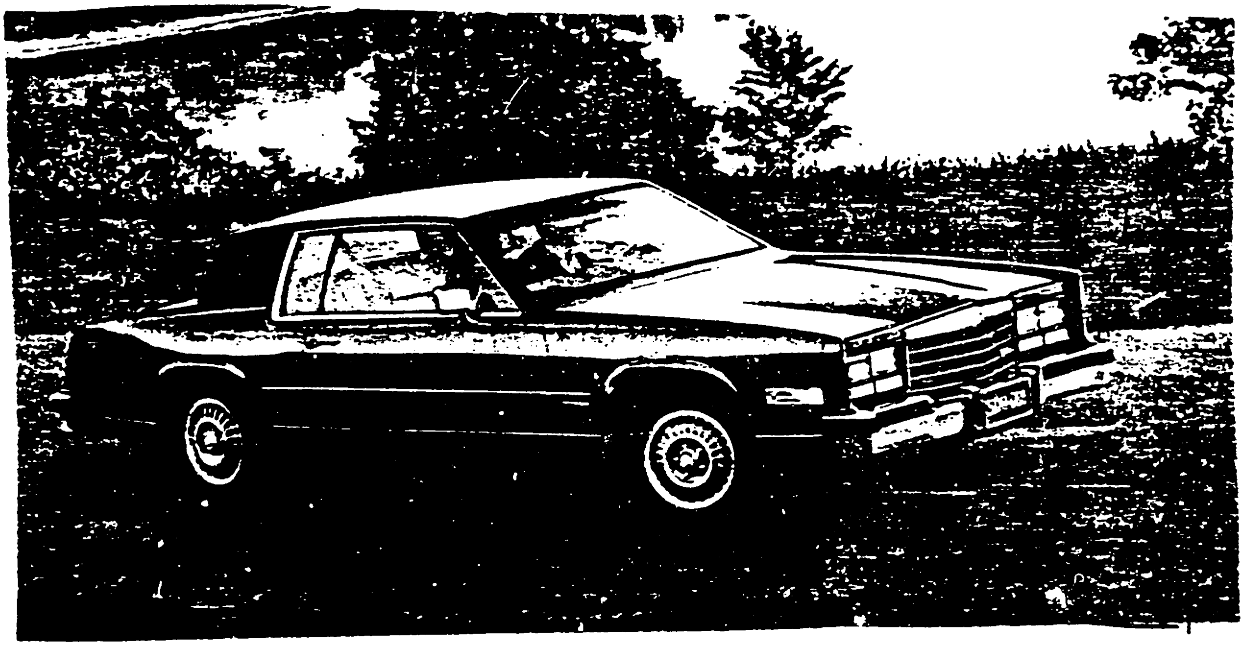
Car Names	Prices Base	Prices Fully Loaded	Fuel Economy (MPG)	Engine Size (in litres)	Engine Size (in cubic inches)
Pontiac					
T1000	$8,802	$9,639	19	3.8	229
J2000	$7,203	$9,561	31	1.8	112
Phoenix (hatch)	$7,087	$8,547	21	2.5	151
Grand Prix	$8,698	$9,535	21	3.8	231
Bonneville	$8,899	$9,736	21	3.8	231
6000	$9,569	$9,294	25	2.8	173
Cadillac					
Cimarron	$12,215	$12,535	23	2.0	121
DeVille	$16,441	$16,441	17	4.1	250
Fleetwood	$19,182	$19,182	20	4.1	250
Eldorado	$19,334	$19,334	17	4.1	249
Seville	$21,440	$21,440	17	4.1	249
Sport					
Camaro	$8,036	$9,298	26	2.5	151
Corvette	$18,290	$18,290	15	5.7	350
Firebird	$8,399	$9,549	26	2.5	151
FORD MOTOR CORPORATION					
Ford					
Escort	$5,846	$7,275	33	1.6	97.6
EXP	$6,426	$7,489	27	1.6	97.6
Mustang	$6,727	$8,201	26	2.3	140
Futura	$6,125	$7,567	26	2.3	140

C.2 TYPICAL CONCEPT STATEMENT

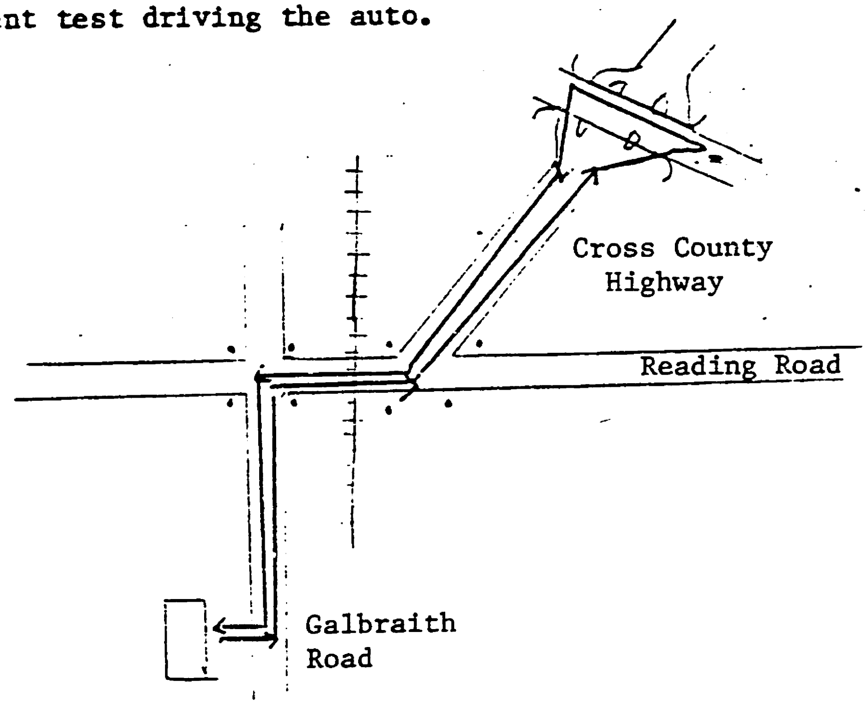


MANUFACTURER	: Oldsmobile
PRICE	: $15,000
EPA MILEAGE (city)	: 18 mpg
ENGINE/POWER	: 6 cylinders, 3.8 litres (232 cu.in.)
DOORS	: Four doors
ESTIMATED RESALE VALUE AFTER 3 YEARS	: 70% of price paid
ESTIMATED MAINTENANCE COST PER YEAR	: $600
FINANCING AVAILABLE	: Financing at standard rates, $750 rebate
FEATURES	: Choice of 5-speed with overdrive or automatic transmission, power brakes, power steering, AM/FM radio, tinted glass, rear window defroster.

C.3 DRIVE ROUTE



Respondent test driving the auto.



Map of Test Drive Course

Route Details:	Urban driving	1.5 miles
	Highway driving	1.7 miles
	Test Drive Route	3.2 miles

C.4 TYPICAL SCRIPT FOR POSITIVE VIDEOTAPE TREATMENT (Male)

2. I prefer American cars and I prefer a bit of style. For a smaller car, it sure is stylish. It's got all of the luxury appointments, though I understand that you're going to have to pay almost as much as [Company's] current luxury cars to get it.

It's smaller than [Company's] current full-sized cars, though I didn't really notice the difference as much as I expected. The trunk's a bit small but nothing like those foreign foot lockers. The other thing about the size is that it was pretty easy on the gas.

I must say, I liked the ride. It's got good pickup and goes over the bumps okay. I think that the center of gravity's probably been lowered because it seems to hold the road fairly tightly. I felt fairly safe in it, better than I would in a smaller car, that's for sure.

The finish is pretty good. They haven't cut corners on quality in trying to hold down the price. I didn't have too much trouble with reliability, for example. About the only problem I had was with the transmission leaking and that was fixed quickly. Apart from that, it's like a dream.

It's a car I certainly wouldn't mind owning.

C.4 TYPICAL SCRIPT FOR NEGATIVE VIDEOTAPE TREATMENT (Male)

6. I think that the car is basically good. I've enjoyed driving it for the last six months. It's got enough power and it holds the road pretty well. On performance, I have to give it fairly high marks, although it dips forward a little if you stop quickly.

There were a few things about it that would bug me about any car, but it seems a pity that they didn't fix them on this car, since [Company name] is really trying to make a splash with their new cars.

I am a bit concerned that reliability and safety might drop with the downsizing and maybe the change to front wheel drive. The reliability was pretty good while I had it, but who's to say what it'll be like when the car's gone another 25,000 miles. And a smaller car just can't be as safe, although obviously, it's better than some of the compacts now flooding the market.

Inside it wasn't too bad; fairly comfortable. The finish was okay, pretty standard [Company name] stuff although the additional seat controls were pretty good. It wasn't as quiet as I've been used to.

Overall, it's not a bad car. Because it's smaller, I think it's going to have a tough job competing against some of those imports which have been making this type of car for a while. It will definitely be in my list of candidates, near the top, but I'm not sure whether it will win.

C.5 Example of Negative Driving Safety and Maintenance Report

CONSUMER LABORATORIES INCORPORATED

CLI

Offices: Boston
Chicago
Los Angeles

CLI 83.2

DRIVE, SAFETY, AND MAINTENANCE REPORT ON THE 1984 PROTOTYPES

PROTOTYPE C

The following ratings are based on careful testing of the 1984 Prototype. These ratings are based on our experience in testing similar automobiles from a variety of manufactureres over the last ten years. Your own experience will depend upon driving conditions. These ratings should be used to evaluate this automobile relative to other automobiles you are considering.

Key To Symbols

We use the following scale throughout our evaluations. Comparisons are to 1983 models which we have tested.

Much better than average

Better than average

Average

Worse than average

Much worse than average

C.5 (continued)

Example of Negative Driving Safety and Maintenance Report (page 2)

EVALUATION OF CONCEPT C

Drive

Engine and Transmission	○
Handling and Braking	○
Convenience*	—
Comfort	○

Maintenance

Frequency of Repair	
Engine and Drivetrain	—
Body	○
Other Equipment**	○
Cost of Repair	
Engine and Drivetrain	○
Body	○
Other Equipment**	—

Safety

Accident Avoidance	○
Crash Test (Driver)	○
Crash Test (Passenger)	○
Relative Mass***	○

*Includes controls, displays, bumpers, parking
**Includes electrical system, options, and minor repairs
***Related to survivability, i.e., fatalities are greater in the smaller, lighter automobiles.

APPENDIX D

EXAMPLES OF MEASURES USED IN THE QUESTIONNAIRE

D.1 PROBABILITY

QUESTION:

D9a. [HAND RESPONDENT CUE CARD 3.]

Now consider your first choice auto. If you were to purchase a car, choosing from the ones you've considered, how likely would you be to purchase this particular automobile?

[RECORD ANSWER ON BACK OF AUTO CARD.]

[REPEAT D9a FOR SECOND AND THIRD AUTO CHOICES.]

D9b. You probably checked more than three autos in the list of autos that I gave you and you might consider other autos after a closer look at what was available. When you next buy an auto, what would you say are the chances that it would be an auto other than the top three choices you that you have given me?

CUE CARD PROBABILITY Cue Card 3

10. Certain, practically certain (99 in 100)
9. Almost sure (9 in 10)
8. Very probable (8 in 10)
7. Probable (7 in 10)
6. Good possibility (6 in 10)
5. Fairly good possibility (5 in 10)
4. Fair possibility (4 in 10)
3. Some possibility (3 in 10)
2. Slight possibility (2 in 10)
1. Very slight possibility (1 in 10)
0. No chance, almost no chance (1 in 100)

D2. PERCEPTIONS AND PREFERENCE

D2.1 Attribute Listing

QUESTION:

D12. Now I would like to know your evaluation of your top three choices of currently available autos, according to the following features.

Your first choice auto was [READ MAKE AND MODEL FROM BLUE CARD.] Please check the boxes that represent your evaluation.

[INTERVIEWER: WAIT FOR RESPONDENT TO COMPLETE EVALUATION.]

RESPONSE SHEET:

AUTO EVALUATION - FIRST CHOICE

	Extremely Poor	Poor	Average	Good	Excellent
Luxury and Comfort	[ ]	[ ]	[ ]	[ ]	[ ]
Style and Design	[ ]	[ ]	[ ]	[ ]	[ ]
Reliability	[ ]	[ ]	[ ]	[ ]	[ ]
Fuel Economy	[ ]	[ ]	[ ]	[ ]	[ ]
Safety	[ ]	[ ]	[ ]	[ ]	[ ]
Maintenance Costs	[ ]	[ ]	[ ]	[ ]	[ ]
Quality	[ ]	[ ]	[ ]	[ ]	[ ]
Durability & Resale Value	[ ]	[ ]	[ ]	[ ]	[ ]
Road Performance	[ ]	[ ]	[ ]	[ ]	[ ]

D.2.2 Value Points

QUESTION: Existing Autos

D1C. Now I would like you to assign points to each of your top three auto choices. In assigning points I want you to consider value, that is the pleasure, benefit, and usefulness that you get for the price paid. For example, some automobiles may be more expensive than others and, hopefully, would provide more pleasure, benefit, or usefulness. However, the less expensive automobiles may provide better, or worse, value considering the benefit you get per dollar spent.

[INTERVIEWER: LAY OUT TOP 3 AUTO CHOICES IN ORDER OF CHOICE. POINT TO THE FIRST CHOICE AUTO.]

This automobile was your first choice automobile. Presumably, it provides you with the best value. We will assign it 100 points.

[INTERVIEWER: WRITE 100 POINTS ON THE CARD.]

If your first choice car gets a value of 100 points, what value would you assign to your second choice automobile? For example, if its value were only half as much, you would assign it 50 points. If you considered an auto such a wreck that you would be indifferent if someone came along and took it off your hands for nothing we would give that zero points.

[INTERVIEWER: RECORD ANSWER ON SECOND CHOICE CARD.]

What value would you assign to your third choice automobile?

[INTERVIEWER: RECORD ANSWER ON THIRD CHOICE CARD.]

D2.2 Value Points (continued)

QUESTION: Concept

F2. Remember that you assigned points to each of your top three auto choices from currently available makes and models, giving 100 points to your most preferred one. On the same scale, how many points would you give the auto which you just drove, taking all factors into account, including price? The number may be more or less than 100 points depending on whether you think that this concept would provide you with better value than your top choice auto or not.

[RECORD ANSWER ON BACK OF GREEN POST-DRIVE AUTO CARD.]

D.3 RISK

D.3.1 Direct Risk Measure

QUESTION

D14. An auto is not always as good as you expect, either because it's a lemon or just because there were undesirable features which you didn't know about. Thus there is always some risk when buying a car, whether it's new or used.

[HAND RESPONDENT CUE CARD 6B.]

Given what you know about it at the moment, which number corresponds to the risk you would associate with buying a [READ FIRST CHOICE AUTO NAME FROM BLUE AUTO CARD.]

[RECORD ANSWER ON FIRST CHOICE AUTO CARD.]

CUE CARD

Cue Card 6B

1. Extremely risky
2. Fair degree of risk
3. Somewhat risky
4. A little risky
5. No risk at all

D.3.2 Risk: Confidence in Choice

QUESTION: (Following Attribute Rating)

D12b [ASK D12b ONLY FOR FIRST CHOICE AUTO].

I appreciate that this evaluation may have been difficult because at the moment you may not know the exact specifications of the auto you picked as your top choice. Additionally, any car, no matter how much you know about it might not live up to your expectations.

[HAND RESPONDENT CUE CARD 6A.]

I am interested in how sure you are of your judgment of your top choice auto. From this cue card, could you tell me the number which corresponds to how confident or sure you are of your judgment of this auto.

CUE CARD Cue card 6A

CONFIDENCE IN CHOICE

Given what I know about this auto at present . . . . . .

1. I am certain of my evaluation of it and am sure that it would be as good as I indicated.
2. I am reasonably confident of my evaluation of it and it would be almost surely as good as I indicated.
3. I am somewhat confident of my evaluation and it would probably be as good as I indicated.
4. I am not totally sure of my evaluation but there is a good chance it would be as good as I indicated.
5. I am not at all sure of my evaluation and there is a good chance that it is not as good as I indicated.

D.3.3 Risk: Fractile Measure

QUESTION: [HAND RESPONDENT CUE CARD 3]

[IF THE RED CARD IS RANKED BELOW THE BLUE SECOND CHOICE AUTO CARD, SKIP TO G7b.]

G7a You most recently allocated [READ POINTS OFF RED CARD] points to the concept which you drove and for which you saw the videotape. You ranked it above the [READ SECOND CHOICE BLUE AUTO CARD NAME]. What would you say are the chances that Concept C turned out to be only as good, or worse than, your second choice [READ SECOND CHOICE OFF BLUE AUTO CARD]? [SKIP G7b]

G7b You most recently allocated [READ POINTS OFF RED CARD] points to the concept which you drove and for which you saw the videotape. You also put it below [READ SECOND CHOICE BLUE AUTO CARD NAME]. What would you say are the chances that the concept car that you drove turned out to be as good as, or better than your second choice [READ NAME OF BLUE SECOND AUTO CHOICE]?

[RECORD ANSWER ON THE BACK OF RED POST-VIDEOTAPE AUTO CARD UNDER PROBABILITY OF 10 POINTS WORSE.]

CUE CARD

Cue Card 3

10. Certain, practically certain (99 in 100)
9. Almost sure (9 in 10)
8. Very probable (8 in 10)
7. Probable (7 in 10)
6. Good possibility (6 in 10)
5. Fairly good possibility (5 in 10)
4. Fair possibility (4 in 10)
3. Some possibility (3 in 10)
2. Slight possibility (2 in 10)
1. Very slight possibility (1 in 10)
0. No chance, almost no chance (1 in 100)

D.3.4 Risk: Unreliability

This measure was the complement of the attribute Reliability given in Appendix D.2.1 (i.e. 6-Reliability).

D.3.5 Risk: Pessemier's Index of Perceptual Clarity

This measure is the standard deviation of normalized value points assigned to a car by members of a segment (e.g., Buick replacers who drive the 1983 control and saw the positive videotape).

Normalized value points are the value points outlined in Appendix D.2.2, normalized to add up to 1 for all cars in the choice set (the top three choice autos or the top three choice autos plus the concept).

D.4 RECOMMENDATIONS

D.4.1 Recommendation Given to the Concept Driven

QUESTION PRE-VIDEO

F1. Now that you have had a chance to drive this auto concept, I am interested in what you would say about it to a friend who might be considering buying an auto in this class.

[HAND RESPONDENT CUE CARD 7.]

What number on this card corresponds to what you would say about Concept C to a friend?

QUESTION POST VIDEO

G1. After seeing the videotape and reading tahe DRIVING, SAFETY, AND MAINTENANCE REPORT, I am interested in what you would now say about the auto to a friend who might be considering buying an auto in this class.

[HAND RESPONDENT CUE CARD 7.]

What number on this card corresponds to what you would say to a friend about the auto you have seen?

[RECORD ANSWER ON BACK OF RED POST VIDEOTAPE AUTO CARD.]

CUE CARD — Cue Card 7

RECOMMENDATION OF CONCEPT AUTO:

1. Very positive
2. Positive
3. Neither positive nor negative
4. Negative
5. Very negative

D.4.2 Recommendation of Videotape and Safety Report Perceived

QUESTION: Videotape

G10. As I said previously, the videotape which you saw was of comments made by potential customers for a new auto who have had a chance to drive the same prototype as the one you drove. Different people could interpret the evaluation which they were giving of the auto in different ways.

[HAND RESPONDENT CUE CARD 7.]

Which number on this card corresponds to the recommendation you feel the people in the videotape were giving the auto?

[RECORD ANSWER ON RESPONSE SHEET 15.]

G11. Also different people could interpret the DRIVING, SAFETY, AND MAINTENANCE report in different ways. Using the same card, what number do you feel corresponds to the level of recommendation which the Report was giving?

[RECORD ANSWER ON RESPONSE SHEET 15.]

CUE CARD

Cue Card 7

RECOMMENDATION OF CONCEPT AUTO:

1. Very positive
2. Positive
3. Neither positive nor negative
4. Negative
5. Very negative

D.5 TASK EVALUATION

We have asked you to do a number of tasks today, some of which you may have found difficult.

We want to find out the level of difficulty, level of interest, and degree of realism which you associated with the various tasks.

I am going to give you 3 cards, each one giving a scale for the above 3 aspects of each task. As I read the task, I would like you to tell me the numbers which correspond to the levels of difficulty, interest, and realism which you experienced with the task.

[Hand respondent cue cards 9, 10, and 11.]

I1. Choosing which durables you would buy.

I2. Giving me details of your currently-held autos.

I3. Evaluating current makes of autos you would consider.

I4. Evaluating the Auto Concepts.

[Record answers to I1-I4 on TASK EVALUATION sheet].

Have you any general comments which you would like to make about the clinic? [If Yes, hand respondent a "TASK EVALUATION SHEET" to fill in.]

Thank you for your assistance.

D.5 TASK EVALUATION (continued)

DIFFICULTY Cue Card 9

1. Not difficult at all
2. Slightly difficult
3. Fairly difficult
4. Extremely difficult

INTEREST Cue Card 10

1. Very interesting
2. Somewhat interesting
3. Slightly interesting
4. Not at all interesting

REALISM Cue Card 11

1. I found the task relevant and found I had considerations similar to those which I would have when actually planning my purchase.
2. There were elements of this task which were analogous to real-life situations, but they did not totally reflect the decision process through which I would go.
3. I could attach little meaning to the task and felt that my answers were almost arbitrary.

APPENDIX E

VARIATIONS ON EXPERIMENTAL DESIGN FOR FUTURE REPLICATIONS

The full field experiment and a thorough analysis of the data have pointed to a number of areas in which improvements to the measurement methodology could be made. The major adjustments proposed are discussed under the headings of stimuli and measures. In addition to these changes, more reliable measures could be gathered if there were more examples for respondents and more practice runs using the measures.

5.2.1 Proposed Stimuli Changes

Videotape, Safety Report, and Advertising. Considerable attention was devoted to ensuring that the videotapes presented an accurate portrayal of the concept car. The author observed actual focus groups discussing the brand, transcribed video recordings of them, and used verbatim comments in scripting the videotape. Company and advertising agency inputs were sought. Professional actors were used with an introduction which gave a rationale as to how three ordinary consumers could have driven the car for six months. The sensitivity of the results to these tapes suggests that such care could even be increased. To overcome a potential source credibility problem, the actors could be filmed with the car and could demonstrate their points on the car. More than two levels of the videotape would allow greater confidence in interpolating about the effect of actual word-of-mouth expected to be generated.

Similarly, the Maintenance and Safety Report could be executed with more than two levels.

Advertising copy should be introduced with a separate measurement to allow its differential effect to be measured. In addition to being a more realistic representation of the influences to which a consumer is exposed, this would allow advertising copy testing. The order in which the videotape, safety report, advertising, and drive are presented should be rotated.

Dealer Module. In order to allow a dealer visit component to be incorporated into the model, current information on number of dealers visited should be expanded. The number of dealers of distinct makes to be visited should be solicited. The probability of visiting specific make dealers (e.g., Chevrolet, Ford, Oldsmobile, etc.) should be collected from at least a part of the sample. MMC repurchase loyalty is 48% while the average repurchase loyalty for specific MMC brands is only 30%. This suggests a model in which the consumer visits a MMC dealer or does not and then makes a brand choice. Such an approach would allow salesperson input to be incorporated.

Evaluation of Currently Available Autos. As the experiment stands, respondents evaluate their top three brand choices from those currently available. This allows the concept car to be compared to the brands against which it will be competing in the consumer's choice process. However, it also means that when we compare the concept to other specific brand names, those evaluations are conditioned by the respondent having put the brand in his top three choices.

It would be interesting to get a subsample of respondents to evaluate a short list of specified brands so that the concept could be compared to its likely competitors across the whole sample. Even though the sample is drawn from likely concept purchasers and thus many would be considering brands with which the concept competes, respondents might need to be given more information about brands on the standard list. Measures of attribute ratings, value, and risk would be taken.

Post Concept Measures. Only probability and value point measures were taken after the respondent had seen a concept description. This limitation was imposed because it was considered that the concept description was too weak a stimulus to allow extensive evaluations. A subsequent analysis of the pre-test data where attribute ratings were collected suggests that the concept description is perhaps a stronger cue than we realized. It is therefore proposed to collect attribute ratings, risk measures, and recommendation levels post description to allow more comprehensive modeling of an earlier stage of the information acquisition process.

Proposed Changes in Measures

A number of changes to measures used in the experiment also seem to be indicated. The following amendments will need pre-testing before incorporation in the questionnaire.

Value Points. The potential contamination of the value point measure with price, after it was meant to be removed, suggests that a total preference measure should be attempted.

A constant sum paired comparison approach between the top three autos and the concept did reasonably well in pre-test before the mini-Troy clinic. It might be desirable to refine that measure to replace or supplement the thermometer preference scale. Its implementation would require three pairs at the current market evaluation stage, three (or less) post concept description, and four or less post drive and post videotape.

Risk. The weakness of the convergent validity on risk may be partially a scaling problem, addressed below. However, the fractile risk measure of asking respondents the chances of a car being worse than their second choice brand does not seem to fit with the other measures. It is cognitively difficult for respondents and therefore should be deleted. Bettman's [1972] pairwise relative risk measure seems an ideal replacement (see Section 2.3). It would fit well with a constant sum paired comparison test for preference of the concept compared to the top three currently available brands. This would overcome the problem that a lot of respondents saw all of the brands as being roughly equivalent in terms of risk.

The question of the inherent product variability of the product has proven important in the analysis and some attempt should be made to explicitly measure it for currently available autos and to obtain management input as to its expected relative level for the new brand. Alternatively, objective measures such as tests and research undertaken by auto magazines (e.g., Car and Driver, Consumer Reports, could be used.

Scales. The use of 5-point scales does not provide sufficient dispersion for reliable measures of the attribute ratings, recommendation levels, and the various operationalizations of risk. Kalwani and Silk [1982] point out that reliability can be expected to improve with the number of points on the scale.

A 9-point scale seems a good compromise between optimal reliability and difficulty for respondent.

Deletion of Sections. In order to keep the questionnaire a manageable length a number of the sections which have not been described in this thesis could be deleted or shortened. These include questions on the buying process, innovativeness, and sociodemographic characteristics.

An alternative, which was practiced in the data collection reported in this thesis, would be to split the sample, asking only subsamples some of the peripheral modules.

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