# FORECASTING SALES OF A NEW CONSUMER DURABLE

+JOHN R. HAUSER, JOHN H. ROBERTS, and GLEN L. URBAN

This paper presents a modeling and measurement methodology for forecasting sales of a new durable product before introduction in the market. Because the forecasts are based on laboratory measurements taken when the product is still in the prototype stage, the methodology provides useful inputs for strategic decisions on: (1) whether or not to produce the product, (2) how to improve the product, and (3) how to position, price, and promote the product. The model integrates economic, existing stock, econometric, multiattribute, and diffusion of innovation theory within a test/control laboratory experiment.

We report our initial model and measurement experience with both a mini-test and a full-scale test for forecasting the sales of 1985 automobiles. We also report top-line analyses based on the mini-test (two-hour interviews with eighty consumers). We show ratings prior to and after test drives and we present the effect of positive and negative word-of-mouth/magazine reports. We close with a brief discussion of our on-going research.

## 1. PERSPECTIVE

It is an interesting intellectual and managerially relevant challenge to accurately forecast sales of a new consumer durable when observations are taken based only on prototypes or pre-production models of the product.

### Important

For durable products such as automobiles, the manufacturer must commit significant capital in plant and equipment to develop and produce a new product. For example, Ford recently committed approximately one billion dollars for the launch of the Tempo and Topaz models. But this production investment is made prior to launch, prior to even an initial sales history. Furthermore, such investments are high risk. Success can mean large profits and rewards to managers who were involved. Failure can mean millions of dollars in losses, significant layoffs, and a stigma to managers who were involved. Any model and measurement methodology that can reduce the risk of failure and provide diagnostic information with which to enhance the probability and magnitude of success will become a valuable resource to managers. It need not predict prefectly, but must predict better than judgment or trend analysis based on past new products.

### Challenging

Forecasts are made based on prototypes and a number of years before launch. For example, in this paper we report results based on a January 1983 measurement for a 1985 automobile. Furthermore, these measurements are based, in part, on consumer reaction to a hand-built prototype. Between now and 1985, we can expect (1) the prototype to be improved, (2) exciting advertising copy to be developed[1], (3) new competition to enter the market, and (4) economic, social, and political conditions to change. All these challenges must be faced in developing a forecast.

In forecasting for expensive durables, like automobiles, we must address a number of challenging consumer behavior phenomena that are particularly prevalent for expensive durables. These phenomena include budget effects, diffusion/word of mouth, existing stock, product positioning, competition, and economic conditions. There are other phenomena, but we feel these are the most important and we choose to address them first.

Budget Effects. Durables are expensive and, therefore, most consumers allocate significant fractions of their budgets to purchase durables. Thus, a new, more expensive automobile is competing with other items such as air conditioners, home video systems, and personal computers.

Diffusion/Word of Mouth. Figure 1 is the sales history of the Ford Granada. Note the rapid growth to a peak over the first year after introduction, and a steady decline thereafter. Without knowing more, we cannot attribute causality to the curve, but we do note that such a sales history is reminiscent of diffusion theory. Thus, at the very least, we must consider diffusion phenomena and word-of-mouth in forecasting lifecycle sales of a new automobile.

Existing Stock. Figure 2 is a plot of the percent of new car purchases versus the age of car traded-in to purchase the new car. Notice the peak at three years and the low percentages after six years. Figure 2 does not attribute causality, but it does caution us that the sales of any class of automobiles, say luxury cars, will depend upon the age of the luxury cars now held by the population. Durables depreciate in value, become obsolete, and simply wear out. The older a consumer's car, the more likely we expect him to demand a replacement.

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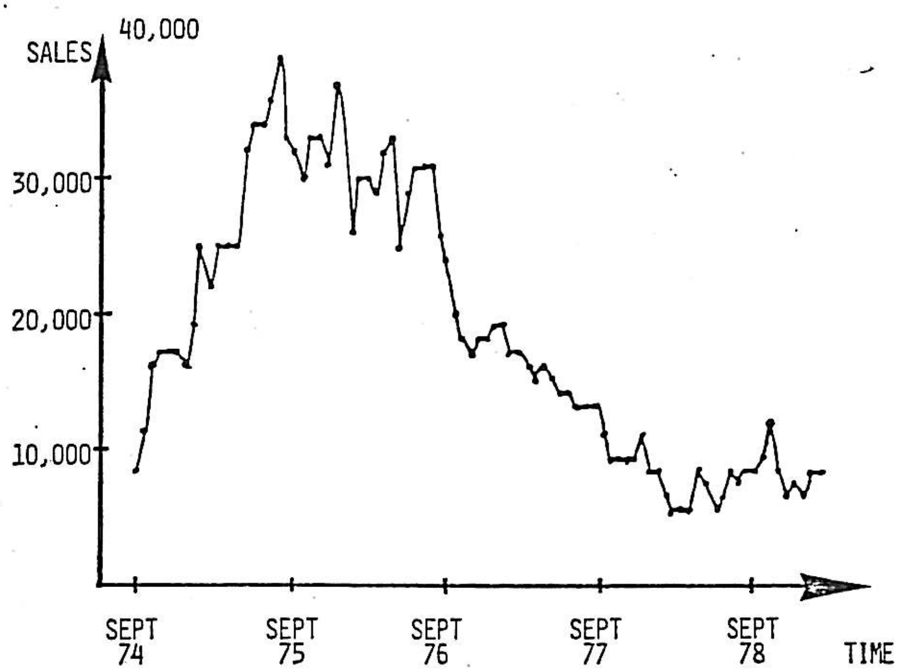



FIGURE 1: EXAMPLE OF DIFFUSION PHENOMENA

Competition. Mercedes Benz is planning a new "mini-Benz" to compete for a lower cost segment of the market, Toyota and Nissan are updating their product lines, and Chrysler and Ford are downsizing and revamping their offerings. All of these moves will affect sales of luxury autos in 1985. For example, if we consider a 1985 Buick, it is not sufficient to measure consumers' reactions to the new Buick vis-a-vis today's market, but we must take measures that allow us to simulate competition in the 1985 market.

Economic conditions. Oil prices went up dramatically after 1974 and caused a switch to smaller cars. In 1982-1983, there was an oil glut causing some people to reconsider larger cars. From 1980-1983 interest rates remained high suppressing automobile sales. (Well over 50 percent of new car purchases are financed.) From 1981-1983 we were in a global recession and auto sales were low. In June 1983, we appear to be recovering from the recession and auto sales are picking up. Economic forecasts for auto industry sales in 1985 are greater than current sales levels, but our consumer measures were taken in January 1983 at a time when unemployment was over 10 percent and fear of unemployment was high. Thus, we must be able to adjust our sales forecasts for changes in economic conditions.

All of these issues are exciting and interesting challenges for marketing science. There are many ways that one could address these issues. The true art is to develop a feasible model that can address these challenges within measurement, information, and data cost considerations. In this paper, we outline one attempt. In this model, we have made a number of tradeoffs that we feel were justified. Other researchers may have made other tradeoffs. Therefore, we present our initial model with the recognition that it will evolve over time.

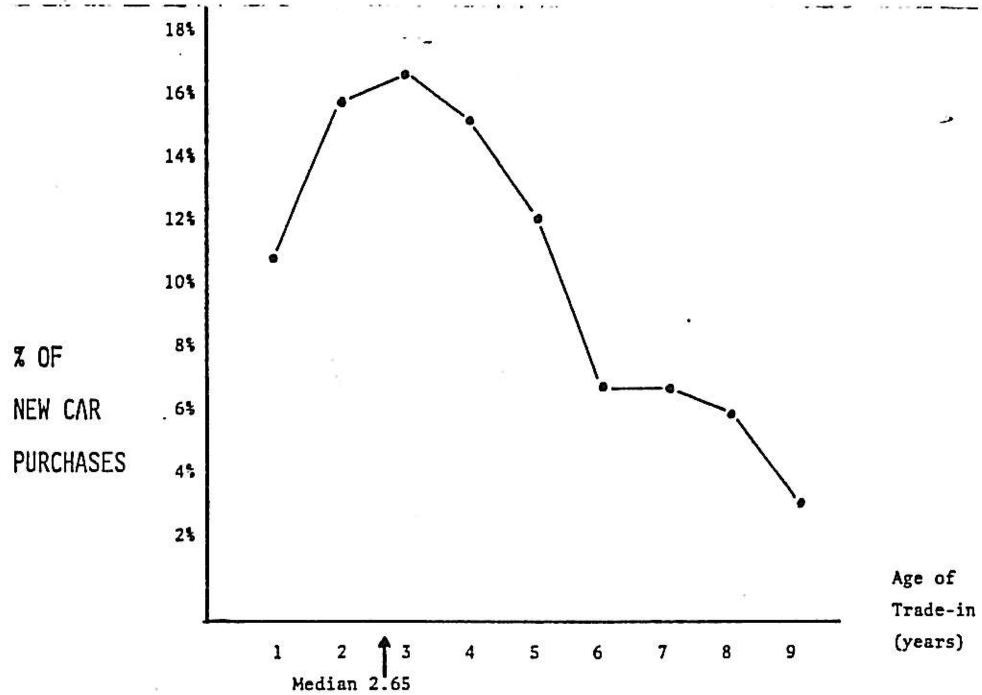
## 2. GOALS OF THE MODEL

Our primary goal is to develop a managerial tool which can be used to understand the appeal of a new consumer durable and to develop a forecast that is adequate for planning purposes. We want this tool to be capable of implementation, thus:

(1) the measurement task must be feasible for respondents,

(2) the managerial inputs, e.g., prototype, word of mouth, videotape, etc., must be available,

(3) the measurement and analysis cost must be reasonable,




25% WITH NO TRADE-IN

FIGURE 2: PERCENTAGE OF NEW AUTO PURCHASES WITH TRADE-IN OF VARIOUS AGES (1981)

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(4) sufficient measures must be taken to deal with budget effects, diffusion/word of mouth, existing stock, competition, and economic conditions, and

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

Clearly, such measurement and analysis are not easy. We report in this paper on the results of 18 months of pre-measures, a pretest, a mini-test, and a full-scale test of the measurement and model system. We feel that many of our measurements are quite innovative.

Designing a feasible managerial tool is only one of our goals. We also need a sound forecasting model so we choose to base our work upon an integration of economic and marketing theories. In particular, we draw upon economic theory to model consumer purchasing within a budget constraint and consumer behavior theory to make the general economic model feasible. We draw upon multiattributed von Neumann-Morgenstern utility theory to explicity model risk and the effects of improved information. And, we draw upon the diffusion modeling literature to motivate predictions which are sensitive to lifecycle phenomena.

## 3. BASIC MODELING APPROACH

Our basic modeling approach is illustrated in Figure 3. We have chosen to explicitly model industry demand and brand choice. In our application to the auto industry, this decoupling makes good sense. Any new model will capture a small share of total market. Thus, it will have some effect on total demand, but that effect will be small relative to other approximations inherent in our modeling effort. In other durables, a new breakthrough brand will cause industry sales to grow. Witness the effect of the IBM/PC on personal computers. Thus, we include a module at the end of our measurement procedure to allow us to capture this phenomena. One of the strengths of this approach is that diffusion effects are modeled at both the market share (brand choice) level and also at the industry sales level using linkages between the two models.

Figure 3 also indicates that we have chosen a convergent approach to forecasting. For both industry demand and for brand choice, we use three semi-independent approaches. We hope that by comparing the forecasts from each approach, we can better understand and identify the potential strengths and weaknesses of each approach. In this way, we hope to evolve our model with experience and improve our measures in each module. Such a convergent approach has proven extremely successful in prelaunch forecasting for consumer frequently purchased items (Silk and Urban, 1978; Urban and Katz, 1983), and we hope to repeat that success here.

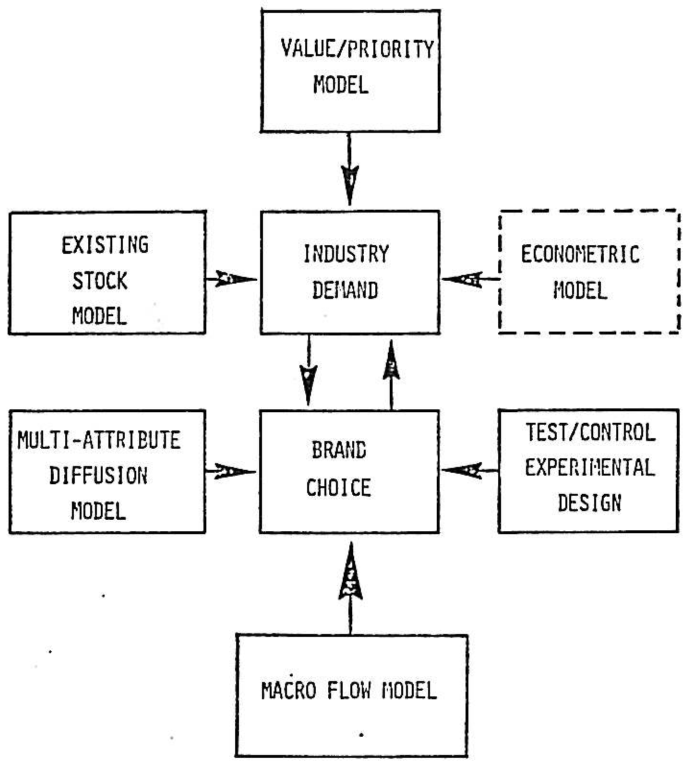


FIGURE 3: BASIC MODELING APPROACH

We now briefly describe the details of each module.

Industry Demand

Econometric Model. The standard method of forecasting industry demand is through one of the large econometric models. For example, Wharton Econometric Forecasting Associates forecast 9.2 million automobiles will be sold in 1983, 10.6 in 1984, and 10.6 in 1985 (Auto News, May 9, 1983). For our purposes, we take this forecast as an input which we will ultimately compare to forecasts based on our other models.

Value Priority Model. This component is an empirical implementation of a theoretical model Hauser and Urban (1982) developed to merge economic theory and consumer behavior theory into a feasible algorithm for forecasting the sales of a new durable category. In our case, we use the model to forecast for the category, "automobiles".

The basic idea behind this model is that consumers maximize utility subject to a constraint on their budget. Under conditions of separable utility, it is easy to show that when search and evaluation costs are considered, a value-priority algorithm (defined below) is a good approximation to a maximum utility algorithm. By "value-priority" we mean that the consumer determines the marginal utility due to purchasing a durable, u, and ranks all possible durables in terms of value, $u/p$, where p is the marginal price of the durable. A consumer will purchase durables as long as value exceeds the shadow price, $\lambda$, of his budget constraint, i.e., as long as $u/p \geq \lambda$. For example, he might rank the following durables in terms of value as shown in Figure 4:

BEDROOM SET
DISHWASHER
STORM WINDOWS
BETAMAX
BUDGET CONSTRAINT ($\lambda$)
AUTOMOBILE
SEWING MACHINE
HOME SECURITY SYSTEM
VIDEO DISK

Figure 4: Buying Priority Example

He would purchase only those that are above $\lambda$. As shown above, he would not purchase an automobile if its value were below his budget cutoff. In order for him to purchase the automobile, it would have to rise in value (higher utility and/or lower price) or his budget would have to expand (lower $\lambda$).

Hauser and Urban (1982) show that the model can be extended to include borrowing, interest rates, depreciation, operating costs, price expectations, quality improvement expectations, replacement, and limited complementarity and substitutability. For example, if $u_{j\ell t}$ were the utility expected from purchasing the $\ell$th version of durable j in period t, if $p_{jt}$ were the expected price, R the interest rate, $\gamma_j$ the depreciation rate of durable j, $c_{jn}$ the operating cost n periods after purchase of j, and if J indexes the existing stock version of durable j, then the consumer would rank all durables and times of purchasing according to:

$$\frac{u_{j\ell t} \sum_{q=0}^{\tau-t} \gamma_j^{\,q} - u_{J\ell}\, \gamma_J^{r+t} \sum_{q=0}^{\tau-t} \gamma_J^{\,q}}{p_{jt} + \sum_{n=1}^{\tau-t} c_{jn} - (p_J\, \gamma_J^{r+t} - \sum_{n=1}^{\tau-t} c_{J,r+t+n})} \cdot \frac{1}{(1+R)^{\tau-t}} \qquad (1)$$

where $\tau$ is the end of the planning period and r is the age of the existing stock at t = o.

Thus, the simplicity of the algorithm extends to encompass complex pheonomena, but the calculation of "value rank" shown in equation one becomes complex. In our situation, the challenge is to measure $u_{j\ell t}$, $u_{J\ell}$, $p_{jt}$, $p_J$, $\gamma_j$, $\gamma_J$, $c_{jn}$, $c_{Jn}$, r, R, and the budget cutoff as perceived by the consumer. We describe measurement below.

<u>Existing Stock Model</u>. The basic idea behind the existing stock model is that consumer will purchase a new durable when the net increase in value due to upgrading exceeds the opportunity cost of money required (Roberts, 1983). Consider a durable class such as automobiles. Let $EU_b$ be the expected utility obtained by owning brand b and let $EU_\ell$ be the expected utility left over the life of the existing stock. Let $p_b$ be the price of brand b and let $p_e$ be the price obtained if the existing stock is sold (traded-in). Assume for the moment that operating costs are the same for all brands and for the existing stock and there are no transaction costs. Then, if $\lambda$ is the opportunity cost (shadow price) of the budget constraint, and if utility is properly scaled the consumer will purchase a new brand if

$$\max_b \frac{EU_b - EU_e}{p_b - p_e} \geq \lambda \qquad (2)$$

or rewriting under alternative assumptions based on consumer surplus:

$$\mathrm{Max}_b \ \{ EU_b - \lambda p_b \} \geq EU_e - \lambda p_e \qquad (3)$$

We can easily extend equations (2) and (3) by subscripting all terms by t and including operating costs in net prices. Finally, if we include depreciation explicitly in net utility and define $\lambda_t = (1+R)^{\tau-t}\lambda$, we see that equations (2) and (1) are algebraically equivalent.

However, we operationalize equation (2) quite differently. With equation (2) we focus our questions on existing holdings. The consumer is asked questions which allow us to infer $EU_b$ and $EU_e$ directly and allow us to compute net price (including operating costs). As operationalized, equation (2) gives us a forecast of that component of sales due to replacement. For automobiles, this is a significant fraction (75% in Figure 2), hence it is a valuable number for management. For first purchasers, existing stock is of zero utility and has zero trade-in value so equation (2) degenerates to the simplest form of the value priority model; the requirement for an auto purchase being that $U/p > \lambda$.

To model the left hand term in equation (2), the maximum over brands, we either

(1) ask the consumer to imagine the best utility-price combination obtainable from a new automobile (durable of target class), or

(2) model the maximum utility-price combination using a choice hierarchy approach. The most common method of applying this approach is the nested logit model[2]. See Guadagni (this conference) or Ben-Akiva and Lerman (1977). It is through such a model that diffusion effects at the brand level will be translated into the diffusion effects at the industry sales level.

For application to automobile demand, we ask detailed questions on existing stock. We then determine those automobiles in the consumer's consideration set and ask him detailed questions about those automobiles and about the automobile prototype we are testing. This question format provides the data necessary for the nested logit approach.

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2 In the nested logit we assume double-exponential errors. The net result is that we replace $\max\{EU_b - \lambda p_b\}$ with $\log[(\Sigma_b \exp(EU_b - \lambda p_b)]$ in the logit model.

## Brand Choice

### Multiattribute Diffusion Model

Consider the brand choice problem implicit in equations (1), (2), and (3). The consumer will choose the brand, b, that maximizes expected value.

Following Currim and Sarin (1983), we assume that utility is given by a von Neumann-Morgenstern utility function and that risk can be modeled by a constant risk averse form based on a "measurable value function".[3] We let

$$u_b = 1 - \exp(-rv_b/P_b) \tag{4}$$

where $u_b$ is the utility of brand b, r is a risk parameter, and $v_b$ is a measurable value function for brand b and $P_b$ is the price of the brand. This function begins at the origin and approaches 1.0 asymptotically.

We further assume that the consumer is uncertain about the value, $v_b$, he will obtain from brand b, and that this uncertainty can be characterized by a normal distribution with mean, $\mu_b$, and variance, $\sigma_b^2$. Recognizing that we can use Laplace tranforms to compute the expected utility (see Keeney and Raiffa, 1976, p. 202), we get:

$$Eu_b = 1 - \exp(-r\mu_b/P_b + r^2\sigma_b^2/2P_b) \tag{5}$$

Thus, expected utility is monotonic in the following expression:

$$(\mu_b - r\sigma_b^2/2)/P_b \tag{6}$$

Finally, if we assume that the measurable value function is linear in product attributes, we have the condition that the consumer will choose the product that maximizes

$$(\Sigma w_k x_{bk} - r\sigma_b^2/2)/P_b \tag{7}$$

where

$w_k$ = importance weight of the kth attribute

$x_{bk}$ = expected level of the kth attribute for the bth brand

$\sigma_b^2$ = variance in expected value for the bth brand.

Equation (7) is linear in the unknown parameters, thus we can readily model the probability that brand b maximizes the expresion. For example, if errors are double exponential, we use the logit model. If errors are normal, we use the probit model.

We now consider the effect of information. Suppose that the consumer receives $n_1$ bits of information on brand b from other consumers or from published sources. Suppose further that he credits his prior beliefs as the equivalent of $n_0$ bits of information. Let $\mu_{b0}$ and $\sigma_{b0}^2$ be his prior beliefs about brand b. Let $v_{bi}$ be his observed bits of information from the sources for $i=1$ to $n_1$. Then define:

$$\mu_{b1} = (1/n_1)\Sigma_i v_{bi}$$

$$\sigma_{b1}^2 = (n_1-1)^{-1}\,\Sigma_i(v_{bi} - \mu_{b1})^2$$

Then, if we add the two sources of information, we get the following update formulae for the impact of new information:

$$\mu_b = (n_1 + n_0)^{-1}\,[n_1\mu_{b1} + n_0\mu_{b0}] \tag{8}$$

$$\sigma_b^2 = (n_1 + n_0 - 1)^{-1}\,[(n_1-1)\sigma_{b1}^2 + (n_0 - 1)\sigma_{b0}^2 + n_1\mu_{b1}^2 + n_0\mu_{b0}^2 - (n_1+n_0)\mu_b^2] \tag{9}$$

If we now substitute equations (8) and (9) into the expression in equation (7), we have the full model.

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[3] The words "measurable value function" are not to be confused with the word "value" which we take to mean utility divided by price. For details, see Currim and Sarin (1983). An alternative form under consideration for equation (4) is $u_b = 1 - \exp(-rV_b + r\lambda P_b)$ which postulates that consumers maximize consumer surplus for each product rather than contribution per dollar.

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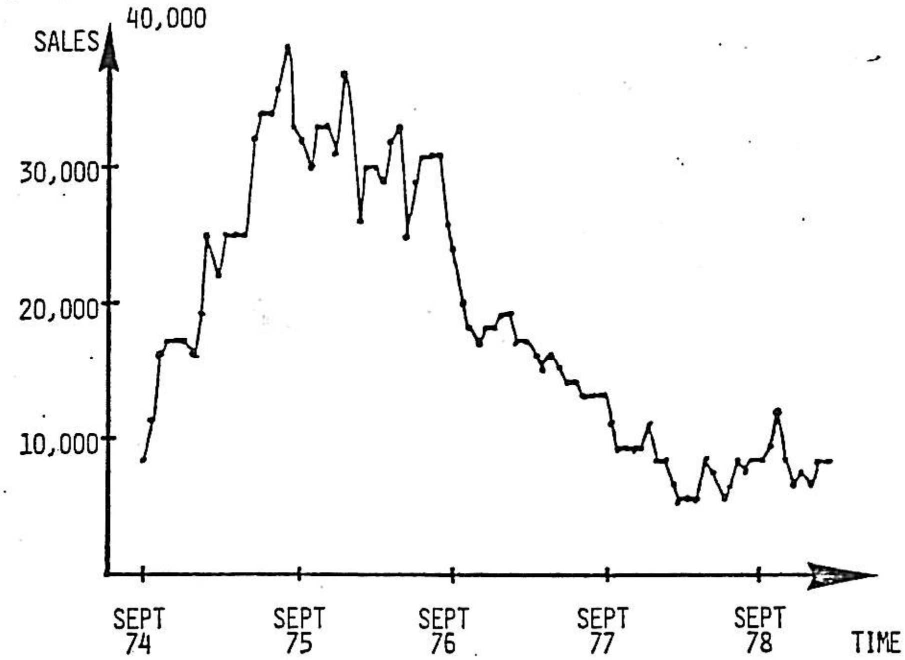


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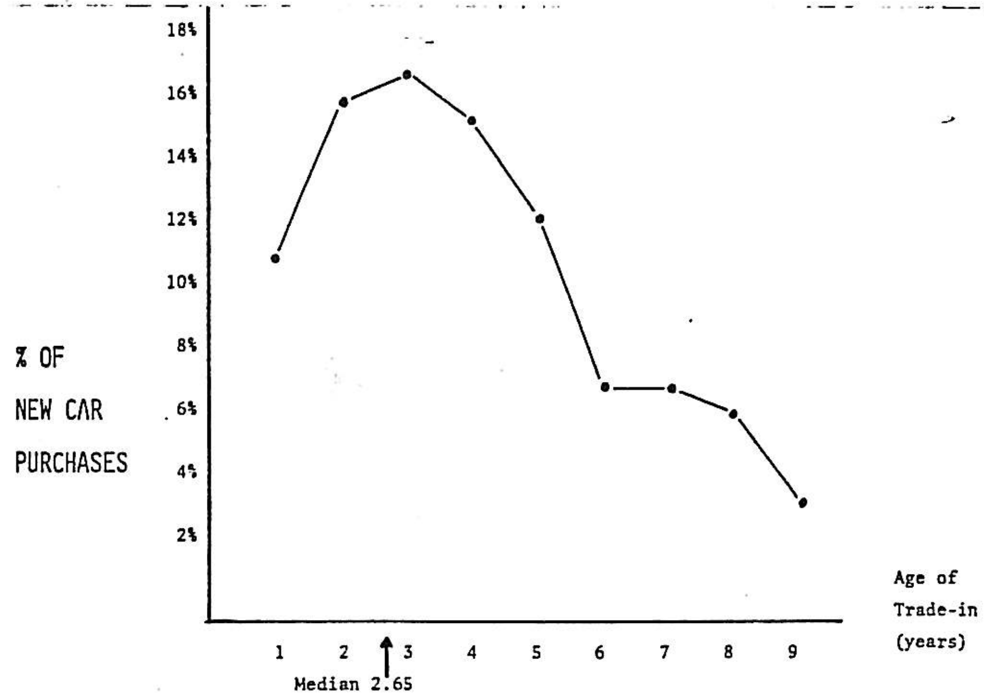


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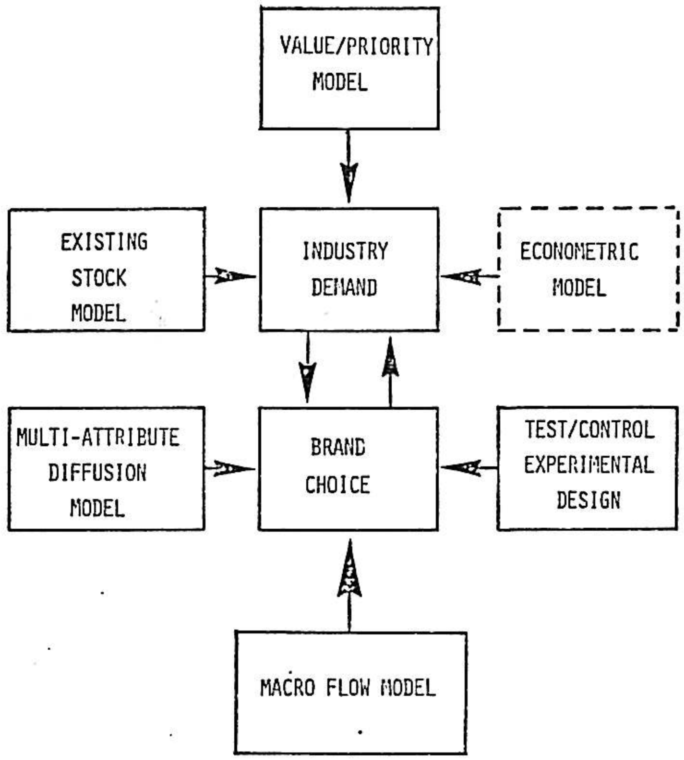


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We further assume that the consumer is uncertain about the value, $v_b$, he will obtain from brand b, and that this uncertainty can be characterized by a normal distribution with mean, $\mu_b$, and variance, $\sigma_b^2$. Recognizing that we can use Laplace tranforms to compute the expected utility (see Keeney and Raiffa, 1976, p. 202), we get:

$$Eu_b = 1 - \exp(-r\mu_b/P_b + r^2\sigma_b^2/2P_b) \quad (5)$$

Thus, expected utility is monotonic in the following expression:

$$(\mu_b - r\sigma_b^2/2)/P_b \quad (6)$$

Finally, if we assume that the measurable value function is linear in product attributes, we have the condition that the consumer will choose the product that maximizes

$$(\Sigma w_k x_{bk} - r\sigma_b^2/2)/P_b \quad (7)$$

where

$w_k$ = importance weight of the kth attribute

$x_{bk}$ = expected level of the kth attribute for the bth brand

$\sigma_b^2$ = variance in expected value for the bth brand.

Equation (7) is linear in the unknown parameters, thus we can readily model the probability that brand b maximizes the expresion. For example, if errors are double exponential, we use the logit model. If errors are normal, we use the probit model.

We now consider the effect of information. Suppose that the consumer receives $n_1$ bits of information on brand b from other consumers or from published sources. Suppose further that he credits his prior beliefs as the equivalent of $n_0$ bits of information. Let $\mu_{b0}$ and $\sigma_{b0}^2$ be his prior beliefs about brand b. Let $v_{bi}$ be his observed bits of information from the sources for $i=1$ to $n_1$. Then define:

$$\mu_{b1} = (1/n_1)\Sigma_i v_{bi}$$

$$\sigma_{b1}^2 = (n_1-1)^{-1} \Sigma_i (v_{bi} - \mu_{b1})^2$$

Then, if we add the two sources of information, we get the following update formulae for the impact of new information:

$$\mu_b = (n_1 + n_0)^{-1} [n_1\mu_{b1} + n_0\mu_{b0}] \quad (8)$$

$$\sigma_b^2 = (n_1 + n_0 - 1)^{-1} [(n_1-1)\sigma_{b1}^2 + (n_0 - 1)\sigma_{b0}^2 + n_1\mu_{b1}^2 + n_0\mu_{b0}^2 - (n_1+n_0)\mu_b^2] \quad (9)$$

If we now substitute equations (8) and (9) into the expression in equation (7), we have the full model.

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3 The words "measurable value function" are not to be confused with the word "value" which we take to mean utility divided by price. For details, see Currim and Sarin (1983). An alternative form under consideration for equation (4) is $u_b = 1 - \exp(-rV_b + r\lambda P_b)$ which postulates that consumers maximize consumer surplus for each product rather than contribution per dollar.

He would purchase only those that are above $\lambda$. As shown above, he would not purchase an automobile if its value were below his budget cutoff. In order for him to purchase the automobile, it would have to rise in value (higher utility and/or lower price) or his budget would have to expand (lower $\lambda$).

Hauser and Urban (1982) show that the model can be extended to include borrowing, interest rates, depreciation, operating costs, price expectations, quality improvement expectations, replacement, and limited complementarity and substitutability. For example, if $u_{j\ell t}$ were the utility expected from purchasing the $\ell$th version of durable j in period t, if $p_{jt}$ were the expected price, R the interest rate, $\gamma_j$ the depreciation rate of durable j, $c_{jn}$ the operating cost n periods after purchase of j, and if J indexes the existing stock version of durable j, then the consumer would rank all durables and times of purchasing according to:

$$\frac{u_{j\ell t} \sum_{q=0}^{\tau-t} \gamma_j^{q} - u_{J\ell}\, \gamma_J^{r+t} \sum_{q=0}^{\tau-t} \gamma_J^{q}}{p_{jt} + \sum_{n=1}^{\tau-t} c_{jn} - (p_J\, \gamma_J^{r+t} - \sum_{n=1}^{\tau-t} c_{J,r+t+n})} \cdot \frac{1}{(1+R)^{\tau-t}} \qquad (1)$$

where $\tau$ is the end of the planning period and r is the age of the existing stock at t = o.

Thus, the simplicity of the algorithm extends to encompass complex pheonomena, but the calculation of "value rank" shown in equation one becomes complex. In our situation, the challenge is to measure $u_{j\ell t}$, $u_{J\ell}$, $p_{jt}$, $p_J$, $\gamma_j$, $\gamma_J$, $c_{jn}$, $c_{Jn}$, r, R, and the budget cutoff as perceived by the consumer. We describe measurement below.

<u>Existing Stock Model</u>. The basic idea behind the existing stock model is that consumer will purchase a new durable when the net increase in value due to upgrading exceeds the opportunity cost of money required (Roberts, 1983). Consider a durable class such as automobiles. Let $EU_b$ be the expected utility obtained by owning brand b and let $EU_\ell$ be the expected utility left over the life of the existing stock. Let $p_b$ be the price of brand b and let $p_e$ be the price obtained if the existing stock is sold (traded-in). Assume for the moment that operating costs are the same for all brands and for the existing stock and there are no transaction costs. Then, if $\lambda$ is the opportunity cost (shadow price) of the budget constraint, and if utility is properly scaled the consumer will purchase a new brand if

$$\max_b \frac{EU_b - EU_e}{p_b - p_e} \geq \lambda \qquad (2)$$

or rewriting under alternative assumptions based on consumer surplus:

$$\text{Max}_b \ \{ EU_b - \lambda p_b \} \geq EU_e - \lambda p_e \qquad (3)$$

We can easily extend equations (2) and (3) by subscripting all terms by t and including operating costs in net prices. Finally, if we include depreciation explicitly in net utility and define $\lambda_t = (1 + R)^{\tau - t}\lambda$, we see that equations (2) and (1) are algebraically equivalent.

However, we operationalize equation (2) quite differently. With equation (2) we focus our questions on existing holdings. The consumer is asked questions which allow us to infer $EU_b$ and $EU_e$ directly and allow us to compute net price (including operating costs). As operationalized, equation (2) gives us a forecast of that component of sales due to replacement. For automobiles, this is a significant fraction (75% in Figure 2), hence it is a valuable number for management. For first purchasers, existing stock is of zero utility and has zero trade-in value so equation (2) degenerates to the simplest form of the value priority model; the requirement for an auto purchase being that $U/p > \lambda$.

To model the left hand term in equation (2), the maximum over brands, we either

(1) ask the consumer to imagine the best utility-price combination obtainable from a new automobile (durable of target class), or

(2) model the maximum utility-price combination using a choice hierarchy approach. The most common method of applying this approach is the nested logit model[2]. See Guadagni (this conference) or Ben-Akiva and Lerman (1977). It is through such a model that diffusion effects at the brand level will be translated into the diffusion effects at the industry sales level.

For application to automobile demand, we ask detailed questions on existing stock. We then determine those automobiles in the consumer's consideration set and ask him detailed questions about those automobiles and about the automobile prototype we are testing. This question format provides the data necessary for the nested logit approach.

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2 In the nested logit we assume double-exponential errors. The net result is that we replace $\max\{EU_b - \lambda p_b\}$ with $\log\ [(\Sigma_b \exp(EU_b - \lambda p_b)]$ in the logit model.

For application, we must measure (1) the perceived attributes of each brand in the consideration set and (2) the perceived variation in $v_b$. Equations (8) and (9) then provide an explicit means by which to incorporate the manager's beliefs about the type of information that will circulate about his product or alternatively, information from focus groups and other sources.

In our application, we measure $x_{bk}$, $\sigma_b^2$, and $P_b$ for existing automobiles in the consideration set and for the prototype being tested. The dependent measure in the logit model is choice in the laboratory. For greater details on this model and for details of measurement and application, see Roberts (1983).

Test/Control Experimental Design. When the new durable is essentially a replacement for an existing offering by the manufacturer, we can compare the replacement and the existing offerings head-on. This has the advantage that errors in measurement will be common to both the test and control products. For example, no matter how careful we are in measurement, we can expect some measurement bias and/or "demand effect". A test/control experimental design with random assignment to either the replacement or existing offering, is one very good way to control for such potential errors.

To forecast, we must consider estimated sales by:

$$S_{t,b} = \frac{\hat{P}_{t,b}}{\hat{P}_{t,c}} S_{t_o,c} \qquad (10)$$

where $S_{t,b}$ = sales for new product in b period t.

$\hat{P}_{t,b}$ = estimated preference for new product b in period t.

$\hat{P}_{t,c}$ = estimated preference for control product c in period t.

$S_{t_o,c}$ = actual sales of the control product c for period when measures were taken.

We can consider the preferences ($\hat{P}_{t,b}$ and $\hat{P}_{t,c}$) as being estimated from the utility diffusion model above. As the diffusion and updating proceeds (Equations 8 and 9), the ratio of $\hat{P}_{t,b}$ to $\hat{P}_{t,c}$ will probably change. If the control car has been in the market for some years, its preference will change little. But the preference of the new car should increase by diffusion of the innovation if it is a "good" car.

Equation 10 must also be adjusted for other changes over time. The total industry volume and competitive effects can be included as indices (values in period to those in period $t_o$). The preference values of equation 10 presume the fraction of consumers considering the new and control products are the same. An index can be used to reflect differences. With these effects, the forecasting equation becomes:

$$S_{t,b} = \frac{\hat{P}_{t,b}}{\hat{P}_{t,c}} S_{t_o,c} V_t K_t C_t \qquad (11)$$

where:

$V_t$ = volume index - total industry sales in period t divided by those in period $t_o$.

$K_t$ = competitive index - sales in period t with a specified set of competitive products divided by the sales in t with the set of products in the initial period $t_o$.

$C_t$ = fraction of target group considering new product in period t divided by fraction considering control product in period $t_0$.

For example, if in the first period of sales for the new product (t=1985), the estimated preference $P_{t,b}$ were .8 for the new product and 1.0 for the control product, if existing sales in 1983 of the control product were 100,000 units, if the industry were growing (Volume index 1.2), if there was stable competition (Competitive index 1.0) and less consideration for the new car (index .9); the sales in 1985 would be 86,400 units (.8 X 100,000 X 1.2 X 1.0 X .9).

Later in this paper, we illustrate the relationship of these indices to our measures by application to a new model 1985 auto.

An important consideration in the use of the preferences, $P_{t,b}$ is the need to simulate the purchase environment to the greatest extent feasible. For example, in our automobile application, word of mouth, magazine reviews (e.g., Consumer Reports, Road and Track, Car and Driver) and test drives all influence consumers' likelihood of purchasing. We simulate these phenomena as follows:

(1) Word of Mouth. Consumers are randomly assigned to one of two groups. Each group is shown a video tape of three "consumers" describing their experiences with the car over a six-month period. Group One sees a tape in which comments are positive; Group Two sees a tape in which comments are negative.

(2) Magazine Reviews. Each of two randomly assigned groups is given either a positive or a negative review.

(3) Test Drive. Consumers are actually allowed to test drive the automobile. If the prototype does not yet have a working engine, consumers are allowed to sit in and examine the car.

In our full-scale procedure, we took purchase measures based on (a) product concept, (b) after-test drive, and (c) after word of mouth and magazine review exposure.

## Macro-flow Model

The last submodel in our prediction of brand choice is an explicit macro-flow model. As detailed in Urban and Hauser (1980), a macro-flow model is a set of behavioral states that describes the information processing dynamics of a given consumer. The model is "macro" because we assume that consumers are homogeneous in the set of behavioral states. Thus, we need to measure and predict how many consumers will flow from state to state in each period.

Since this submodel is still under development and since the technical details are contained in Urban and Hauser (1980), we provide only a simplified example of the type of macro-flow model we are developing.

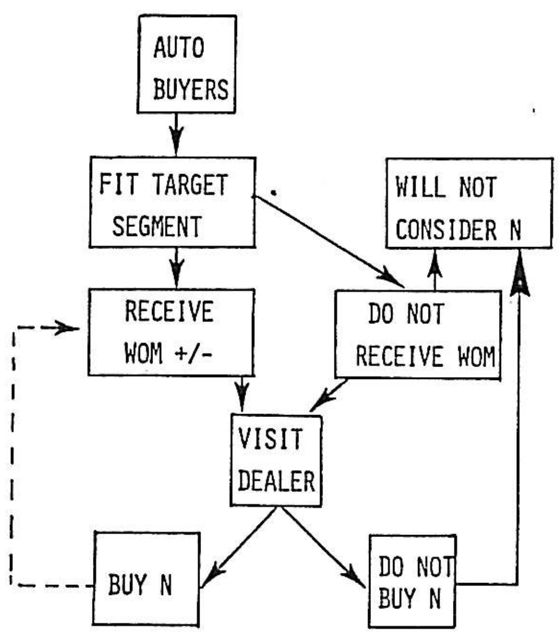


FIGURE 4: SIMPLIFIED EXAMPLE OF MACROFLOW DIAGRAM

This completes our brief summary of the three industry sales and the three brand choice submodels shown in Figure 1. Before describing our measurement and some initial results, we describe a number of design challenges and how we handle these challenges within the theoretical framework.

## 4. DESIGN CHALLENGES

There are a number of challenges that must be faced in achieving a feasible prototype-based durable forecasting system. These challenges include changing economic scenarios, new competition, the need for a pseudo-purchase measure, the family decision nature of the choice, and the effects of search by the consumer. There are a number of ways to handle these challenges. This section describes how we choose to address them.

### Economic Conditions

Within the value priority measurement, we had consumers specify all the products they intend to buy in 1983, 1984, 1985, and later. They indicated expected price, expected utility, and reservation prices for each product. Consumers were then randomly assigned to one of four groups. Each group was given a new economic scenario—for example, a change in interest rates (up or down), or a change in salary. Each group then indicated how they would modify their budget under the given scenario. A convergent measure asked respondents the importance of economic conditions that may precipitate auto buying (e.g. changing incomes, interest rates, or gas prices). These measures help specifiy changes in industry volume and its effect on sales of the new product ($V_t$ in Equation 11).

### New Competition

Besides the target concept, each consumer was asked to evalute four other concept statements. These four concepts were chosen from a fractional factorial conjoint experimental design on features and brand names. For measurement in our auto application, we chose:

Brand Names: Audi, Ford, Chrysler, Buick, Toyota, Nissan, Pontiac, Oldsmobile.
Body Type: Sedan, Econobox, Target Car-Old, Target Car-New, Slippery Shape
Price: $8-10K, $10-12K, $12-16K
MPG: 15-25, 26-35, 36-45
Doors: 2-door, 4-door, hatchback
Resale: 40%, 60%, 80% of purchase price after 3 years
Yearly Maintenance: $200, $400, $800
Features: Minimum, Moderate, Loaded

Body type was implemented with line drawings, and "features" with lists of features such as air conditioning, power door locks, rear window defogger, etc.

Following procedures in Addelman (1962), we were able to reduce this design to an orthogonal structure of 64 crossed with 8 Brand Names. Each consumer only saw four of the conjoint concepts, so we had to estimate the conjoint parameters across consumers. With these estimates we can simulate the effects of new entrants or changes in competition on sales (see $K_t$ in Equation 11).

### Purchase Measure

Since only a few prototypes exist at the time of our measurement, we cannot observe true purchase. Thus, we use instead a variety of hopefully convergent measures of potential purchase. These include:

(1) Eleven point probability intent scales,
(2) Reservation prices, (i.e. price increase that results in an item being dropped from budget plan)
(3) Placement within the budget
(4) Ratio-scaled value points
(5) Rank orders among lottery prizes, and
(6) Attribute measures

These measures are inputs to the utility diffusion model (Equations 7-9) and the forecasting equation (Equation 11).

### Family Decision

Both husbands and wives were invited to the laboratory. In each measurement, including the test drive, the spouses were encouraged to discuss their decisions and arrive at a joint decision. Most found this process enjoyable and felt that the answers represented their joint views. This is a very heuristic approach to modeling family decision making, but we hope this approximation is sufficient for the managers GO/NO GO forecasting requirements.

### Search Process

By allowing consumers to examine and test drive the automobiles, we simulated showroom visits. By showing the consumers videotapes of other "consumers", we simulated word of mouth. By showing consumers an "independent" safety and maintenance report, we simulated information from sources such as Consumers Reports, Car and Driver, or Road and Track. These measures are used to modify the preference for the new product as diffusion proceeds $P_{t,b}$ in Equation 11.

## 5. MEASUREMENT

The basic measurement upon which our forecasts are based are two-hour personal interviews with consumers in a laboratory setting. Consumers were asked to complete a series of modules including a durable purchase study, economic scenario analysis, inventories of currently owned cars, an auto buying process, a consideration set and top choice evaluation, competitive scenario concepts, post-test drive evaluation, and post-videotape/report evaluation. In this section we describe our initial measurement effort as applied to autos.

### Measurement Tests and Pretests

Qualitative beginnings. We began with qualitative interviews at the 1981 Boston Auto Show. These interviews, coupled with internal focus group studies, provided initial question wordings. Throughout January to June 1982, we developed a series of successively improved measurement instruments which were modified based on convenience samples.

Pretest. Thirty consumers were run through a pretest in Troy, Michigan, in June 1982. The target car was the 1985 model. Full test drives were possible. Based on the pretest, the utility measurement emerged as the most troublesome. Throughout Fall, 1982, we developed eight alternative measures which were then tested at the 1982 Boston Auto Show. Of these, a reservation price measurement and a 1-100+ value point scale proved to be the most feasible and consistent.

Mini-test. Eighty consumers were run through a laboratory clinic in Phoenix, Arizona, in January, 1983. The target car was a new 1985 model. Since the car was a raw prototype, test drives were not possible.

Full-scale test. A full-scale laboratory clinic was run with 340 consumers in Cincinnati, Ohio, in February-March, 1983. The target car was the 1985 model cited above. Full test drives were used.

Tasks and Modules. The basic questionnaire is divided into a number of modules. Each module is different and adds to the variety of tasks. Both interviewers and interviewees find this variety enjoyable.

Durable Purchase Study. In the first task, consumers are asked to examine a set of 3x5 cards, where each card corresponds to a different class of durable, and lay out their budget for 1983, 1984, and 1985. For each durable in their budget, they are asked to indicate its expected price and the number of value points that it represents.

They are then asked to specify the reservation price for each durable in the budget. The reservation price is the level to which the price of the durable would need to rise such that it would be excluded from the budget. Consumers also specify reservation prices for the top three items in terms of value, not in their budget. Consumers are also asked to rank order and compare pairs of items as if they were prizes in a lottery.

Economic Scenario Analysis. Each consumer is given an economic scenario, e.g., a $4000 raise in salary above expected levels, and asked to re-evaluate his budget allocations.

Existing Stock. Consumers provide detailed accounts of the cars they now own including model, year, feature level, price paid, price for which they are willing to sell, value points, usage, operating costs, etc. They also indicate which car they plan to replace next.

Auto Buying Process. Consumers provide details on their auto buying process including information sources, dealer visits, knowledge, factors which would cause them to buy a car, etc.

Consideration Set. Consumers are given a comprehensive list of the automobile makes and models and are asked to indicate which ones they would consider.

Top Choice Evaluation. Consumers are asked to evaluate in more detail their top three choices. In particular, they provide expected prices, value points, and probabilities of purchase. Some consumers are also asked to evaluate these automobiles on a set of perceptual scales.

Competitive Concepts. Consumers are given five graphic concept statements representing new cars. One concept describes the car they will see and the other four are chosen from the conjoint design. (See above for levels used.) Consumers rank order these concepts and provide value points, probabilities, and perceptual ratings.

Post-drive Evaluation. Consumers are given the opportunity to examine and test drive the new car (either the test or the control car). After driving, they indicate what they would tell others and then they evaluate the car in terms of value points and probability of purchase.

Post Videotape and Report. Consumers are shown (1) a videotape of three "consumers" (actors) relating their "experiences" with the car for the past six months, and (2) a safety and maintenance report from "Consumer Laboratories, Inc." The same videotape and report are shown for both best and control, but one-half the consumers see positive evaluations and the other half see negative evaluations. Consumers again evaluate the car with value points, probabilities, and perceptual ratings.

Demographics, Sociographics, Interview Evaluation. The study closes with self-administered questionnaries on demographics and sociographics, followed by a series of questions on task interest, realism, and relevance.

## 6. MINI-TEST ANALYSIS

At the time of paper, we have only begun to analyze the data from the mini-test and the full-scale test. We present here some "top-line" managerial results. These results were presented to management who found them useful in early planning subject to the caveats of small samples and a developing methodology.

### Disguising Procedure

In the interest of confidentiality, we have not identified the new model and have translated and suppressed the vertical scale on value points and probabilities.

### Sample

The sample consisted of 78 usable responses. For the pretest we did not require a fully random sample so 36 were domestic car owners of automobiles produced by the division of the company producing the new model, 29 were foreign car owners, and 13 owned other domestic cars. Remember the test car is a 1985 model. Consumers were screened on either having purchased a car in the last five years or being in the market for a new car. The sample is not representative but allows the measurement system to be tested.

### Consideration Set

Figure 5 indicates the distribution of the number of cars considered. The median number of cars considered was 5 out of possible hundreds of cars on the list given respondents or evoked by them.

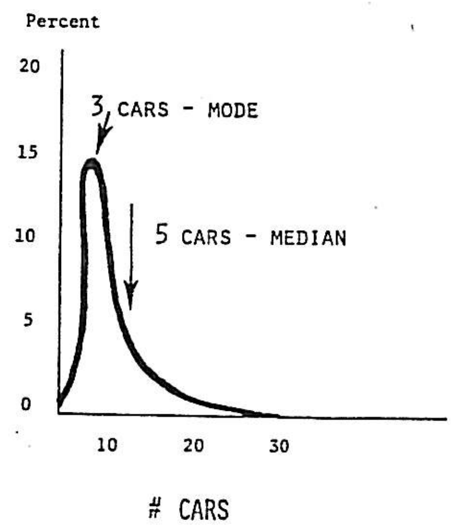


FIGURE 5: NUMBER OF CARS CONSIDERED

## Conjunctive Screen

In considering a car, many consumers identify certain attributes which the car must either have or not have before they will consider it. We asked questions about attributes which would cause a respondent not to consider a particular auto. Six of these relate to the target car (See Table 1). Notice the difference in thresholds among the people in our sample who were previous domestic owners and previous import owners.

TABLE 1

CONJUNCTIVE SCREEN
(Percent people who would reject a car because:)

| | Overall | Domestic Owners | Import Owners |
|---|---|---|---|
| Two Door | 22% | 6% | 25% |
| Domestic | 14% | 6% | 25% |
| GM | 5% | 0% | 13% |
| Front Wheel Drive | 5% | 0% | 13% |
| Compact | 40% | 53% | 25% |
| Over $10,000 | 14% | 18% | 6% |

## Normalized Value Points

We have a number of ways to compare the test and control car in terms of preference ($\hat{P}_{t,b}$ and $\hat{P}_{t,c}$, Equation 11.) At present, we can only rely on previous experience and intuition to indicate which is the best forecasting tool. However, our research plans call for validating our forecasts with (1) call backs to our sample, and (2) actual observation of sales. After validation, we will know better the accuracy of our methods and will be able to choose the best scale.

Basically, we can compare the test and control cars on:

(1) value points
(2) value points normalized by all cars in consideration
(3) probability intent
(4) probability intent normalized by all cars in consideration
(5) percent of people who prefer test vs. control car.

Based on internal consistency and consistency with attribute ratings, we feel that a leading contender is normalized value points.

For example, Figure 6 plots the normalized value points for the test and control cars before and after drive. We have plotted these scales for previous domestic and previous import owners. Notice that the control car A appeals significantly more to domestic owners than to foreign owners and that, based on the "drive", it tends to live up to the concept statement. On the other hand, the new Car B appeals more than Car A to import buyers but less than control Car A to domestic buyers. Furthermore, it does not live up to its concept statement.

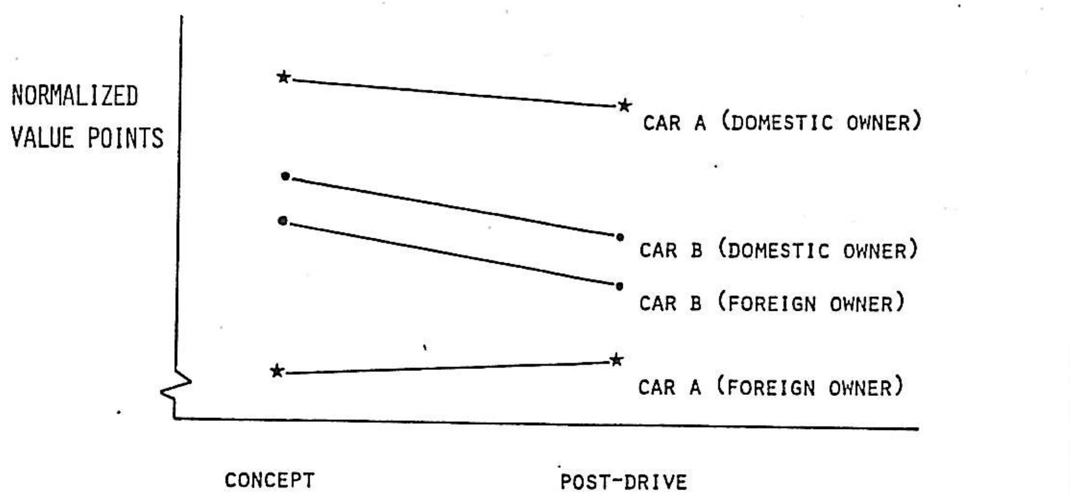


FIGURE 6: NORMALIZED VALUE POINTS FOR TEST AND CONTROL CARS

Word-of-Mouth Mouth Videotapes and Magazine Reports

Figure 7 reports the effect of the positive and negative treatments on normalized value points. They do have an effect, we have successfully influenced evaluations of both the new (Car B) and control (Car A) cars. Notice also that the effect is different for the two cars. For the negative treatment, evaluations of both cars are negatively influenced by about the same amount. However, for the positive treatment, the evaluation of Car A increases significantly (remember Car A did not change pre- to post-"drive") while for Car B, the positive word of mouth was not sufficient to offset the negative effect of the "drive".

Since these videotapes and reports are based on comments recorded in previous focus groups in which consumers were shown the test car, it appears that they are one way to begin to capture, in the laboratory, the influence of word of mouth.

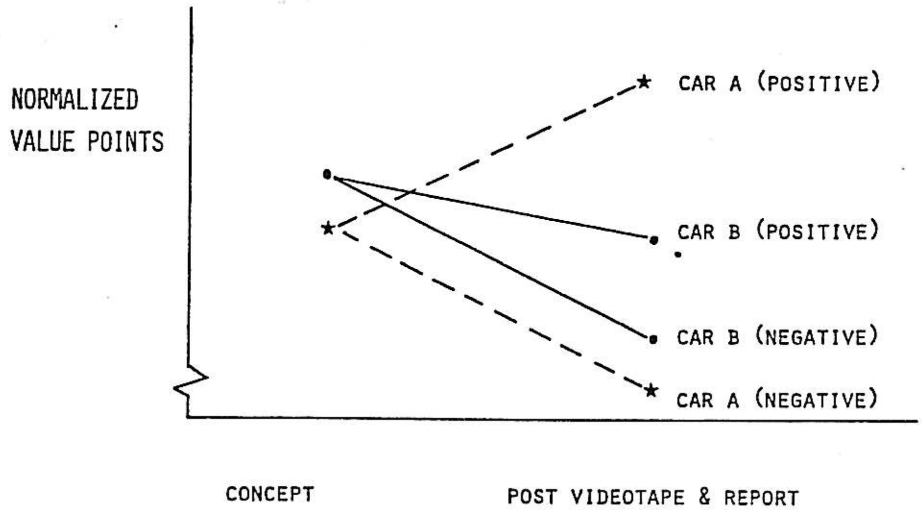


FIGURE 7: THE EFFECT OF POSITIVE AND NEGATIVE WORD OF MOUTH

Value Priority

Two questions are relevant to the value priority forecast of industry sales. First, 67.5% of the sample indicated that they plan to include a new or used car in their budget in the next three years. Second, according to the eleven-point intent scale, on average consumers indicated that there is a 64% probability that they will buy a new or used car in the next three years. Applying these percentages to approximately 80 million households in the United States and approximately 40-60% of car purchases are new cars, gives a forecast of industry sales for the next 3 years of about 20-32 million. We did not have sufficient sample size in the pretest to analyze the effect of an upturn in the economy.

Thus, all things considered, including the small size, non-randomness, and geographic limitation of the sample, the value priority prediction is the same range as the Wharton Econometric Association forecast of 30 million.

Forecast

A forecast of 1985 new car sales was made using Equation 11 with the ratio of normalized value points, $\hat{P}_{t,b}/\hat{P}_{t,c}$, the econometric forecast as a basis of the industry index ($V_t$), and managerial judgment for the consideration ($C_t$) and competitive ($K_t$) indices. For confidentiality, we do not report the exact numbers but, the above graphs indicate that the car does not do well among existing domestic owners. However, it does relatively well in the foreign segment. Management recognized that this forecast was only an indicator because of the caveats due to the sample size and pretest nature of the analysis.

In summary, the mini-test analysis to date indicates that the measures are reasonable, show internal consistency and face validity, and pick up the word-of-mouth/report treatments. By the time of the Marketing Science Conference in 1984, we plan to have more complete results on both the mini-test and the full-scale test.

## 7. FUTURE RESEARCH

We are encouraged with the development of this methodology to date . As indicated in Figure 3, we have drawn on economic theory (the value-priority algorithm), existing stock analysis, econometric inputs, experimental design, multiattribute marketing theory, risk analysis and diffusion theory, and macro-flow analysis to specify a unified forecasting model. However, the measurement requirements of such an integrated model are severe.

Our plans over the next eighteen months include:

(1) analysis of the full-scale test to estimate the detailed theoretical models;
(2) forecasting based on the representative random sample in the full-scale test;
(3) conditional analyses based on alternative economic and competitive scenarios;
(4) evolution of the theoretical models based on the data analysis;
(5) validation through call-back interviews and tracking sales of the 1983 and, in the future, the 1985 cars; and
(6) replications with other auto models.

If this research is successful we feel that we will have a practical, valuable prelaunch forecasting system for new consumer durables.

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