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PRELAUNCH FORECASTING OF NEW AUTOMOBILES*

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This paper develops and applies a prelaunch model and measurement system to the marketing planning of a new automobile. The analysis addresses active search by consumers, dealer visits, word-of-mouth communication, magazine reviews, and production constraints—issues that are important in understanding consumer response to durable goods. We address these issues with a detailed consumer flow model which monitors and projects key consumer transitions in response to marketing actions. A test-vs.-control consumer clinic provides data which, with judgment and previous experience, are used to "calibrate" the model to fit the sales history of the control car. We illustrate how the model evolved to meet management needs and provided suggestions on advertising, dealer training, and consumer incentives. Comparison of the model's predictions to actual sales data suggests reasonable accuracy when an implemented strategy matches the planned strategy.
(MARKETING—NEW PRODUCTS, PRODUCT POLICY, MEASUREMENT)

Consumer durable goods purchases (e.g., appliances, autos, cameras) represent a huge market, but relatively few management science models have been successfully implemented in this area of business. In this paper we attack the marketing problems of a subset of the durables market—automobiles—in an effort to understand the challenging issues in marketing durables and how they can be modeled.

Our purpose is to describe a model and measurement system developed for and used by the automobile industry managers. The system forecasts the life-cycle of a new car before introduction and develops improved introductory strategies. Such models are applied widely in frequently purchased consumer goods markets based on test marketing (see Urban and Hauser 1980, pp. 429–447 for a review) and on pre-test market measures (e.g., Silk and Urban 1978; Pringle, Wilson, and Brody 1982; and Urban and Hauser 1980, pp. 386–411). But standard models must be modified for premarket forecasting of new consumer durable goods such as an automobile.

After briefly highlighting some important modeling challenges in applications to autos, we describe two modeling approaches to forecasting the launch of a new model car offered by General Motors. We extend existing models for production constraints and measure customer reactions after conditional information that simulates word-of-mouth and trade press input; but our emphasis is on how state-of-the-art science models can be used to affect major managerial decisions.

Challenges in Modeling Automobiles

Automobiles represent a very large market; sales in the 1988 model year were over 100 billion dollars in the U.S. and over 300 billion world wide. A new car can contribute over one billion dollars per year in sales if it sells a rather modest 100,000 units per year at an average price of $12,000 per car. Major successes can generate several times this in sales and associated profits.

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These potential rewards encourage firms to allocate large amounts of capital to design, production, and selling of a new model. Ford spent three billion dollars developing the Taurus/Sable line (Mitchell 1986). General Motors routinely spends one billion dollars on a new model such as the Buick Electra. Most of this investment occurs before launch; if the car is not a market success, significant losses result.

Rates of failure are not published for the auto industry, but many cars have fallen short of expectations. Most failures are not as dramatic as the Edsel which was withdrawn from the market, but significant losses occur in two ways. When sales are below forecasts there is excess production capacity and inventories. In this case, capital costs are excessive and prices must be discounted or other marketing actions undertaken to clear inventories. Losses also occur when the forecast of sales is below the market demand. In this case not enough cars can be produced, inventories are low, and prices are firm. The car is apparently very profitable, but a large opportunity cost may be incurred. Profits could have been higher if the forecast had been more accurate and more production capacity had been planned.

For those readers unfamiliar with the automobile industry we describe a few facts that will become important in our application.

Consumer Response

Search and Experience. In automobiles, consumers reduce risk by searching for information and, in particular, visit showrooms. Typically 75 percent of buyers test drive one or more cars. The marketing manager's task is to convince the consumer to consider the automobile, get the prospect into the showroom, and facilitate purchasing with test drives and personal selling efforts.

Word-of-Mouth Communication/Magazine Reviews. One source of information about automobiles is other consumers. Another is independent magazine reviews such as *Consumer Reports* and *Car and Driver*. Given the thousands of dollars involved in buying a car, the impact of these sources is quite large.

Importance of Availability. Eighty percent of domestic sales are "off the lot," i.e., purchased from dealer's inventory. Many consumers will consider alternative makes and models if they cannot find a car with the specific features, options, and colors they want.

Managerial Issues

No Test Market. Building enough cars for test marketing (say, 1,000 cars) requires a full production line that could produce 75,000 units. Once this investment is made, the "bricks and mortar" are in place for a national launch and the major element of risk has been borne. Therefore, test marketing is not done in the auto industry.

Replace Existing Model Car. Occasionally the auto industry produces an entirely new type of car (for example, Chrysler's introduction of the Minivan), but the predominant managerial issue is a major redesign of a car line such as the introduction of a downsized, front-wheel drive Buick Electra to replace its larger, rear-wheel drive predecessor.

When the management issue is a redesign, the sales history of its predecessor provides important information for forecasting consumer response to the replacement. Even when no direct replacement is planned, say, the introduction of the two-seated Buick Reatta, the sales history of related cars such as the Toyota Supra provides anchors to forecasts.

Production Constraints. The production capacity level must be set before any actual market sales data can be collected. Once the production line has been built, production is limited to a rather narrow range. The maximum is the plant capacity (e.g., two shifts with the machines in the plant and their maintenance requirements) and the minimum is one eight-hour shift of production unless the plant is shut down completely.

The need to make production commitments early in the new product development process produces a two-stage sequence of decisions. First, a market strategy is developed, advanced engineering specification and designs are created, consumer reaction is gauged, and a GO or NO GO production commitment is made. See, for example, Hauser and Clausing (1988). Because of the long construction times, this usually occurs three or more years before introduction. As market launch nears (24 months or less), the second set of decisions is made. A premarket forecast is generated and a revised marketing plan (e.g., targeting, positioning, advertising copy and expenditure, price, promotion, and dealer training) is formulated. In the first decision, production level is a variable, but in the prelaunch forecasting phase (the focus of this paper) the capacity constraints are taken as given.

"Price" Forecasting Problem. Production capacity is based on the best information available at the time, but as engineering and manufacturing develop the prototype cars, details change as do external conditions in the economy. At the planned price and marketing levels consumers may wish to purchase more or fewer vehicles than will be produced. The number of vehicles that would be sold if there were no production constraints is known as "free expression." Naturally, free expression is pegged to a price and marketing effort.

If the free expression demand at a given level of price and marketing effort is less than the production minimum, the company and its dealers must find a way to sell more cars (e.g., target new markets or change price, promotion, dealer incentives, and advertising). If the forecast is in the range, marketing variables can be used to maximize profit with little constraint. If free expression demand is above the maximum production, then opportunities exist to increase profit by adjusting price, reducing advertising, or by producing cars with many optional features.

Existing Literature and Industry Practice

Marketing Science

Marketing science has a rich tradition of life-cycle diffusion models which describe durable good sales via phenomena such as innovators, imitators, and the diffusion of innovation. These models focus on major innovations such as color TV or computer memory (Bass 1969, Robinson and Lakani 1975, Mahajan and Muller 1979, Jeuland 1981, Horsky and Simon 1983, Kalish 1985, and Wind and Mahajan 1986). However, for forecasting, these models require substantial experience with national sales (Heeler and Hustad 1980). In prelaunch analysis no national sales history is available for the new auto model. Thus, the parameters for initial penetration, diffusion, and total sales over the life cycle would need to be set based on judgment, market research, or analogy to other product categories. In our application we incorporate these "data" sources, but in a model adapted to the details of consumer response and the managerial situation in the automobile industry.

One model of individual multiattribute utility, risk, and belief dynamics has been proposed for use in prelaunch forecasting of durables (Roberts and Urban 1988). This model can be parametized based on market research before launch, but our experience with this complex model suggests that it is difficult to implement and does not deal with production constraints and the "price" forecasting problem.

Industry Practice

Industry practice has included market research to obtain consumer response to new durables. In the auto industry concept tests, focus groups, perceptual mapping, conjoint analysis, and consumer "clinics" have been utilized. The clinics traditionally collect likes, dislikes, and buying intent with respect to currently available cars. After exposure to a fiber-glass mockup of a new car in a showroom setting, free-expression "diversion" from the consumer's most preferred currently-available model is measured. (That is, consumers indicate which make and model car they would have purchased. The clinics measure the percentage of these consumers who would now purchase the new car.)

These analyses are useful in very early forecasting before the production commitment, but do not include search and experience, word of mouth, magazine reviews, life-cycle dynamics, and availability constraints. Nor do such analyses incorporate *traditional* marketing science concepts such as advertising response functions. Thus, it is difficult to use these traditional clinics to identify the best marketing strategy to maximize profit within the constraints of production.

Prelaunch Forecasting Clinic Design

We build upon the marketing science literature and industry practice to address the managerial problems of prelaunch forecasting. In keeping with the magnitude of the investment and the potential profit impact of prelauch decisions, our analyses are based on a heavy commitment to measurement to get consumer-based estimates of the relevant inputs. To build upon industry experience a clinic format is used; however, we add a control group to minimize response task biases. Usually the control group sees the existing car model which is being replaced. The control group does not see the new model. If the car does not replace an old one, the most similar existing car (or cars) is used for control purposes. The model structure is based, in part, on differences between the test and control group and the (known) sales history for the control car.

We apply marketing science concepts by modelling explicitly the consumer information flow (dealer visits, word-of-mouth, advertising) and production constraints. The method we use is a probabilistic flow model called macro-flow (Urban 1970, Urban and Hauser 1980, Chapter 15). This method is a discrete time analog of a continuous time Markov process (Hauser and Wisniewski 1982a, b) and represents an expansion in the number of states and flows of diffusion models such as that by Mahajan, Muller, and Kerin (1984), which includes positive and negative word-of-mouth. We begin by describing the sampling scheme and consumer measurement.

Sampling Scheme

If cost were not an issue we would select a random sample of consumers and gauge their reactions to the test and control vehicles. However, there are a large number of automobiles available (over 200), the automobile market is highly segmented (luxury, sport, family, etc.), and automobile purchases are infrequent. Not every consumer is in the market for a car or in the right segment. Random samples would be inefficient and very expensive. (A car model can do well if every year a few tenths of one percent of the American households purchase that model.)

To balance costs and accuracy we stratify our sample by grouping consumers by car model that they purchased previously. To get a representative sample that has a good chance of being interested in the automobile category (segment) being studied, we select the sizes of the strata in proportion to past switching to the target category. For example, if 2 percent of last year's category buyers had previously purchased Volvo 700 series cars, then 2 percent of the sample is drawn from these Volvo owners. If the managerial team is interested in "conquest" outside the target category, random or targeted strata are added. The names, addresses, and telephone numbers of these consumers are available from commercial sources (e.g., R. L. Polk and Co.).

Once selected, consumers are contacted via telephone, screened on interest in purchasing an automobile in the next year, and recruited for the study. Consumers who agree to participate are scheduled to come to a central location, a clinic, for a one-hour interview. They are paid $25–50 for their participation. If both spouses participate in the decision to buy a new car, both are encouraged to come.

Basic Clinic Design

Upon arrival two-thirds of the consumers are assigned randomly to the test car group and one-third to the control car group. In both cases they are told they are evaluating next year's models. (This is believable to consumers because most year-to-year changes in an automobile model are relatively minor.) (See Figure 1 for the basic measurement design.)

After warmup and screening questions, the consumer(s) is asked to describe car(s) that he (she or they) now own, including make, model, year, miles per gallon (if known), options, maintenance costs, etc. This task puts them in a frame of mind to evaluate cars and provides valuable background information.

They are next presented with a list of the 200 or so automobile lines available, along with abridged information on price (base and "loaded" with options), fuel economy and engine size, and asked to indicate which automobiles they would consider seriously. The modal consideration set consists of about three cars; the median is five cars. In addition, they indicate the cars they feel would be their first, second, and if appropriate, third choices. They rate these cars on subjective probability scales (Juster 1966) and on a constant sum paired comparison of preferences across their first three auto choices. These questions allow us to estimate "diversion," the percent of consumers who intended to purchase another car who will now purchase the target car.

Now the experimental treatments begin. Two-thirds of the consumers are shown concept boards (or rough ad copy) for the test car in an effort to simulate advertising exposure. One-third are shown concept boards (or rough ad copy) for the control car. They rate the concept on the same probability and preference scales as the cars they now consider.

In the market, after advertising exposure, some consumers will visit showrooms for more information, others will seek word-of-mouth or magazine evaluations. Thus, as shown in Figure 1, the sample is split. One half of each test/control treatment cell sees

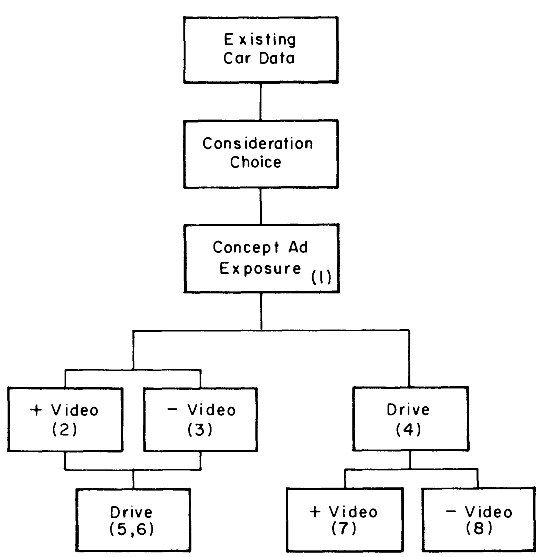

FIGURE 1. Experimental Design of Sequential Information Exposure in Clinic [(x) = Sequence Codes].

video tapes which simulate word-of-mouth[1] and evaluations which represent consumer magazine evaluations (e.g., *Consumer Reports*); the other half are allowed to test-drive the car to which they are assigned. The video treatment is divided into positive and negative exposure cells. Probability and constant-sum paired-comparison preference measures are taken for the stimulus car and the respondents' top three choices among cars now on the market. The half which saw the videotapes and magazine abstracts now test drives the car; the half which test drove is now exposed to the videotape and magazine information. Again probability and preference measures are taken. More elaborate designs can be used. For example, management needs may require splitting the sample further on two-door vs. four-door or adding measurement modules for consumer budget planning and/or conjoint analysis with respect to potential feature variations. It is also possible to split on alternative positioning strategies. All such options in the experimental design require tradeoffs with respect to sample size and length of interview. In the application we are describing, the design in Figure 1 was used.

A New Mid-Sized Car—Phase I Analysis

This application takes place in the Buick Division of General Motors. General Motors had made a strategic decision to downsize all of its luxury cars—its 1983 Electra/Park Avenue had been launched. In the fall of 1984, 18 months prior to launch, we began analysis of the next downsized car—the division's largest selling mid-sized model. Sales targets were set optimistically at 450,000 units—a 15 percent share of the mid-sized market. This represented doubling of current sales volume and a 50 percent increase in market share.

The clinic was run in Atlanta, Georgia. The sample size was 534 and drawn randomly from car registration data but stratified by current ownership: 119 from previous buyers of the target car, 139 from previous buyers of other cars from the division, 128 from other domestic cars, and 148 from imports.

Top-line Analysis

In 1970, Little studied how managers react to marketing science models. In that seminal article he proposed a "decision calculus," a set of guidelines marketing models should follow to be accepted and used.

A tenet of his proposal was that managers want models they can trust, which match their intuitions, and which are readily understandable. In the late 1980s managers have the same needs. Thus, before we introduce the more complex analysis with its probabilistic modeling of consumer information flow, we describe top-line diagnostic information from the clinic and an initial forecast based on an index model.

Our first diagnostic indicator is relative preference. Recall that the consumers rated three currently available cars plus the new car (or, for the control group, the control car) on constant-sum paired comparisons.[2] One indicator of relative preference is the preference value of the new car divided by the sum of existing and new cars. Another measure is the percent of consumers who rate the new car higher than the existing cars. We have

[1] The videotapes include a commentator and three consumers. Professional actors are used, but an attempt is made to match the demographics of the target market. The semantics come from earlier focus groups on prototypes of the car being tested. One script is positive in its content and another is negative. Both use the same actors. The magazine exposure is a mock-up from the fictitious "Consumer laboratories, Inc." and put in a format similar to *Consumer Reports*. The quantitative evaluations are chosen to match the qualitative video tapes. We have found through pretesting that consumers find the videotapes and magazine reports believable and realistic.

[2] A few consumers rated only two cars because that is all they considered.

found both measures give similar results, thus Table 1 reports only the relative measure. The test/control design is critical here. Exposure to concepts can be inflated (deflated) due to the specifics of the task, but such inflation should be constant across test or control. Thus, although each specific measure may be inflated, their ratio should be unbiased.

Table 1 was a disappointment to management. Although not all differences were significant, all test car values were below the control. It was clear that the test car would not do as well in terms of preference as the rear-wheel drive car it was scheduled to replace.

Furthermore, relative values of preference decrease when consumers have more information. They decrease from a ratio of 0.94 for concept only exposure to 0.88 for concept and positive word-of-mouth (wom) and magazine exposure, 0.87 for concept and drive, and 0.84 for full positive information. (The latter is the average of ratios of concept/exposure to drive and to positive word-of-mouth and magazine exposure in either order: $(0.78 + 0.90)/2$.) A doubling of sales volume did not look promising.

At this point it became important for managers to obtain a "ballpark" estimate of the potential sales shortfall. If it was sufficiently large, they would have to consider radical strategies. To obtain top-line, "ballpark" forecasts, we developed an index model similar to those used by Little (1975, 1979) and Urban (1968).

Top-line Forecasts

In an index model we modify a base sales level, in this case the sales history of the control car, by a series of percentage indices. From previous research (Silverman 1982), we knew that the sales pattern for mid-sized car models followed a four- to five-year "life-cycle" which had an inverted U-shape. Not until a sufficiently novel relaunch did the life-cycle restart. In this case management felt the new front-wheel drive car would restart the life-cycle and that the pattern, but not the magnitude, would be similar to the rear-wheel drive car.

Management felt that the sales of the new car t years after its introduction, $S(t)$, would follow the pattern of the sales history of the control car, $S_c(t)$, if all else were equal. We would modify this forecast by factors due to preference, $P(t)$ (defined as the ratio of preference of the new car to the control car) as measured in the clinic; industry volume, $V(t)$ as estimated by exogenous econometric models; and competitive intensity, $C(t)$ (nominally 1.0 if no new competition enters and less than one when new competitive

TABLE 1

Relative Preference Conditioned by Information Sequence

Information Sequence$^{\triangle}$	New Car (n = Sample Size)	Control Car (n = Sample Size)	Difference (New − Control)	Ratio (New/Control)
1. concept awareness	13.3 (336)	14.2 (167)	−0.9	0.94
2. concept then wom (+)	14.7 (85)	16.6 (82)	−1.9	0.88
3. concept then wom (−)	10.3 (86)	16.6 (46)	−5.3*	0.62
4. concept then drive	18.5 (165)	21.2 (82)	−2.7	0.87
5. concept → wom (+) → drive	16.4 (85)	21.0 (37)	−4.6*	0.78
6. concept → wom (−) → drive	14.0 (86)	23.1 (46)	−9.1*	0.61
7. concept → drive → wom (+)	16.7 (91)	18.5 (41)	−1.8	0.90
8. concept → drive → wom (−)	16.6 (74)	18.2 (46)	−1.6	0.91

* Significant at 10% based on comparison of means across subsamples.

$^{\triangle}$ See Figure 1 for experimental flow diagram for sequence codes.

cars enter) as judged by the managers. (In other applications further indices are added as the situation demands.)

In symbols, the top-line forecast is given by:

$$S(t) = S_c(t) * P(t) * V(t) * C(t). \tag{1}$$

The preference index was based on the clinic measures. Because information reaches consumers over the life-cycle, and because the preference ratios decrease in Table 1 as more information is gained, we felt it was reasonable for the preference indices to start near the concept level and decrease over the four years of the forecast. After discussion of the clinic results and based on the managers' automobile experience, management felt that an evaluation of 0.92, 0.90, 0.88 and 0.85 was reasonable for years 1, 2, 3, and 4 of this forecast. (No exact formula was used; rather the integration of data and judgment. More sophisticated analyses are described in the next section.)

From General Motors' econometric models, we obtained industry volume indices, $V(t)$, of 1.26, 1.61, 1.2, and 1.2 for years 1, 2, 3, and 4 of the car's life-cycle. The competitive index, $C(t)$, was based on judgment with regard to the impact of new competitive cars not now on the market and past conjoint studies done for other cars. The relevant indices of 1.0, 0.98, 0.94, and 0.86 were deemed reasonable by management.

Putting these indices together with historic sales of the control car gives the forecasts in Table 2.

Management Reaction

Management faced a marketing challenge. The shortfall from target was dramatic. Perhaps advertising could increase the consideration index and, perhaps, promotion and dealer incentives could increase the preference index. Furthermore, detailed examination of the data suggested that women who drive small cars were the best target consumers. The preference index was 1.17 for this group.

However, simulation of these changes (via judgment with the index model) and other sensitivity analyses suggested a major shortfall of sales versus planned production. Management faced a difficult decision. With demand likely to be well below production levels and with major redesign not possible in the short run, some action needed to be taken to keep the plants in operation. Management decided that the only potentially viable option to retain sales volume was to delay retooling of the existing car plant and to produce, temporarily, both the existing rear-wheel drive car *and* the new downsized front-wheel drive car.

At this point we see the managerial need for a more advanced model. The index model identified the need for managerial action, but could not forecast the effect of maintaining the existing car while producing the new car. Furthermore, it was clear that specific marketing actions would be necessary to decrease the shortfall. While management trusted their judgments for top-line "ballpark" forecasts, they became convinced of the need for greater detail on dealer visits, word-of-mouth, advertising, and production constraints in order to select the appropriate marketing strategy.

TABLE 2

Top-Line Forecasts for New Mid-Size Car

Year of Life Cycle	Sales	Share	Difference from Target
1	274,000	9.8	176,000
2	326,000	11.0	124,000
3	247,000	8.5	203,000
4	191,000	7.4	259,000

Probabilistic Flow Model for Dealer Visits, Word-of-Mouth Advertising, and Production Constraints

Detailed modeling, to forecast the effects of increased advertising, repositioning, dealer incentives, and the availability of both the old and the new cars, provides management with a tool to evaluate strategic decisions. Such modeling is also useful to monitor and fine-tune marketing decisions made throughout the launch.

Basic Modeling Methodology

Our more detailed structure is based on a probability flow model that has been used successfully in the test market and launch analyses of consumer frequently purchased goods (Urban 1970) and innovative public transportation services (Hauser and Wisniewski 1982b). The modeling concept is simple. Each consumer is represented by a behavioral state that describes his/her level of information about his/her potential purchase. The behavioral states are chosen to represent consumer behavior as it is affected by the managerial decisions being evaluated. We used the set of behavioral states shown in Figure 2; they represent information flow/diffusion theory customized to the automobile market.

In each time period, consumers flow from one state to another. For example, in the third period a consumer, say John Doe, might have been unaware of the new car. If, in the fourth period, he talks to a friend who owns one, but he does not see any advertising, he "flows" to the behavioral state of "aware via word-of-mouth." We call the model a "macro-flow" model because we keep track, probabilistically, of the market. We do not track individual consumers. For details of this modeling technique see Urban and Hauser (1980, Chapters 15 and 16). The flow probabilities are estimated from the clinic or industry norms, but supplemented by judgment when all else fails. For example, after consumers see the concept boards which simulate advertising, they are asked to indicate how likely they would be to visit a dealer.

In some cases the flow rates (percent of consumers/period) are parameters, say, X percent of those who are aware via ads visit dealers in any given period. In other cases, the flows are functions of other variables. For example, the percent of consumers, now

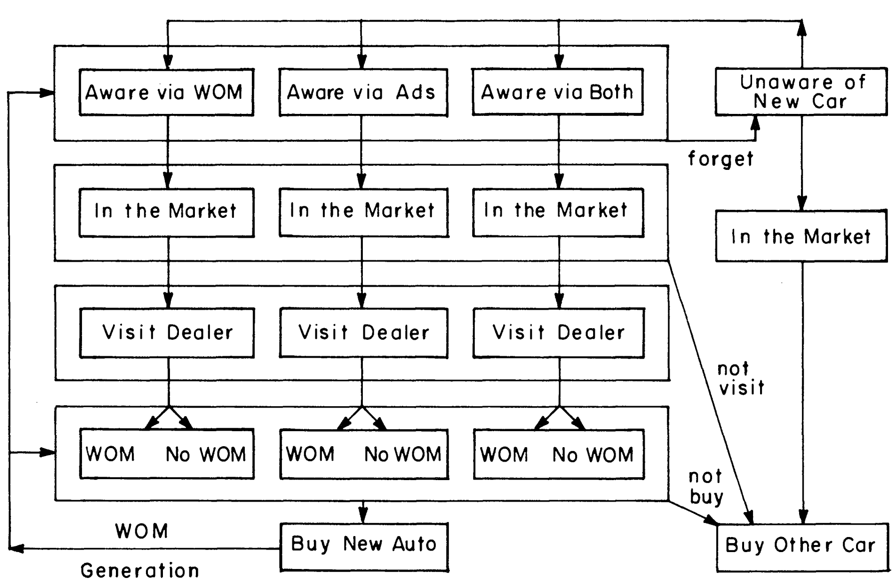

FIGURE 2. Behavioral States Macro-Flow Model for a New Automobile.

unaware, who become aware in a period is clearly a function of advertising expenditures. The exact functions chosen for a given application are chosen as flexible yet parsimonious, parameterized forms. Whenever possible, they are justified by more primitive assumptions. When we have experience in other categories we use that experience as a guide to choose functional forms.

Example Flows

Figure 2 requires 20 state equations to specify the 25 nonzero flows and the conservation conditions.[3] Rather than repeat those equations here we select one conservation equation and three of the more complex flows to illustrate the technique.

Conservation Equation. For every state in Figure 2 there is a conservation equation. That is, the number of people in a state at the end of a period equals the number in that state at the start of a period, plus the number who flow in during that period, minus the number who flow out during that period.

For example, let $N_{aa}(\tau)$ = the number aware via ads in period τ and let $N_u(\tau)$ be the corresponding numbers of consumers in the unaware state. Let $f_a(\tau)$ be the flow rate in period τ from unaware to aware via ads, that is, the probability of awareness given initial unawareness. Let $f_w(\tau)$ be the flow rate due to word-of-mouth, let $f_f(\tau)$ be the forgetting rate, and let $f_{ia}(\tau)$ be the flow into the market among those aware by ads only. Then,

$$\begin{aligned} N_{aa}(\tau) = {} & N_u(\tau-1)*f_a(\tau)*[1-f_w(\tau)] + N_{aa}(\tau-1) - N_{aa}(\tau-1) \\ & *f_f(\tau)[1-f_{ia}(\tau)] - N_{aa}(\tau-1)*f_w(\tau)[1-f_{ia}(\tau)] - N_{aa}(\tau-1)f_{ia}(\tau). \quad (2) \end{aligned}$$

Other conservation equations are in this form. Their specification is tedious, but straightforward.

The next task is to flow people to new states. Most flow rates are a parameter indicating the rate of flow (e.g., the fraction of aware consumers who visit a dealer). A few equations are more complex. We now detail these more elaborate equations for advertising, word-of-mouth prior to dealer visit, word-of-mouth posterior to dealer visit, and production constraints.

Advertising Flow. At zero advertising this flow from the unaware to the aware state is zero percent; at saturation advertising we expect some upper bound, say α. We also expect this flow to be a concave function of advertising spending. The negative exponential function is one flexible, concave function that has been used to model this flow. Note that this function can also be justified from more primitive assumptions. For example, if we assume advertising messages reach consumers in a Poisson manner with rate proportional to advertising expenditures and that only α percent watch the appropriate media, then in a given time period, τ, the probabilistic flow, $f_a(\tau)$, from unaware to aware via advertising, is given by

$$f_a(\tau) = \alpha[1 - \exp(-\beta A(\tau))], \quad (3)$$

where $A(\tau)$ is the advertising expenditure in period τ.

Word-of-Mouth, Prior to Test Drive. In this application we assumed that: (a) word-of-mouth contact is proportional to the number of consumers who purchased in each previous period but (b) the effectiveness of this contact decays exponentially. If $M(\tau)$ is the number of consumers who purchased in time period τ, then these assumptions yield:

[3] The source code is written in "Stella", a personal-computer based, commercially available system dynamics language. For system disks contact High Performance Systems, 13 Dartmouth College Highway, Lyme, NH 03768. For the program of this auto model, contact the authors. A more cumbersome basic version in the BASIC programming language is also available for interested readers. For greater details see Goettler (1986) and Srinivasan (1988).

$$f_w(\tau) = \rho \sum_{i=1}^{\tau} [M(\tau - i)/M_\tau] \exp[\gamma(i - 1)] \tag{4a}$$

where M_τ is the total number of potential customers.

Flows from advertising and from word-of-mouth are treated as independent probabilistically.

An alternative formulation, somewhat more attractive theoretically, assumes that: (a) Poisson incidence comes from consumers who purchased in each previous period; (b) the incidence is proportional to the number of people who purchased in that period and decays proportionally to the number of periods since purchase; (c) the incidences from each consumer are independent; and (d) only ρ percent of consumers are susceptible to word-of-mouth:

$$f_w(\tau) = \rho\{1 - \exp[-\gamma \sum_{i=1}^{\tau} M(\tau - i)/(\tau - i)]\}. \tag{4b}$$

Future controlled experiments might improve these specifications and/or identify which specification is appropriate for which application. This research is beyond the scope of the present paper. Equation (4b) is preferred on theoretical grounds, but (4a) might be more robust empirically.

Word-of-Mouth Posterior to Test Drive. From qualitative research it was clear that once consumers visit dealers they seek advice from others more actively in order to evaluate their final decision. Management felt that this meant that word-of-mouth intensity would not decay posterior to test drive. For example, for the post-test-drive conditions analogous to equation (4a), the word-of-mouth flow, $f'_w(\tau)$, is given by:

$$f'_w(\tau) = \delta \sum_{i=1}^{\tau} M(\tau - i)/M_\tau. \tag{5}$$

Equations (3)–(5) have a number of unknown parameters. We discuss calibration of these parameters and of the other flows after indicating how we handled production constraints.

Production Constraints

The forecast for the new, front-wheel drive, mid-sized car was below planned production capacity, but such is not always the case. In fact, the sales of the old, rear-wheel drive, mid-size car were constrained at many times in its sales history by availability. In auto industry terms, free expression was above production.

Ultimately, in a model year, a car model's sales will equal production. (Rebates, special incentives, end-of-model-year sales will be used if necessary.) However, our probabilistic flow model makes forecasts month-by-month. Thus, we used some special characteristics of the auto market to incorporate production constraints. In particular,

(1) As stated earlier, traditionally about 80 percent of domestic sales are "off the lot" or purchased from dealer inventory. If inventories are low, it is likely consumers will not find the specific features, options, and color they want and sales will be lost.

(2) Inventory is expensive in terms of interest, insurance, and storage. At high levels of inventory the dealers allocate effort and sales incentives to switch consumers to overstocked models.

(3) The numeraire for inventory is generally accepted by all concerned as "days supply," the number of units in stock divided by the current sales rate. It is this stimulus to which dealers react.

To incorporate these phenomena we expand the set of behavioral states to include availability. See Figure 3 for new and old car flows. In the model, the awareness shown in the Figure 3 boxes is broken down as shown in Figure 2, but for expositional simplicity this is not done in Figure 3. We then model the availability probability, $p(\tau)$, as:

$$p(\tau) = 1 - \exp(-\lambda D(\tau) - \theta) \tag{6}$$

where $D(\tau)$ is days supply at time period τ: λ and θ are parameters.

Days supply for the control car is observed from historical data and calculated for the new car. Initial days supply for the test car is based on management judgment and then calculated from the simulation results in later periods. Management acceptance of the $D(\tau)$ is critical. It must be consistent with the macro-flow forecasts as well as consistent with their own projected fine-tuning.

The number of people buying the car is now calculated as the fraction of all potential purchasers who want to buy the car "off the lot" multiplied by the availability ($p(\tau)$). Those who place a custom factory order and wait (usually 8–12 weeks) are not reduced by the availability probability.

Calibration and Fitting

The models shown in Figures 2 and 3 are practical models. They incorporate phenomena management feels are important in a way management can accept. Yet, the models are complex—we need many flow probabilities.

It is tempting to develop a clinic design so that each flow in Figure 2 (or 3) can be measured directly. However, clinics are expensive—they can cost upwards of a quarter-of-a-million dollars. Realistically, we must balance the tendency to prefer direct measures with the cost of obtaining those measures. We obtain directly those estimates that are available, say purchase likelihood given ad & drive. We approximate others; for example, we assume the purchase likelihood from a sequence of {wom → ad → drive → wom} is not much different from a sequence of {ad → drive → wom}. We obtain others from

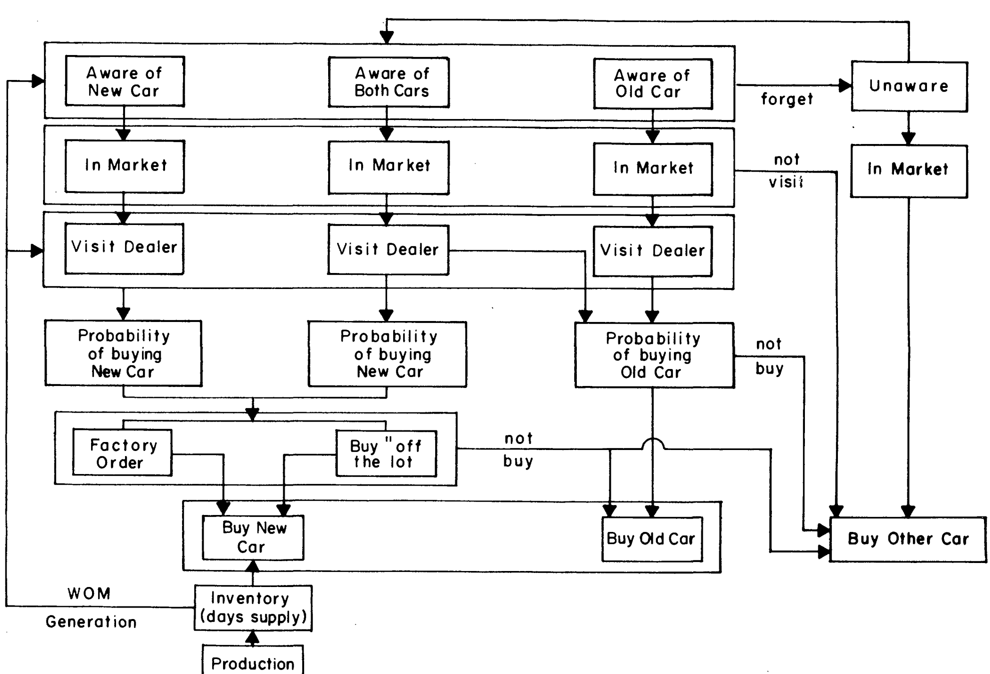

FIGURE 3. Production Constrained Macro-Flow Model for Two Cars.

internal studies, for example, the likelihood that a consumer will visit a dealer after an ad exposure. Still others are obtained from managerial judgment.

Table 3 lists the flows in Figure 3 and the data sources. Note that some of the flows are based on equations (3)–(5) which contain the unknown parameters, α, β, γ, ρ, δ,

TABLE 3

*New Inputs and Sources for Two-Car Model**

Inputs	Source
Target Group Size	Set in plan for number of buyers
Category Sales (monthly)	G.M. econometric forecasts
Awareness	
—advertising spending (monthly)	planned levels
—α, β, forgetting (flow from aware of ad, WOM, or both to unaware) (see equation 3)	fit to past awareness, spending and sales for control car and modify judgmentally for changes for new car
—aware of both cars	awareness proportion for new car times awareness proportion for old car
In Market	
—fraction of those aware who are in market	calculate as category sales divided by target group size for all awareness conditions
Visit Dealer	
—fraction who visit dealer given ad aware	clinic measured probability of purchase after ad exposure (see Figure 1)
—fraction who visit dealer given ad and WOM aware	clinic measured probability of purchase after WOM video tape exposure
—fraction who visit dealer given WOM aware	judgmentally set given above two values
—probability of visit dealer if aware of both cars	probability of visit for new car in clinic after awareness among those respondents who were aware of the old car before the clinic
Purchase	
—probability of buying new car given awareness condition:	
(1) ad aware before visit and no other awareness	clinic measure probability of purchase after ad exposure and test drive
(2) ad aware before visit and WOM	clinic measure probability of purchase after ad, test drive and WOM exposure
(3) ad and WOM aware before visit	clinic probability of purchase after ad, WOM and test drive
(4) ad aware before and after visit	judgmentally set based on (1), (2), (3)
(5) WOM aware before and no other awareness	judgmentally set based on (1), (2), (3)
(6) WOM before and after visit	judgmentally set based on (1), (2), (3)
—probability of buying new car if aware of new car and old car	probability of buying new car in clinic among those respondents who were aware of the old car before the clinic
Word of Mouth Communication	
—ρ, γ (equation 4a)	managerial judgment and fit to past data on fraction of awareness due to word of mouth and control car sales
—δ (equation 5)	past survey data, judgment, and fit to control car sales
—aware of ads and WOM	probability of ad aware times probability of WOM aware
Production	
—levels of production (monthly)	planned levels
—λ, θ (equation 6)	managerial judgment, fit to past data on control car sales, and past research studies
—fraction of buyers who want to buy "off the lot"	past studies and judgment

* Analogous procedures are used for control car based on control cell measures in the clinic and past data.

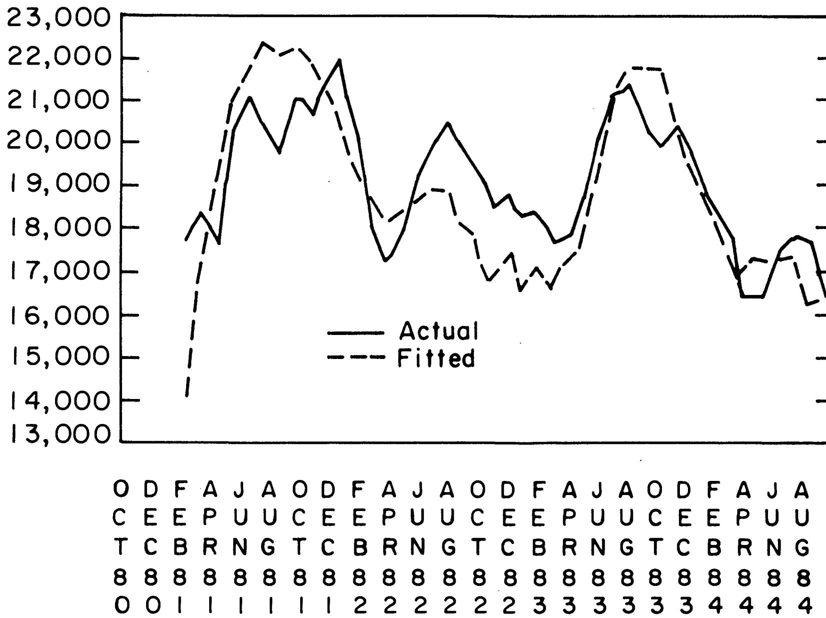

FIGURE 4. Actual vs. Fitted Sales of Control Car. Five-Month Moving Average with Production Constrained Macro-Flow.

λ, and θ. We "calibrate" the model by interactively selecting parameter values to maximize the fit to the actual sales for the control car.

The results of the calibration are shown in Figure 4. The "predicted" sales are simply the number of consumers who flow into the "buy new auto" state in each period, i.e., the fraction of consumers times the total potential market. It is obtained by running the model forward in time with the fitted parameter values.

The macro-flow model fits the data reasonably well with a mean percent error of 5.6% in the five-month moving average and the model appears to capture the major swings in the data, including the partial seasonal pattern.[4] This fit clearly outperforms simple three-parameter life-cycle models. (For example, they would not capture the double peak in sales.) But our model has many more parameters than a simple life-cycle model. We claim only that the model has face validity and that this fit is better than that which had been obtainable previously by the automobile division. To examine further whether or not the fit is adequate we compare predictions to actual data in a later section.

Two-Car Macro-Flow Model

The desire to examine management's decision to keep both the new and old models in production caused us to extend the flow model to include the effects of two competitive models on the market. Once the one-car production-constrained macro-flow model is calibrated, it is straightforward to expand the model to incorporate two cars. See Figure 3. Behavioral states are added for "awareness of both," "visit dealers given awareness of both," and "probability of buying given both." Clinic measures and judgment are used for preference among the test and control cars in this study (see Table 3). Only two-thirds of the people, who had prior awareness of the old rear-wheel drive car, preferred the new car to the old auto when exposed to the new front-wheel drive car.

[4] The five-month moving average of the actual data smoothes transient effects due to special rebate and interest programs. The behavioral states in Figure 3 do not model these effects explicitly.

Managerial Application of Flow Model

Table 4 reports forecasts based on the macro-flow model. The base case predictions are close to those in Table 2—still well below the production target.

The projected shortfall in sales put pressure on management to develop strategies that would improve free expression sales. We simulated three marketing strategies that were considered. The first strategy was a doubling of advertising in an attempt to increase advertising awareness (the model was run with advertising spending doubled). Table 4 indicates this would increase sales somewhat, but not enough. Given its cost, this strategy was rejected.

The next strategy considered was a crash effort to improve the advertising copy to encourage more dealer visits. Assuming that such copy would be attainable, we simulated 40 percent more dealer visits. (The model was run with dealer-visit flow-parameters multiplied by 1.4 for ad aware conditions). The forecast was much better and actually achieved the sales goals in year 2. Although a 40 percent increase was viewed as too ambitious, the simulation did highlight the leverage of improved copy that encouraged dealer visits. A decision was made to devote resources toward encouraging dealer visits. The advertising agency was directed to begin work on such copy, especially for the identified segment of women currently driving small cars.

The final decision evaluated was the effect of incentives designed to increase the conversion of potential buyers who visit dealer showrooms. We simulated a 20 percent increase in conversion (all dealer-visit flow were parameters multiplied by 1.2). The leverage of this strategy was reasonable but not as high as the improved advertising copy. This simulation coupled with management's realization that an improvement would be difficult to achieve on a national level (competitors could match any incentive program) led management to a more conservative strategy which emphasized dealer training.

The net result of the sales analysis was that management decided to make an effort to improve dealer training *and* advertising copy, but that any forecast should be conservative in its assumptions about achieving the 40 percent and 20 percent improvements.

The shortfall in projected sales, dealer pressure to retain the popular rear-wheel drive car, and indications that production of the new car would be delayed, led management to the decision (described earlier) to retain both the old and the new cars. Initial thinking was that the total advertising budget would remain the same but be allocated 25/75 between the old and new cars. Evaluation of this strategic scenario required the two-car macro-flow model.

The forecasts for the two-car strategy with the above advertising and dealer's incentives tactics are shown in Table 5. The combined sales were forecast to be higher than a one-car strategy in years 1 and 4, but lower in years 2 and 3. Overall the delayed launch caused a net sales loss of roughly 48,000 units over 4 years. This is not dramatic, especially given potential uncertainty in the forecast. However, the two-car strategy did not achieve the sales goal and made it more difficult to improve advertising copy and dealer training. Once the production decision had been made and the production delays were unavoidable,

TABLE 4

Sales Forecasts and Strategy Simulations (in Units)

Year	Base Case	Advertising Spending Doubled	Advertising Copy Improved 40%	Dealer Incentives Improved 20%
1	281,000	334,000	395,000	340,000
2	334,000	370,000	477,000	406,000
3	282,000	330,000	405,000	345,000
4	195,000	225,000	273,000	234,000

TABLE 5

Sales Forecasts for Two-Car Strategy (in Units)

Year	New Model	Old Model	Combined Sales
1	181,000	103,000	284,000
2	213,000	89,000	301,000
3	174,000	80,000	254,000
4	121,000	84,000	205,000

management was forced to retain the two-car strategy. Our analysis suggested that it be phased out as soon as was feasible.

This chain of events illustrates the value of a flexible, macro-flow model. The world is not static. Often, unexpected events occur (dramatic sales shortfalls, production delays) that were not anticipated when the initial model was developed. In this case we could not evaluate the overall two-car strategy with the Mod I analysis; management proceeded on judgment and the information available. Once we developed the two-car macro-flow model we could fine-tune the strategy to improve profitability and, in retrospect, evaluate the basic strategy. More importantly, we now have the tool (and much of the calibration) to evaluate multiple-car strategies for other car lines.

Predicted vs. Actual Sales

We turn now to a form of validation. Validation is always difficult because management has the incentive to sell cars, not provide a controlled laboratory for validation.

There are at least two components of deviations between actual and predicted sales. If planned strategies are executed faithfully, the model is likely to have some error and actual sales will not match predicted sales. To evaluate this model, we are interested in this first component of error. But as sales reports come in and unexpected events happen, management modifies planned strategies to obtain greater profit. This, too, causes predicted sales to deviate from actual sales. For example, excess aggregate inventories (across all car lines in the corporation) often encourages rebate or interest rate incentives. Both of these increase and/or shift sales. We are interested in these deviations to identify those actions which need to be added in future model elaborations.

To examine both components of deviations we report two comparisons of actual vs. predicted sales. In the first we compare predictions made prior to launch with sales obtained during launch. In the second we input managerial actions as they actually occurred and compare the adjusted predictions to actual sales. When any adjustments are made we are conservative and we include adjustments which hurt our accuracy as well as help our accuracy. Together, the two comparisons give us an idea of which deviations are due to model error and which deviations are due to changes in managerial actions.

In our application, the advertising allocation changed, industry sales were above the econometric forecast, special interest rate promotions were employed, and production

TABLE 6

Comparison of Actual Sales to Unadjusted Predictions

	1st 6 months	2nd 6 months	3rd 6 months	Total
Actual	97,000	119,000	90,000	306,000
Unadjusted prediction	133,000	151,000	162,000	446,000
Percent difference	37%	27%	80%	46%

was delayed further for the new car. We report first the unadjusted comparison and then a comparison adjusted for the changes in advertising, industry sales, incentives, and production.

Table 6 reports the unadjusted predictions. Actual sales for the two cars were well below the forecast. However, almost all of this deviation occurs when we compare predicted sales for the new car to actual sales. The forecasts for the existing car were close to actual. Recall the new car was production constrained while the old car was not.

We now attempt to decompose these deviations into deviations due to the model and deviations due to management decisions. We do this by computing the adjusted prediction.

The actual advertising allocation was 50/50 not 25/75 as planned. We modify the direct inputs to the macro-flow model accordingly (see equation (3)). Industry sales were above the economic forecasts. We modify the macro-flow inputs accordingly. (Note

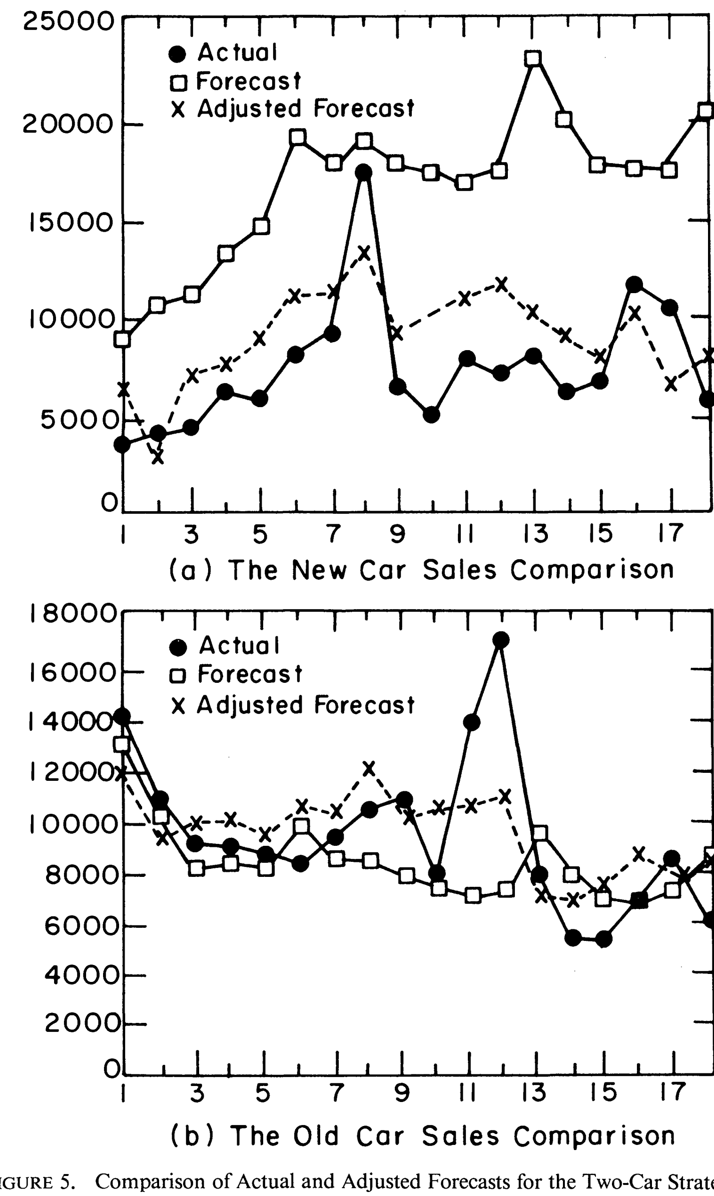

FIGURE 5. Comparison of Actual and Adjusted Forecasts for the Two-Car Strategy.

that this modification works against improving our fit.) There was a special interest rate incentive program for the old car in months 11 and 12. We have no way to include this explicitly, but will scrutinize months 11 and 12 carefully in the final comparison. Production of the new car was delayed significantly. Production problems reduced the availability of the popular V6 engines causing 80% of the old cars in months 13 to 18 to be produced with the less popular V8 engines; similar problems in months 13 to 18 caused a substitution of the less popular standard transmissions in 33% of the new cars. We make these adjustments with the production constrained model using the free expression preferences among engines and transmissions from periods 1 to 12.

The adjusted forecasts are shown in Figure 5. The agreement is acceptable—the mean model error for the 18 months is now 8.8% (down from 46% in the unadjusted comparison). The agreement would have been much closer had we been able to adjust for the incentive program on the old car in months 11 and 12. The overall cumulative predictive accuracy is good, but monthly forecasts would have to be used with some caution.

This application demonstrates the difficulty and complexity of validation for durable goods forecasts. Production and marketing changes from the original plan have a significant effect; adjustments must be made. However, adjustments have the danger of being ad hoc and fulfilling the researchers' desire for predictive accuracy. We have tried to guard against these dangers with conservative adjustment and by reporting these adjustments as fairly as possible. We recognize that full evaluation must await independent applications of the model.

Subsequent Applications

We have implemented the model in three other major car introductions. The first was a new downsized "top of the line" luxury car that replaced its larger predecessor. Clinic data indicated that the new car would be preferred by a factor of 1.1 to the old car and the detailed dynamic forecast indicated a 25 percent improvement in sales volume. But this was less increase than had been desired. Because the clinic data indicated that the old brand buyers liked the new car and were secure, the marketing was oriented through increased advertising spending and copy towards import-buyers who were identified as a high potential group in the clinic responses. Copy also was based on building a perception of improved reliability which was found in the market research to be a weak point (e.g., ads showed testing the car in the outback of Australia). After those improvements, the car was successfully launched and sales increased 25 percent above the old levels as predicted by the model.

The next car studied was a full-size luxury two-door sedan that was downsized in an attempt to double sales and meet the corporate fuel economy standards. The clinic data indicated that the old buyers found the car to be small and ordinary, and they would have little interest in buying it. The only group that liked it was import-buyers, but they did not like it as much as other import options. The sales were forecast to be 50% of the old car's level of sales. Advertising and promotion changes were of little help. Unfortunately for the company, the forecast was correct and the first 12 months were 45% of the previous levels. This car should have been repositioned but a subsequent change in the marketing management of the company just after the final forecasts were made caused the bad news to be ignored. The new division director wanted a success and wanted to believe that the car could be "turned around" before the launch.

The final car was a small two-door sports car that was subsequently launched successfully. The clinic data showed that sufficient "free-expression" demand existed to make an exclusive and efficient launch possible in the first six months. That is, large advertising spending would not be required and fully featured cars could be offered to those "lucky enough to get one" because of limited production volumes. Private car showings were arranged for target customers to position the launch as exclusive. Higher prices could be supported in the first 9 months when production capability was low, but management chose to keep a lower price initially to avoid the perception of distress pricing and to maintain the special tone of the introduction. Test drives were promoted because the clinic showed significant increase in probability of purchase after people experienced the comfortable and roomy, but sporty, ride and handling. After six months, sales are within one standard deviation of predictions.

The durable goods model proposed in this paper has also been implemented on a PC home word-processing system and on a new camera. In all cases the model, measures, and simulations were key components in management decisions on how to target, position, communicate, and price the new product.

Discussion

When we undertook the challenge to develop a prelaunch forecasting system for new automobiles we hoped to develop a deeper understanding of the managerial needs and the special challenges of durable goods forecasting. We feel we have learned a lot in the seven years of applications.

Durable goods do present unique problems. The "price" forecasting problem, validation of production-constrained forecasting, search and experience, and word-of-mouth (magazine reviews) are critical phenomena relevant to durable goods. Addressing these issues has been challenging and scientifically interesting. We hope that the applications described in this paper enable the reader to appreciate better the needs of automobile (durable goods) marketing managers. Clearly, many challenges remain. We summarize a few here.

Applications Challenges

Perhaps the biggest challenge is efficient measurement. Clinics are expensive—sites must be leased, cars obtained, cars maintained, videos produced, test drives set up, names obtained, consumers recruited, etc. Macro-flow models are data intensive. The advantage of making every flow explicit leads one to recognize the need for detailed (and expensive) consumer intelligence. In the applications described in this paper we made what we believed to be efficient tradeoffs among data needs and data costs. The industry would benefit from explicit cost/benefit analyses to optimize data collection.

We can foresee the use of a computer with video disk interface as a method to provide information more efficiently and effectively. Perhaps the word-of-mouth spokesperson could be selected from a number of candidates stored on the video disk. The spokesperson might be matched to demographic and attitudinal characteristics of respondents to simulate the availability to the respondents. The information would be respondent controlled and responses recorded simultaneously as the information is processed and perceptions and preferences change.

Another challenge is the cost of the vehicles. Hand-built prototypes can cost $250,000 or more. Such prototypes are built as part of the engineering development, but the operating division must obtain them for clinic. Work is underway in the industry to determine whether fiberglass mockups or other substitutes can be used to provide earlier forecasts of consumer response. For example, at MIT, holograms are being used as full-scale auto representations.

Scientific Challenges

Equations underlying the flow model (equations (3)–(5) and Figures 2 and 3) represent the authors' experience but they are still somewhat ad hoc. Research is needed on the best specifications of these flows. How many levels should be created and how much segmentation by awareness should be done?

In our applications to date we relied on "calibration" which mixed direct measurement, modeling, judgment, and fitting. As we gain clinic experience, one might consider constrained maximum-likelihood or Bayesian estimation. For example, work is underway at Northwestern University to adapt the continuous-time equations (Hauser and Wisniewski 1982a) to maximum likelihood estimation via super computers.

Extensions

A number of extensions are possible to our auto prelaunch forecasting model. For example, the two-car model could be extended to a full product-line formulation. A number of new phenomena could be added: dealer advertising, dealer visits without prior awareness, multiattribute effects on preference, risk, and consumer budgeting. These modifications are feasible, but they add to the complexity and increase measurement/analysis costs. In each case these extensions should be evaluated on a cost and benefit basis before embarking on a more complex model.

Perhaps the most important extension is the use of marketing science analyses for preinvestment as well as prelaunch decisions. Early modeling of the "voice of the customer" should prove valuable in integrating marketing, engineering, and production to develop automobiles that satisfy long term consumer needs.

The auto industry is now experimenting with test/control clinic methodologies to understand the causal links between engineering design features and attributes that consumers desire. Perhaps future macro-flow analyses can link design improvements, such as anti-lock brakes, to sales.

Although much research is suggested by our efforts, the initial results suggest customer-flow models are useful in capturing the unique aspects of durable goods marketing. The models can be calibrated empirically and implemented with managers.

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