

BRANDAID II

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Abstract

Marketing managers make decisions about price, advertising, promotion, and other marketing variables on the basis of factual data, judgements, and assumptions about how the market works. BRANDAID is a flexible, on-line model for assembling these elements to describe the market and evaluate strategies. The structure is modular so that individual decision areas can be added or deleted at will. The model has an aggregate response form. By this it is meant that the effects of decision variables are related closely to specific performance measures such as market share and product class sales. Retail distribution and competition can be considered explicitly.

The calibration of the model is approached eclectically. Stages include judgement, analysis of historical data, tracking, field measurement, and adaptive control. Examples are cited.

A three-year case study is described. Model implementation is conducted in a multiple step process. The introductory steps include orienting management, forming a team, selecting and formulating a problem, calibrating the model and initial use. The on-going steps include firefighting, tracking and diagnosis, updating and evaluation, and re-use.

In conclusion, the emerging role of the model in the marketing management process is discussed. The model is seen not only as a means of evaluating strategies in annual planning and day to day operations but also as part of a monitoring system which compares model predictions with actual sales to uncover marketing problems and opportunities and focus managerial attention upon them.

1. Introduction

A marketing manager bases his planning and operating decisions on a heterogeneous collection of data, judgements, and assumptions about how the market works. Today's technology in computers and management science should make him more productive by organizing this material and delivering it to him in the right form at the right time. Toward this end, an on-line marketing mix model called BRANDAID is presented. The model provides a structure for relating brand sales and profit to the manager's potential actions so that he and his staff can quickly and easily analyze strategies. In a specific application the model is customized and calibrated in terms of the marketing problem at hand.

The preparation of the annual marketing plan for an established consumer product often proceeds as follows. First a sales forecast is made. This is usually done by extrapolating past trends and adjusting them judgementally for marketing information obtained from the field. Then production, materials, and overhead costs are calculated on the basis of the forecasted sales. The difference between sales dollars and cost is the gross contribution of the product. After aggregation across products, these funds are divided into (1) marketing budgets, (2) investment-like items such as new products and plant improvement, and (3) earnings. A jostling then takes place among internal advocates of each use of the funds until an allocation is achieved that is not too uncomfortable. The final marketing budgets are strongly influenced by historical precedents and by rules of thumb such as "so many dollars/case" or a fixed percentage of sales.

From an outsider's point of view, a remarkable feature of the process is that it does not formally acknowledge that marketing affects

sales. Marketing budgets appear as a consequence of the sales forecast not a cause. Equally surprising, profit comes as a decision, not a result. Sometimes a sales forecast will be raised to put more money into the plan without an attendant increase in marketing funds. Sometimes price may be adjusted without a change in the units forecasted to be sold.

We should understand why the system works the way it does. In the first place management does not know in precise terms how marketing affects sales. Yet control must be exercised over the operation. A reasonable assumption is that, if the company does next year about what it did last year, the results will be similar. Changes can be made incrementally. For established products this can be the rationale for a reasonably satisfactory operation.

Clearly an opportunity exists for doing the job better. It should be possible to make conditional forecasts, in which projected sales levels depend on the marketing actions taken. The best current information on how the market works can be marshalled in easy to use form through models. Then a variety of alternatives can be explored and a more efficient allocation of resources worked out.

Another point to understand is that the present system is not just predicting the future but, perhaps more important, it is setting goals for the organization. Forecasts are meant to be self-fulfilling prophecies. Notice that the goal-setting function appears to be in conflict with using a model, because a model seems to predict fatalistically that, if the company spends so-and-so much money on marketing, such-and-such profit will result. On closer examination a model is obviously

not all that automatic. Just because a given media efficiency or promotional boost is planned does not mean that it will occur. What a model does is relate an overall sales or profit goal back to individual assumptions about performance in various sub-areas. It then offers an opportunity to pinpoint subgoals that can be put together to achieve a desired overall goal.

In marketing, no sooner are objectives established and plans set than the firefighting begins, if it ever stops. Competitive actions, strikes, sudden promotional opportunities, and other unexpected happenings keep life from becoming dull. Key decisions are often made by small groups of people on rather short notice. In one company such a group, known as the "kitchen cabinet" is alleged to make important decisions on Friday afternoons after everyone else has gone home. How can critical marketing information be suitably summarized and transmitted to such groups? Hopefully, the technology we shall discuss can help by providing easy access to data and calibrated models which can be used on the spot.

When sales or profits differ from expectations, the marketing manager wants to know why and may wish to take action. But what are the expectations? The forecast? In one sense, certainly if sales are less than forecast the manager will seek to do something, but quite likely a number of unexpected events will have occurred since the forecast was made. By running a model with the actual marketing actions that have taken place, a predicted sales figure can be generated for comparison with the actual results. Causes of any differences can be sought. Such a diagnosis produces new understanding of the market and leads to both

improved marketing actions and better model calibration.

Thus, we see the following opportunities for a model to improve managerial productivity: In planning, a model can be used for conditional forecasts, making possible the examination of many new alternatives. In setting goals, data and judgements can be synthesized in a consistent way so that overall company goals can be related to performance in individual sub-areas. In day to day operations, the model and the information system of which it is part permit problem analysis on short notice. For on-going market diagnosis, model predictions can be compared with actual results to uncover and measure unexpected events, thereby triggering managerial action and model improvements. Finally, the discipline of the model organizes information needs and motivates relevant marketing research.

In an earlier paper [1], we have discussed the requirements placed on the design of a model for it to be used by a manager. A manager needs a decision calculus, that is, a model-based set of procedures whereby he can bring data and judgements to bear on his decisions. The model should be understandable to him or else he is likely to reject it. The model should be robust, in the sense that the user should not be able to push it to extremes that produce absurd results. The model should be evolutionary so that the user can start simply and expand in marketing detail. Finally, the model should be easy to use.

These requirements stand in contrast to much of the marketing models literature. A surprisingly small fraction of published models focus on decision-making. Of those that do, most consider a single control variable, advertising having been studied most. Much of the latter work is reviewed in a recent paper by Parsons and Schultz [2].

Our concern here is with marketing-mix decisions for established brands and, in this area, relatively few models or measurement studies have been published. Kuehn, McGuire, and Weiss [3] consider price and advertising, although their emphasis is on the latter. Weiss [4] examines the same two variables. Montgomery and Silk [5] estimate response parameters for several elements of the communications mix. Lambin [6] builds a model of a gasoline market and considers the number of service stations, the number of other outlets, and advertising. Farley and Ring [7] take an ambitious cut at testing and calibrating the Howard-Sheth buyer behavior model.

With the exception of the last, these models are generally developed about a specific data base. Including the last, most of them have been econometrically structured, that is, relatively simple transformations render them linear in the parameters, which can then be estimated by regression or simultaneous equation techniques. Often a number of structures are tried and compared with respect to R^2 or other statistical criterion in an attempt to find a structure that best fits the data.

The goals and style of the present work are different. We seek an a priori structure that is normatively oriented and general. The desire is to encompass a wide variety of products and situations. (The Howard-Sheth model is also general but contains little that is explicitly normative.) The structure to be developed here is motivated by views about how the market works rather than by a given data base. The origins of the views are varied, coming in part from the ideas and empirical studies of researchers such as those already mentioned and in part from marketing managers and analyses of their data. Notable differences from previously published works are (1) a general inclusiveness (at the cost of leaving

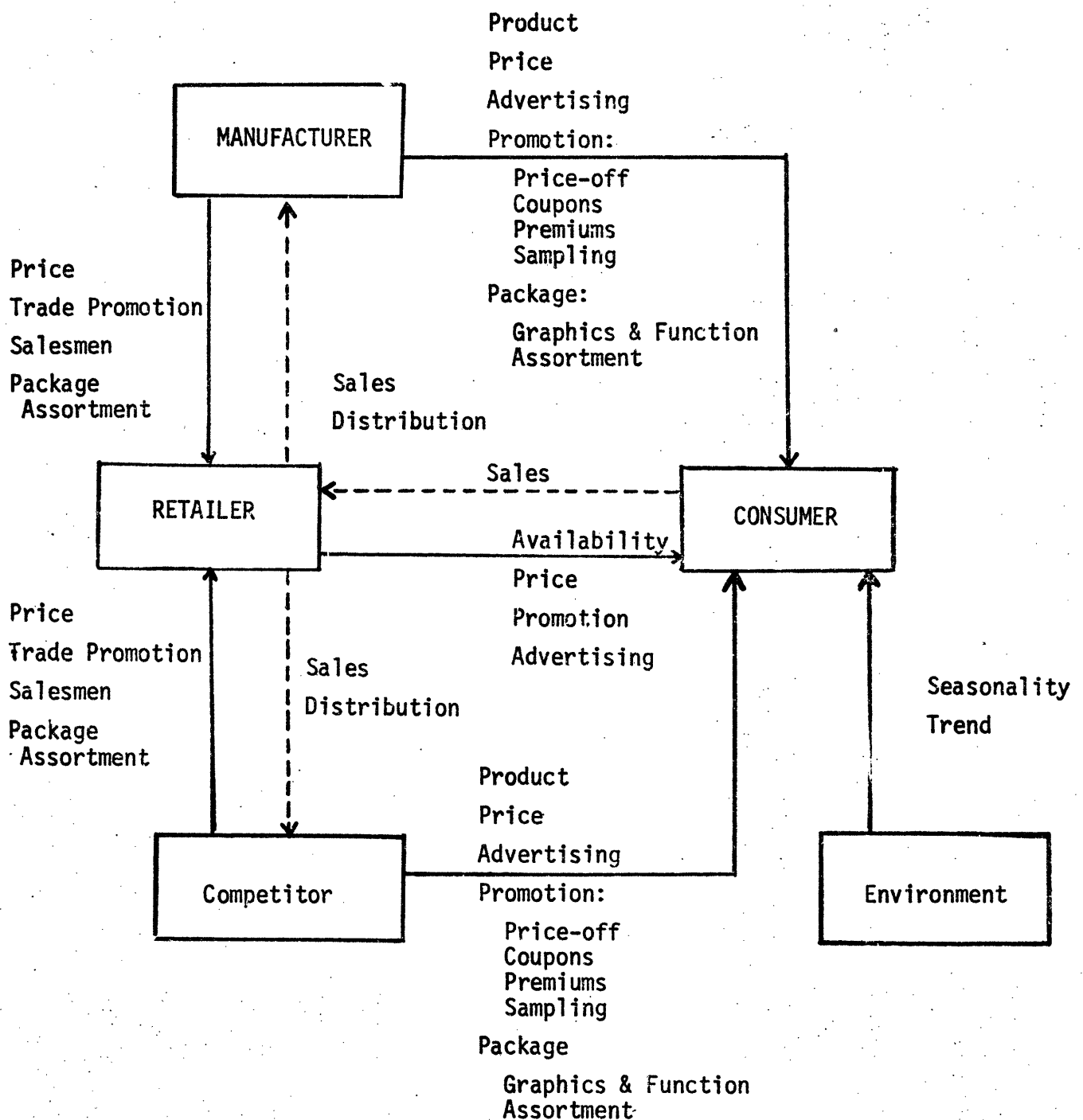


Fig. 2.1. The market system to be modeled.

ment. The retailer affects the consumer by product availability (including shelf-position and facings), price, special promotions and display, and sometimes by media advertising.

Meanwhile certain environmental forces affect the consumer, including seasonality and economic trends. The flow of product and marketing activities down the pipeline creates a flow of sales back up. Consumer sales affect the retailer with respect to stocking and displaying the product. Similarly the retailer presents the manufacturer with a distribution and sales situation to which the manufacturer reacts. Competitive manufacturers enter the system with essentially the same control variables but presumably they hinder rather than help the sales of the brand under consideration.

Many, perhaps most, of the elements of the system vary with time. Furthermore, it is often important to view the market as consisting of multiple segments, e.g. different geographic areas.

2.2 Model Structure

BRANDAID can be described as an aggregate response model. This is in distinction to flow models like that of Urban [8] and micro-simulation models like that of Amstutz [9]. An aggregate response model seeks to relate sales, share, distribution, or other criterion variables directly to the marketing actions involved. Flow models follow population groups from state to state over time. Micro-simulation models take individual customers through various steps of communication and decision-making. The distinctions are, of course, not completely clean, there being intermediate and composite forms, and the evolution of an aggregate model may often be in the direction disaggregation.

By and large, the market measurements, staff support, and managerial time required to use a model increase as one goes from aggregate response to flow to micro-simulation. This is because more detailed consumer and store measurements are needed and the models themselves become more complicated and take more time to understand and use. As a result, aggregate response models seem particularly useful for existing products. Flow and possibly micro-simulation models are well suited to new products where a detailed look at the market is usually necessary.

BRANDAID is intended to be many models in one. For tackling the marketing-mix problem, we want a tool that is flexible, expandable, and widely applicable. The approach is to create a general model with a modular structure which can be customized for different specific applications and can evolve in marketing detail as an application progresses.

2.3 Sales, Share and Profit

A company's principal measures of performance are sales, share, and profit. Most other measures can be derived from these. To speak of share is to imply the existence of a product class or total industry within which the brand competes. Although an ambiguity often exists in defining the exact limits of competition, if a brand manager is asked for the market share of his product, he usually has a number. For most companies market share is an important measure of brand performance because share can often be traded for short run profit or built by increased marketing effort.

We define notation as follows:

$s_b(t)$ = sales rate of brand b in time period t (sales units/customer/year).

$g(t)$ = sales rate of the product class in period t (sales units/customer/year).

$m_b(t)$ = market share of brand b in t (fraction)

$$S(t) = \sum_b s_b(t) \quad (2.1)$$

$$m_b(t) = s_b(t) / S(t) \quad (2.2)$$

In the above definitions, nominal units are indicated in parentheses. Sales might be cases, gallons, kilograms, etc. A customer might be a person, household, or store, etc. In some cases the "customer" might be a geographic area; for example, in an aggregate national model the customer might be the entire country. Time is taken in discrete units, say, months, quarters, or years. Sales are modeled as a rate. Notice that a sales rate of 1.5 pounds/customer/year can apply to a month (just as a car can go 50 miles/hour for 10 minutes). By adopting a basic sales rate with dimensions of physical units/customer/unit time, comparisons of different time periods and different geographic areas can be made easily. For some purposes these units are awkward, but straightforward aggregation will produce the more usual form of sales in dollars or units.

In some situations managerial attention is directed toward individual package sizes within a brand. In this case the b subscript may be thought of as referring to a brand-pack combination.

Profit is the difference between income and outgo. Let

$P_b(t)$ = profit rate of brand b in t (dol/cust/yr),

$g_b(t)$ = gross contribution of brand b in t (dol/sales unit),

$c_b(i,t)$ = cost rate in t for brand b resulting from the i^{th} marketing activity (dol/cust/yr.)

Then

$$P_b(t) = g_b(t) s_b(t) - \sum_i c_b(i,t) \quad (2.3)$$

Various aggregations of brand profit (or contribution to profit, if not all costs are considered) over time and market segment can readily be calculated from the basic $p_b(t)$. It is of course, possible to develop more sophisticated profit models than (2.3), involving say, time lags in the cash flows, but the above suffices for most marketing planning purposes.

In the exposition of the remainder of this section and throughout the next, we shall consider an individual brand in isolation. Then, in the treatment of competition in Section 4, the interaction among brands will be worked out. For notational simplicity, we shall drop the brand subscript until Section 4.

2.4 Models in Product Form

Brand sales rate will be expressed as a reference value modified by the effects of marketing activities and other sales influences.

Let

s_0 = reference brand sales rate (dol/cust/year)

$e(i,t)$ = effect on brand sales of i^{th} sales influence (index)

I = the set of influences on brand sales

We take

$$s(t) = s_0 \prod_{i \in I} e(i,t) \quad (2.4)$$

In most situations we wish to deal explicitly with market share.

Let

m_0 = reference brand market share (fraction),

S_0 = reference product class sales rate (dol/cust/yr)

$$s_0 = m_0 S_0 \quad (2.5)$$

The quantities s_o , m_o , and S_o introduce the idea of reference conditions. An established product has an existing situation and planning is primarily concerned with changes from that. Accordingly, a set of reference conditions are defined, usually from sales and marketing activities in the recent past.

The terms $e(i,t)$ will be called effect indices. As used here, an index is a number with nominal value 1.0 which expresses fractional changes from a reference value. An example is a seasonal index. A product class seasonality of 1.3 for March implies that March sales are 30% above the reference value.

The same concept can be applied to other phenomena. For example, under reference conditions, $e(i,t)$ for advertising would be 1.0. Under increased advertising, $e(i,t)$ might rise to 1.1, indicating a 10% increase in effect on sales. The use of indices makes it easy to add or delete marketing detail, since an activity can be dropped from the model by setting its index to 1.0. The effect is then absorbed into reference conditions.

The use of a multiplicative form in (2.4) implies a specific assumption about the interaction of marketing effects in the neighborhood of reference values. It says that an improvement in the effect of one marketing variable increases the improvement that can be obtained from another. Thus a 20% improvement in each of two sales indices implies a 44% increase in sales ($1.2 \times 1.2 = 1.44$). This form of interaction is automatically built in. Other degrees of interaction can be provided by adding effect indices that depend on more than one marketing activity.

The above model equations (2.1-2.5) make no mention of geographic areas or other market segmentation. When market segmentation is part of the problem, the equations are assumed to apply to each segment but presumably with different parameter and control variable values. A fundamental time and storage saving characteristic of the computer

software that has been developed for the model is that, although virtually any parameter or control variable can depend on time or segment, the same value is used for each unless the user specifically requests differently.

3. Submodels

The effects of individual marketing activities and other influences on sales are modeled in two principal ways, direct indices and response curves. Response curves can be either user-supplied or built-in. In addition, customized submodels can be developed for special phenomena.

By a direct index we mean a specific numerical representation of a given sales influence in a given time period. A good example is the treatment of seasonality as a set of numbers one for each time period. Direct indices are particularly appropriate for discrete marketing actions such as a new package, a change in product specifications, or a promotion based on a premium. Test data, past experience, or judgement are used to determine the sales improvement to be anticipated. The cost inputs for such actions are usually straightforward to obtain.

A response curve specifies an effect index as a function of some controllable quantity, for example, sales as a function of price. Sometimes the response curve is part of a more extensive structure, perhaps involving time lags or other phenomena.

The principal sales influencing activities currently considered in the model are those shown in Fig. 2.1. Many influences are treated by simple direct indices, but the more significant ones are modeled in considerable detail. In particular, this is true of manufacturer price, promotion, and advertising and retail availability. In applications to date, by far the most important control variables have been advertising, promotion, and price. For describing the marketing effects of these we

have had occasion to use, in one situation or another, each of the main model options; direct indices, built in response submodels, and customized submodels. In working with a particular marketing submodel, we shall reduce notational clutter by replacing the general effect index $e(i,t)$ by $e(t)$, since the specialization to the particular activity will be clear from the context.

3.1 Advertising

If a brand starts out with its sales rate at its reference value and marketing conditions other than advertising at their reference values, then there is some advertising rate that will maintain sales at reference. This advertising will be designated as the maintenance or reference advertising rate. If advertising is less than reference, sales rate will presumably sag, and, after a while, level off at a new lower value. Similarly if advertising is increased over the reference rate, sales would be expected to rise and level off at a higher value. (Higher advertising may decrease sales. This can easily be accommodated but we use the increasing case for illustration.)

Figure 3.1 sketches these phenomena. We observe that the steady state sales at each advertising rate define a curve of long run sales response to advertising. Thus, the asymptotic values might be read off Figure 3.1 and plotted as in Figure 3.2 to give the long run curve.

Notationally, let

$a(t)$ = advertising rate at t (index)

$r(a)$ = long run sales response to advertising (index)

$e(t)$ = effect of advertising on sales at t (index)

$\alpha(a)$ = carry-over rate for advertising effect on sales (fraction/period)

We model the sales response process as follows

$$e(t) = \alpha e(t-1) + (1-\alpha) r(a(t)) \quad (3.1)$$

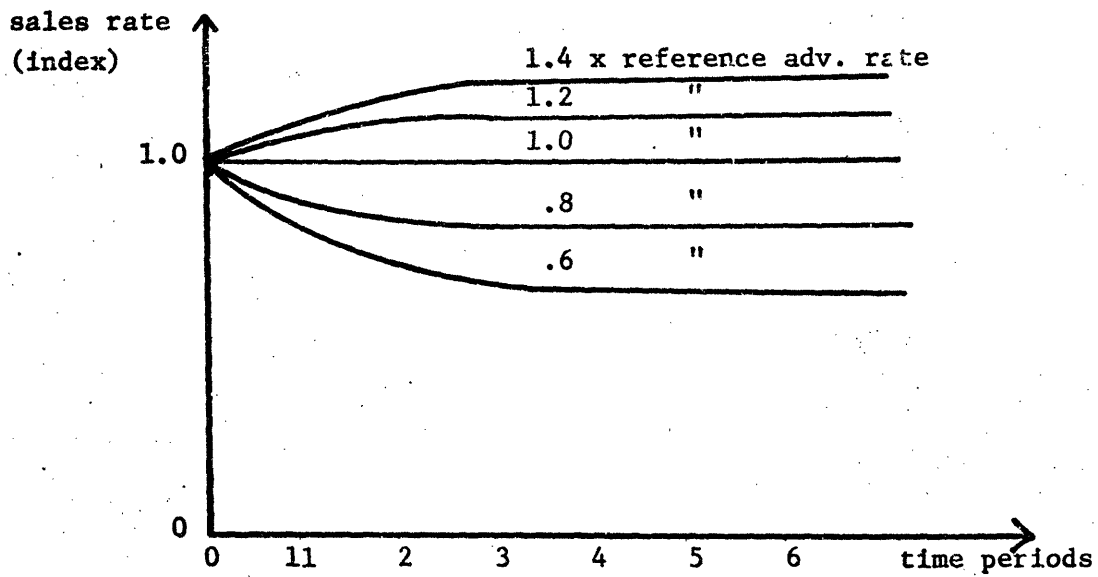


Fig. 3.1. Sales response over time to different advertising rates (sketch).

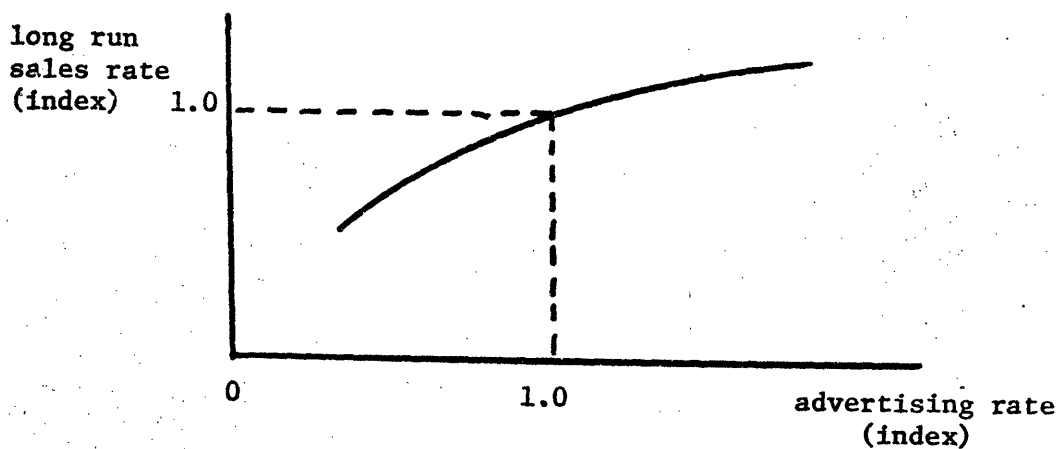


Fig. 3.2. Long range sales response to advertising corresponding to Fig. 3.1 (sketch).

The value of α determines how quickly long run sales rate is reached; $\alpha = 0$ means immediately, $\alpha=1$ never. Some people feel that α itself depends on the advertising rate and so α is indicated to be a function of a .

The next question is what is meant by advertising? The motivating idea is that advertising consists of messages delivered to individuals by exposures in media paid for by dollars. This will be expressed by

$$\text{advertising rate} = (\text{copy effectiveness}) \times (\text{media efficiency}) \times (\text{spending rate})$$

Spending rate has dimensions such as dollars/customer/year, media efficiency could be exposures/dollar and copy effectiveness would usually be a dimensionless weighting factor with a value of 1.0 for the copy used under reference conditions.

Thus let

$h(t)$ = media efficiency in time period t (exposures/dollar),

$k(t)$ = copy effectiveness in t (dimensionless),

$x(t)$ = advertising spending rate in t (dol/cust/year),

Using the subscript 0 to denote the reference value of these quantities, we model advertising rate by

$$a(t) = h(t) k(t) x(t) / h_0 k_0 x_0 \quad (3.2)$$

Note that under reference conditions $a(t) = 1.0$ and by definition $r(1.0) = 1.0$.

Then if $e(t-1) = 1.0$ so does $e(t)$ and sales holds at its reference value.

Note also that, if $a(t)$ is held constant and $0 \leq \alpha < 1$, the steady state solution of (3.1) is $e = r(a)$.

An exponential growth or decay of sales to a long run value has a certain amount of empirical support. For example, the model of Vidale and Wolfe [24] is similar. More complicated dependencies can be modeled but usually are hard to justify.

There is, however, another phenomena that is worth including as an option. Friedman [10] observes that, in his data, following a cut off of advertising, sales continue to hold up for a while and then sag. He explains this by saying that advertising has a cumulative effect due in part to present advertising and in part to past advertising. He takes a weighted sum of present and past as his "effective" advertising.

Let

$\hat{a}(t)$ = effective advertising at t (index),

β = memory constant for advertising (fraction/period)

A basic model is:

$$\hat{a}(t) = \beta \hat{a}(t-1) + (1-\beta) a(t). \quad (3.3)$$

Now \hat{a} would substitute for a in (3.1). Again more complex models can be customized into the structure.

The above pair of dynamic models, (3.1) and (3.3), can be viewed as representing two types of consumer processes. Equation (3.3) represents an advertising exposure and forgetting model, similar to that used by Little and Lodish [11] and has considerable empirical support. See Lodish [17]. Equation (3.1) represents a product loyalty model. Various forms of such models exist, the one used here being a simple exponential decay. By appropriate choice of α , β , and r , most of the repetition phenomena reported by Ray and Sawyer [13] can be represented.

There are many types of advertising. For example, some firms do national advertising and supplement it with local buying in key markets. Different types of advertising can be weighted to give a composite total.

Let

$w(j)$ = weight for j^{th} type of advertising (dimensionless).

Media efficiency, copy effectiveness, spending rate and reference conditions now vary with advertising type. Eq. (3.2) generalizes to

$$a(t) = \sum_j h(j,t) k(j,t) w(j,t) x(j,t) / \sum_j h_0(j) k_0(j) w_0(j) x_0(j) \quad (3.2a)$$

One application of multiple types of advertising is to different media.

However, the form (3.2a) adds up total weighted exposures without considering overlap between media. Since $a(t)$ feeds into a non-linear response function $r(a)$, (3.2a) is adequate for overall spending rate decisions but is not appropriate for intermedia decisions in which audience duplication is an important consideration. For that case the model structure should be extended to consider overlap effects like those found in MEDIAC [11].

Some companies feel on intuitive or empirical grounds that short pulses of advertising separated by gaps give the most value for the money spent. Others prefer an even effort. Sasieni [14] discusses the issues. The difference is related to the shape of the sales response to advertising curve. A concave curve like that of Figure 3.3a will favor an even spending rate, except for modifications due to seasonality and interaction effects. On the other hand, for an S-shaped curve like that of Figure 3.3b, an even spending rate in the low, flat part of the curve would be almost worthless and the same annual budget could better be spent in a series of pulses, each extending higher on the curve. Thus use of an S-shaped curve can lead to pulses. In addition, when the carry-over rate for advertising depends on the advertising rate, pulsing may also be profitable.

3.2 Promotion

The term promotion covers a wide variety of sales stimulating devices, including temporary price reductions, premiums, coupons, and sampling. Some kinds of promotion are best treated by direct estimates of effect

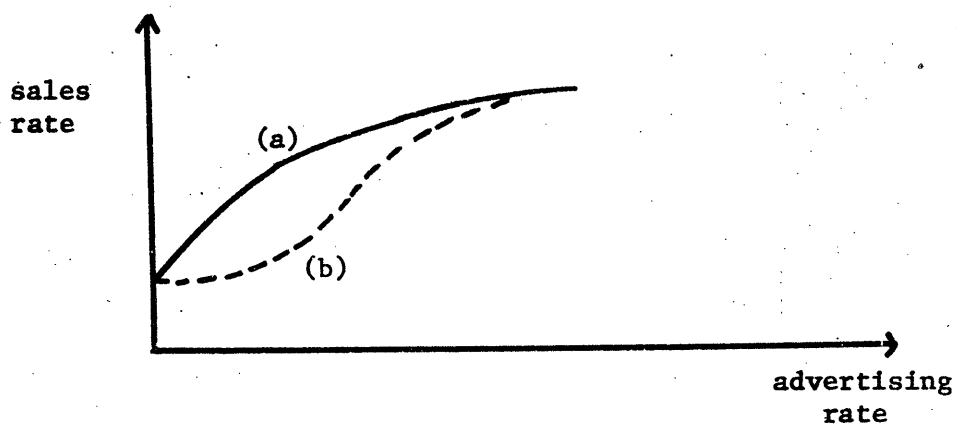


Fig. 3.3. Curve (a) favors an even spending rate, whereas, curve (b) may favor pulsed advertising.

and the index method. Often such estimates can be based on market research pretests or prior experience with similar promotions. On the other hand, certain promotions are relatively fixed in form but have an intensity that varies with the amount of money involved. These can be modeled by a response curve.

An important promotion of this type is the temporary price reduction to the trade. The amount of the price reduction, the duration of the offer, and the fraction of the product line involved control the cost of the promotion. The term, cost, is partly a misnomer since no out-of-pocket expense is incurred and revenue goes up not down. However, the difference between the dollars that the goods would have brought in at full price and those actually received at the reduced price is usually taken as the cost of the promotion.

Price-off promotions are common in package goods marketing. Typically, stores stock up on the product at these times, put it on special display, reduce the shelf price, and sell much more than they normally would. Usually a period of promotion and high sales is followed by a period of depressed sales, at least in terms of factory shipments. This is the result of an extra stocking-up by the retailers and in certain cases by the consumers. Sometimes retailers will discover that a promotion is coming and will hold back on their orders, causing sales to be depressed in advance of the promotion. The sales of promoted packs may reduce the sales of other packs in a process that can be called cannibalization.

The basic promotional submodel will consist of a promotion time pattern and a promotion response function. The time pattern is considered a characteristic of the given type of promotion. For an

illustration, see Figure 3.4. The response function provides a scale factor which multiplies the basic pattern and depends on the promotional intensity, i.e. the promotional offer relative to the offer in a reference promotion. A typical promotional response function for price-off promotions might look like Figure 3.5. At small values of price-off, the promotion works poorly, either because the retailers do not accept it or because the salesmen do not push it very hard. In the middle range response rises fast until a plateau is reached where most major retailers have accepted the promotion and are doing as much with it as they are going to.

To express these ideas analytically, let

$q(\tau)$ = time pattern: the sales index for a reference promotion in the τ^{th} period after the start (index).

$a(t)$ = promotional intensity of a promotion starting in t .
 $a=1$ for a reference promotion, $a=0$ for no promotion (index).

$r(a)$ = sales response to promotional intensity; a scale factor that multiplies the time pattern. $r(1.0) = 1.0$, $r(0) = 0$. (index).

If we suppose that the sales of the product line with no promotion is s_{np} then the effect at t of a reference promotion at t_p is a net sales gain of $s_{np} [q(t-t_p) - 1]$. If the promotional intensity is a , the net gain is $s_{np} [q(t-t_p) - 1] r(a(t_p))$. Usually, only a portion of the line is promoted, say, a particular pack. Also there may be cannibalization. Therefore, let

l = portion of the line promoted (fraction)

b = fraction of sales gain in promoted portion cannibalized from rest of line (fraction).

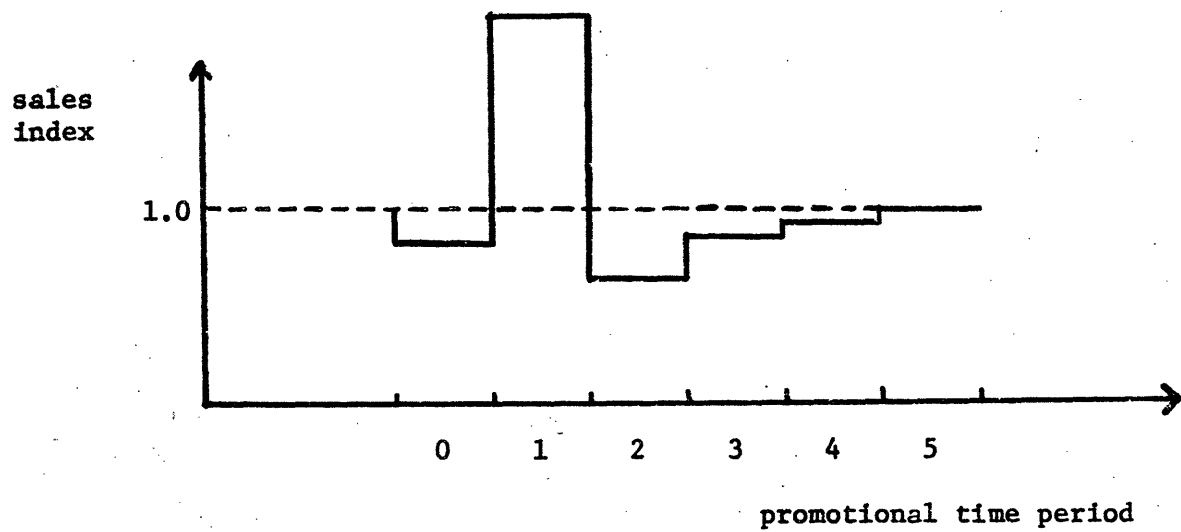


Fig. 3.4. Time pattern of response to a reference promotion (sketch).

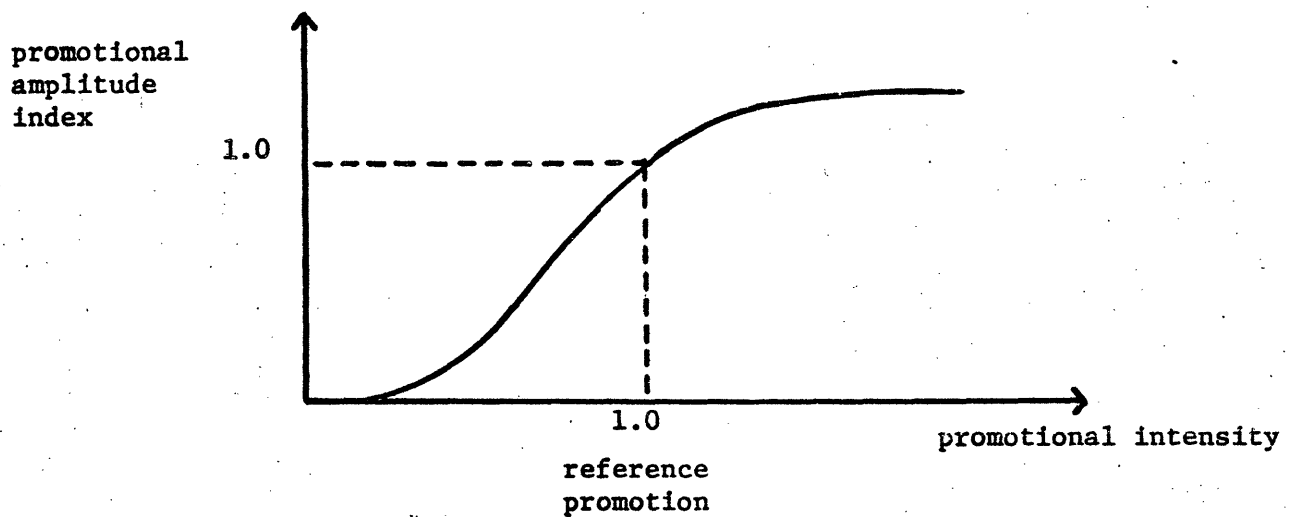


Fig. 3.5. Sales response to promotional intensity, a scale factor on the amplitude of the time pattern (sketch).

Then the sales gain at t of the promoted portion is $s_{np} [1+r(a(t_p)) [q(t-t_p)-1]]$ of which only a fraction $(1-b)$ is a gain for the whole line. The total sales of the line are therefore $s_{np} [1+r(a(t_p)) [q(t-t_p)-1] (1-b)]$.

Reference conditions usually contain promotions and so an adjustment to reference sales is needed to obtain normal sales with no promotion.

Let

e_0 = effect on reference sales if all promotions are deleted (index).

$e(t)$ = effect of promotion on sales at t (index).

Therefore, for a promotion run at t_p ,

$$e(t) = e_0 [1+r(a(t_p)) [q(t-t_p) - 1] (1-b)]$$

The usual situation is a schedule of promotions.

Let them be indexed by p . The promotional effect submodel is

$$e(t) = e_0 [1 + \sum_p \lambda_p r_p(a(t_p)) [q_p(t-t_p) - 1] (1-b_p)] \quad (3.4)$$

As written in (3.4) each promotion can have its own set of parameters, but usually the same time pattern $q(\cdot)$ and response function $r(\cdot)$ will apply to all of a given type.

Next we wish to look more closely at promotional intensity. The basic promotional offer may come in various forms, for example, price-off per case to the trade, cents-off per package to the consumer, the cost or value of a sample or a premium, or the redemption amount of a coupon. In certain cases, factors analogous to the media efficiency and copy effectiveness of advertising will be useful. They may be called "coverage efficiency" to indicate the degree of reaching the customer population, and "consumer effectiveness," to express the effect of point-of-sale materials, premium quality, or other consumer-oriented enhancement of the basic promotional offer. Let

$x(t)$ = promotional offer at t (dol/sales unit)

$h(t)$ = coverage efficiency at t (fraction of customers)

$k(t)$ = consumer effectiveness at t (dimensionless)

Using the subscript zero to denote the reference promotional offer, we have for the promotional intensity

$$a(t) = h(t) k(t) x(t) / h_0 k_0 x_0 \quad (3.5)$$

The costs of a promotion may be fixed or variable or both. Fixed costs are simply an input. The total variable cost however, depends on the promotional offer and degree of response. One helpful use of the model is, in fact, to estimate the cost of a promotion. Let

$$c(t) = \text{cost of promotion at } t \text{ (dol/cust/yr)}$$

$$c_f(t) = \text{fixed cost of promotion at } t \text{ (dol/cust/yr)}$$

We shall consider the case where the variable cost is incurred on all the normal sales in the portion of the line being promoted and on all incremental sales. Normal sales in the absence of promotion are $s(t) [e_0/e(t)]$.

Let

$$[\tau_1, \tau_2] = \text{interval during which promotional allowance is paid on sales.}$$

Then

$$c(t) = \sum_p c_{fp}(t_p) + \sum_p \{x_p(t_p) \} s(t) [e_0/e(t)] [1 + [q_p(t-t_p)-1] r_p(a_p(t_p))]\} \\ (t-t_p) \in [\tau_1, \tau_2] \quad (3.6)$$

Frequently it is desirable to model the promotion in a finer grain of time than the main model, say, weeks instead of months. Weeks might result in useless detail for the main model whereas months might be too crude for a promotion which started in the middle of one month and ended at an odd time in another. The procedure is to develop a main model index by averaging submodel indices for submodel periods falling within the main model period. Prorating is done if the ends of the periods do not coincide. The process is straightforward, if cumbersome, and we do not develop the notation for it here.

3.3 Price

Price is a sensitive control variable and, in inflationary times, a frequently used one. The price under consideration is the basic wholesale price charged by the manufacturer. Temporary price reductions are considered to be promotions.

Figure 3.6 shows a possible curve of share response to brand price. Reference price is defined to be that price which will result in reference share if other reference conditions hold. Response to a price change is usually quite rapid and will be assumed to take place in the period of the price change.

For the most part, retailers take the wholesale price and apply a standard markup to set retail price. Consumer buying, however, is often considered subject to a price-ending effect whereby a shelf price jump from 49 cents to 51 cents may produce a bigger loss than one from 51 cents to 53 cents. As the manufacturer moves his price, an increasing percentage of retailers may go over (or under) a critical price. The net additional effect might appear as in Figure 3.7. Note that the effect is triggered by the manufacturer's absolute price whereas other price effects are likely to be produced by changes relative to norms set by the product class.

Let

- $e(t)$ = effect of brand price on share at t (index),
- $x(t)$ = manufacturer's brand price (dol/unit),
- x_0 = reference brand price (dol/unit)
- $a(t)$ = normalized brand price (index), i.e.,
- $a(t) = x(t)/x_0$ (3.9)
- $r(a)$ = share response to brand price (index),
- $\psi(x)$ = additional effect of retail price-ending (index).

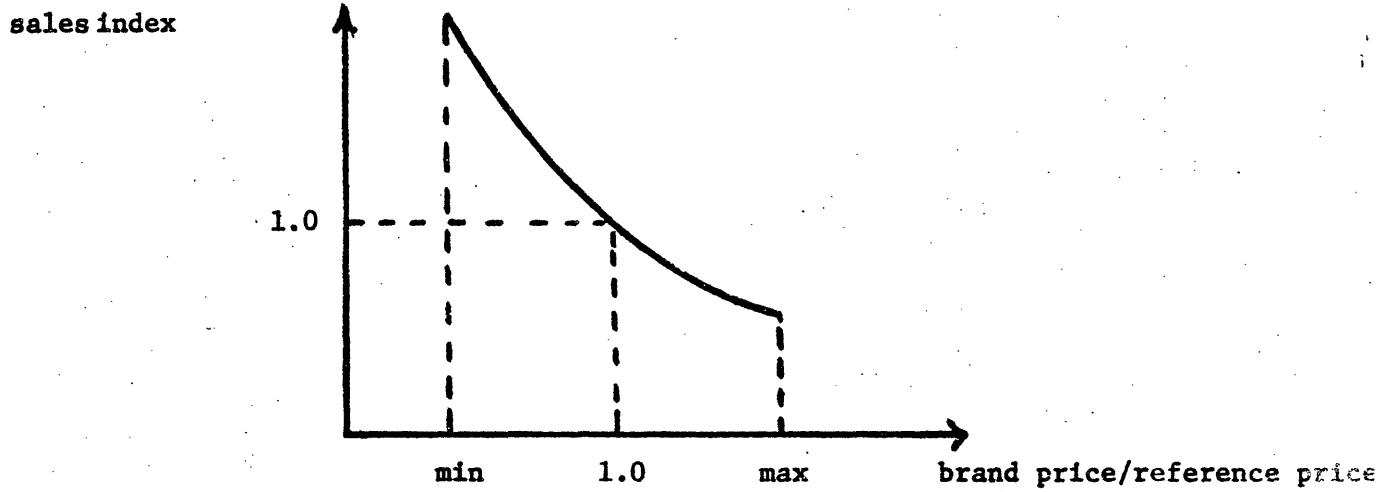


Fig. 3.6 Sales response to manufacturer's price (sketch).

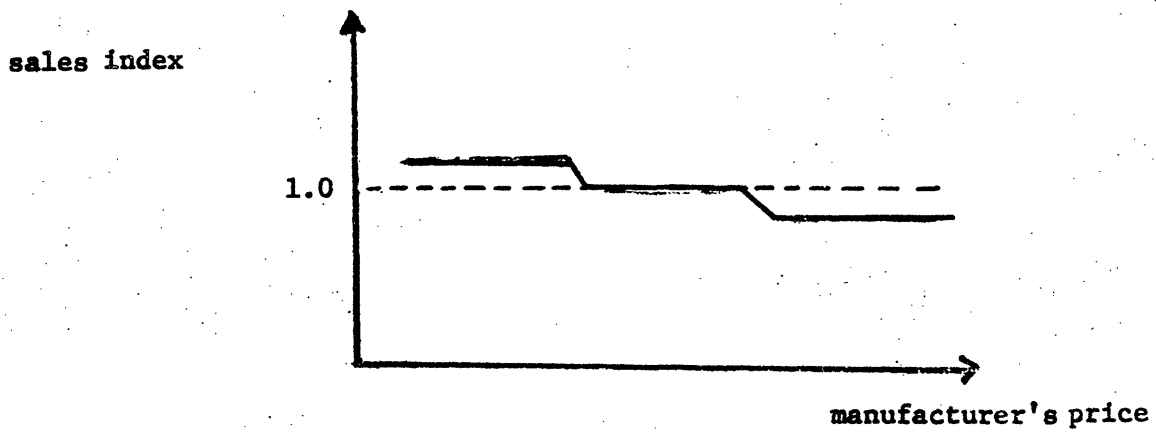


Figure 3.7. Additional sales effect of retail price-ending (sketch).

We take

$$e(t) = \Psi(x(t)) r(a(t)) \quad (3.10)$$

In times of inflation, reference price would not be expected to be constant, but would presumably follow the consumer price index for the product class. Care should be taken in dealing with extremes of price. As Garbor and Granger [15] have shown, the curve may turn down at low prices because the customer starts to attribute low quality to the product. Figure 3.6 depicts the price response curve extending over a limited range of price. By restricting changes to those that can be supported by empirical analysis or managerial judgment, the model is kept robust.

Several cautions are necessary in using a price model. More than any other variable, price changes are likely to precipitate competitive reaction. Furthermore measurements show that competitive prices usually have an important effect on a brand's share. Therefore, if brand price is modeled, so should competitive price. Then any application of the model which includes a price change will contain explicit assumptions about expected competitive reaction.

The manipulation of price exposes important trade-offs for a company. An established brand can often reap substantial short term profits by price increases but only at the expense of a loss in share. A well-calibrated model will show this. Longer term price considerations, such as corporate concern for inflation and competitive entry into the product class, may also affect price decisions.

3.4 Salesmen

A difficult and neglected area in model building is the effect of salesmen on sales. Important recent efforts, however, include those of Montgomery, Silk and Zaragoza [16] and Lodish [17]. We shall propose

a model which is similar but slightly more general than that of the former.

The structure of the model is much the same as used earlier for advertising. Salesmen call on customers and deliver messages. The contact builds up a stock of accumulated effort or good will which is remembered but gradually forgotten. The current and accumulated effort have a positive effect on sales according to a response function. The store's experience with the product, if successful, develops a product loyalty which also has persistence. The salesman's effort rate can be expressed as a spending rate (salary and expenses), an efficiency (calls/dol) and a message quality (effectiveness/call).

Let

- $x(t)$ = salesmen effort rate (dol/cust/year)
- $h(t)$ = coverage efficiency (calls/dol)
- $k(t)$ = effectiveness on store (effectiveness/call)
- $a(t)$ = normalized salesman effort rate (index)

Again letting the subscript 0 denote maintenance or reference effort, we take

$$a(t) = h(t) k(t) x(t) / h_0 k_0 x_0. \quad (3.11)$$

Let

- $\hat{a}(t)$ = effective effort at t, including remembered effort (index)
- β = carryover constant for remembered effort (fraction/period)
- $\hat{a}(t) = \beta \hat{a}(t-1) + (1-\beta) a(t) \quad (3.12)$

Let

- $e(t)$ = effect of salesman effort on sales (index)
- α = carryover constant for product loyalty (fraction/period)

$r(\hat{a})$ = long run sales response to salesman effort (index)

$$e(t) = \alpha e(t-1) + (1-\alpha) r(\hat{a}) \quad (3.13)$$

We are not proposing any behavioral measure of remembered effort. The terminology is designed to motivate a structure which can describe both the immediate and accumulated impact of salesmen's calls.

3.5 Other Influences on Sales

A variety of other marketing activities are shown in Fig. 2.1. These include packaging (graphics and function), the size or package assortment, and changes in the product. Still others often become apparent when a specific application is undertaken. Some, like discrete package and product changes, seem most appropriately handled by direct indices. Others may deserve custom models. The question of changes in pack assortment, i.e., the mix of different sizes or packages of the same product, can be handled by defining the packs as separate entities, but often a direct index will be more manageable.

Two other sales influences are seasonality and trend. Seasonality enters as a direct index affecting product class sales and, for a few products, share. Product class sales may have a trend, which can be treated either by a direct index or a growth rate. In the latter case, let

e_0 = starting point for trend (index)

$r(t)$ = growth rate in t (fraction/period)

then
$$e(t) = e_0 \prod_{\tau=1}^t [1.0 + r(\tau)] \quad (3.14)$$

From time to time, sales will be limited by production. For example, a strike may occur. A production constraint is modeled, simply by clamping sales to the maximum amount that can be manufactured.

A more sophisticated version could be developed to consider pipeline effects. Several of the submodels involve time lags, i.e., the value of a quantity in one time period depends on its value in the previous period. This means that initial conditions must be set. The way this is handled is that, if the user wishes to set them he may, and, if he does not, reference values are automatically inserted.

4. Competition

Consumer markets are competitive. Companies try to differentiate their products to reduce their vulnerability, but, even so, actions by one brand usually affect the sales of other brands in the product class. The thinking of a brand manager, although primarily focused on his own product and its relation to the consumers and retailers, is sensitive to what the competing brands are doing or might do.

Here are the obstacles to modeling competition. First is data. The quantity and quality of data on sales and marketing activities of competitive brands are usually vastly inferior to that for the company's brands. Second is the multiplicity of competition. If each competitive brand is modeled in as much detail as the company's brand, the effort required to calibrate and use the model is multiplied by the number of brands. Third is the specification of competitive actions. Seldom is the competition kind enough to announce its future plans. In the absence of this, a neutral assumption of "next year will probably be about like last year" is likely to be made. If so, one may as well absorb the competition into the reference conditions and not model it all.

Our response to these issues is as follows: With respect to data, one does the best one can, balancing cost of data collection against the

anticipated value of the information. Fortunately, the desire for competitive data is so widespread that syndicated services keep increasing their coverage of competitive activities.

We treat the problem of multiplicity of competitors by flexibility of aggregation and detail. Competition may be ignored, represented by a single "them", or treated severally, by identifying each of the major competitors separately and lumping all others. Different levels of marketing detail can be assigned to different brands. Untreated aspects are absorbed in reference conditions.

Although lack of knowledge of competitive plans hinders easy application of multi-brand models and lessens the urgency of using them, several circumstances, favor their use. For one thing, an important planned action, e.g. a price change, may require the evaluation of competitive counter-moves. For another, the company may wish to estimate the effect of its own actions on its competitors. For still another, the company may have several competitive brands of its own in the same product class and wish to analyze their interaction.

Most important, however, if a company believes it can affect its own share by marketing, it should grant the same ability to its competition. It follows that any true understanding of a brand's past history and present position requires the study of competitive activity. The use of a model for representing knowledge and tracking performance will facilitate diagnosis of marketing successes and failures and is likely to produce better future decisions.

Our guidelines for modeling competition are modularity and symmetry. Modularity is achieved by considering each effect separately; symmetry by having the same basic structure for every brand.

The input of competitive relationships will be expressed by a source of sales method. This approach was stimulated by a manager who described how he analyzed his own marketing plans. He developed the incremental sales of a new program, in part, by directly estimating the total new business and, in part, by estimating its pieces and adding them up. This means estimating how much would come from each competitor and how much would be generated newly for the product class. Such a mode of thinking seems natural to many people and puts the input in a form which permits judging its reasonableness.

If this is to be the approach, there remains a question of how to manipulate inputs for all brands into a net for each. The inputs for an individual brand generate unadjusted incremental sales. After taking into account competitive interactions, adjusted sales will be obtained. All incremental sales are measured relative to reference conditions.

To be specific, consider a single sales influence, say, price or promotion. The basic sales model is still

$$s_j = s_{oj} e_j \quad (4.1)$$

where s_j = adjusted sales rate for brand j (sales units/cust/yr)

$$s_{oj} = m_{oj} S_o \quad (4.2)$$

= reference sales rate for brand j (sales units/cust/yr)

e_j = effect on brand j of the sales influence, taking into account competitive interactions (index).

Brand inputs generate:

e_j' = unadjusted effect index for brand j (index)

$$s_j' = s_{oj} e_j' \quad (4.3)$$

= unadjusted sales rate for brand j (sales units/cust/yr)

Finally γ_{jk} = fraction of unadjusted incremental sales of brand k that comes from brand j (fraction).

The unadjusted incremental sales of brand k relative to reference conditions are $s_k' - s_{ok}$ so that adjusted sales for brand j will be

$$s_j = s_j' - \sum_{k \neq j} \gamma_{jk} (s_k' - s_{ok}) \quad (4.4)$$

Dividing by s_{oj} and using (4.1 - 4.3), we obtain

$$e_j = e_j' - \sum_{k \neq j} \frac{m_{ok}}{m_{oj}} \gamma_{jk} (e_k' - 1) \quad (4.5)$$

Generalizing to an arbitrary sales influence i and making time dependence explicit, we obtain

$$e_j(i, t) = e_j'(i, t) - \sum_{k \neq j} [m_{ok}/m_{oj}] \gamma_{jk}(i) [e_k'(i, t) - 1] \quad (4.6)$$

Equation (4.4) expresses the fundamental model of competitive interaction. Equation (4.6) puts it in calculational form for use in the general expressions:

$$s_j(t) = s_{oj} \prod_i e_j(i, t) \quad (4.7)$$

$$S(t) = \sum_j s_j(t) \quad (4.8)$$

$$m_j(t) = s_j(t)/S(t) \quad (4.9)$$

Notice that, because the model is fully competitive, product class sales are defined as the sum of the sales of the individual brands. Share is then the ratio (4.9).

It is useful to define

$$\gamma_{kk} = 1 - \sum_{j \neq k} \gamma_{jk} \quad (4.10)$$

This is the fraction of unadjusted incremental sales of brand k coming from a product class sales gain.

Notice the differences in orientation between the above method and a Markov chain approach. The latter would specify the fraction of j 's sales going to k . The source of sales method specifies the fraction of k 's new sales coming from k . We argue that this is a more natural collection of parameters for describing what happens when a brand tries to generate more business. (However, an inconsistency could conceivably arise if k 's constants require more sales than j can deliver. This is handled by setting $e_j = \max [0, \text{RHS of (4.6)}]$).

Another point to notice is the restriction of the source of sales adjustments to incremental sales measured from reference conditions. If the source of sales matrix were applied to all brand sales, we would usually find a large rearrangement of shares. This would be especially true if we required some kind of equilibrium flow between brands. We do not do this. Implicit is a belief that markets have considerable stability arising from customer loyalty, distribution system behavior etc., which is hard to change. However, the market is also presumed to have a component which reacts more quickly and quite possibly differently. Incremental changes from reference are, almost by definition, concerned with this flexible component.

Relatively permanent changes in the market also take place. An example would be a brand dropping out of the market. The model accepts such permanent changes and distributes them across brands according to a source of sales matrix. Subsequent time periods treat such changes as part of the reference conditions.

It should be noticed that a different source of sales matrix is permitted for each sales influence. This is because different parameter values may be required. For example, advertising by a national brand may pull sales primarily from other national brands, whereas a price-off

promotion to consumers may draw heavily from private labels.

Often a sensible assumption is that a brand draws its incremental sales from competing brands proportional to their reference shares.

$$\text{Then } \gamma_{jk} = (\text{const}) m_{oj} \quad \text{Normalization gives } \gamma_{jk} = m_{oj} (1 - \gamma_{kk}) / (1 - m_{ok}) \quad (4.11)$$

5. Retail Distribution

By retail distribution we mean a cluster of marketing activities that are conducted by the retailer and affect the sales of a brand. Each such activity will be presumed to have an observable variable associated with it. Examples would be retail price, retail advertising, availability, quality of shelf position and facings, number of in-store promotional displays, or some composite measure of distribution made up from several of these.

Previously we have avoided explicit consideration of distribution and have, for example, modeled the effect of salesmen directly on sales without the intermediate step of distribution. As shown in Figure 2.1, some manufacturer actions primarily affect the basic consumer purchase intention, but others are aimed at the retailer to enhance distribution and so turn intentions into sales. If relevant data can be obtained, the model can be made stronger and more useful by representing retailer activities explicitly.

In this expanded view of the system, a sale is a consumer action resulting from manufacturer activities, retail activities, environmental influences, and possibly other effects. The retailer activities, in

turn, are substantially affected by manufacturer actions. Let

$$I_M = \{i_1, \dots, i_M\} = \text{set of manufacturer activities}$$

$$I_R = \{i_1, \dots, i_R\} = \text{set of retail activities}$$

$$I_E = \{i_1, \dots, i_E\} = \text{set of environmental and other influences}$$

Thus sales for a given brand are

$$s(t) = s_0 \prod_{i \in I_M} e(i,t) \prod_{i \in I_R} e(i,t) \prod_{i \in I_E} e(i,t) \quad (5.1)$$

Submodels connect the consumer sales effect indices for $i \in I_R$ with their corresponding retail activity variables. Let

$$d(i,t) = \text{the } i^{\text{th}} \text{ retail variable, } i \in I_R$$

$$f(i,d) = \text{response submodel for } d(i,t)$$

$$e(i,t) = f(i,d(i,t)) \quad i \in I_R \quad (5.2)$$

The retail activity variables, however, are affected by the manufacturer actions and possibly by environmental and other influences.

This is treated in our standard way by multiplicative indices:

$$d(i,t) = d_0(i) \prod_{k \in D(i)} e(k,i,t)$$

where $e(k,i,t)$ = effect of k^{th} manufacturer, environmental, or other influence on retail variable $d(i,t)$. (index)

$D(i)$ = set of influences on $d(i,t)$.

$d_0(i)$ = reference value of $d(i,t)$.

Typical manufacturer actions with an important effect on the retailer are salesman effort, trade promotion, and package size assortment. The retailer is also affected by the inherent sales rate of the product, since stores favor those items that sell well. Seasonality is also likely to enter.

Among the various possible distribution variables, we shall build a specific new submodel for availability. Retail price and promotion will

be handled through earlier models. Certain other retail activities, such as advertising, seem best handled at this point by use of direct indices or by subsuming them within other variables.

To build an availability submodel we need two relationships, one between sales and availability and the other between availability and the manufacturer's control variables. Availability is taken to include such items as the presence or absence of the product, its shelf position, and the number of its facings. These items could be split up into separate measures of retail activity, but, as a practical matter, we presently consider only a single measure and intend it to be tailored to the application. For example, we might use "all commodity distribution". This is the fraction of stores carrying the brand, the stores being weighted by their size as measured by their all commodity sales. For products like paint or small appliances, which tend to be sold in lines, this type of distribution is often highly variable by region and important to sales success. Measures more complicated, but still single, might be constructed to take into account the presence or absence of individual packages, and, if information is available, shelf space and position. Considerations in a particular application determine how much detail is worth modeling and when several measures should be considered individually.

Suppressing subscripts, let

$d(t)$ = availability of brand at t (fraction)

$e(t)$ = effect on consumer sales rate at t (index)

$r(d)$ = sales response to availability (index)

$e(t) = r(d(t))$

(5.4)

Figure 5.1 sketches a possible sales response to availability curve.

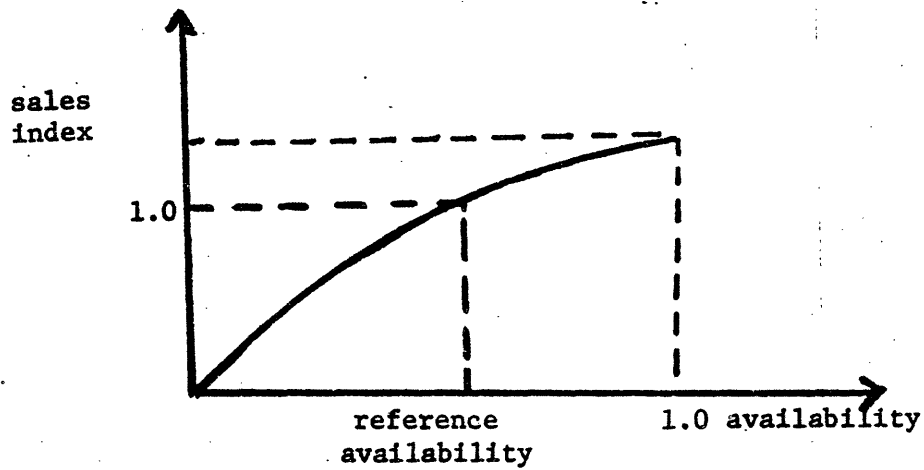


Figure 5.1 Retail distribution effects: sales response to availability (sketch).

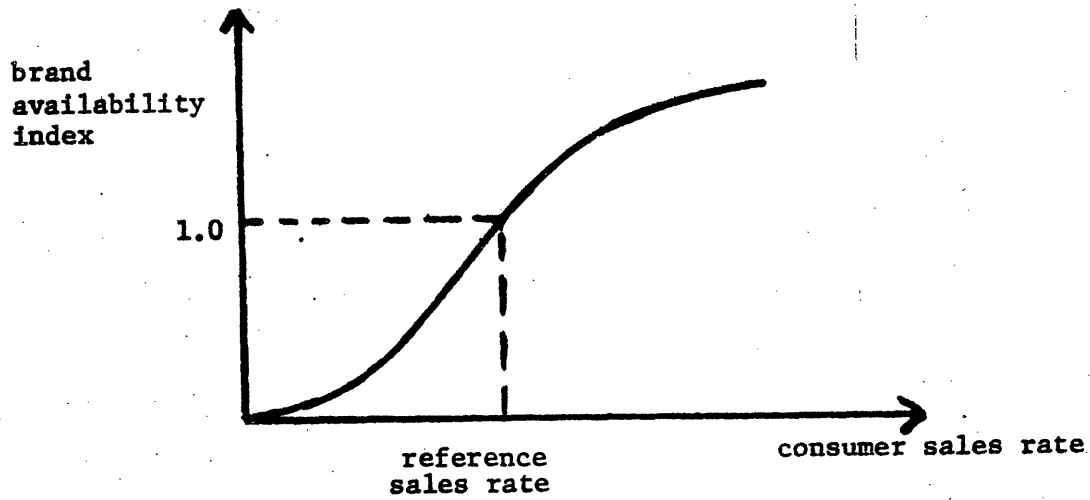


Figure 5.2 Response of retail availability to consumer sales rate (sketch).

To relate $d(t)$ to marketing activities, let

d_0 = reference availability (fraction)

D = set of manufacturer and other activities influencing $d(t)$

$e(k,t)$ = effect of k^{th} activity on $d(t)$ (index).

$$d(t) = d_0 \prod_{k \in D} e(k,t) \quad (5.5)$$

The set, D , of activities affecting availability will ordinarily include seasonality, salesmen, brand sales rate, and possibly promotion. Seasonality is straightforward. Salesman effort has been modeled earlier in (3.11 - 3.13). The same structure is used here but the effect is now on availability rather than directly on sales, so that $e(t)$ of (3.13) becomes one of the $e(k,t)$ of (5.5), and $r(a)$ of (3.13) must reflect this. Trade promotions are discussed separately but may have some effect on normal availability measures. Therefore, if desired, some of the promotion effect on sales can be backed out of (3.4)-(3.5) and included as an $e(k,t)$ here.

The most interesting component of $d(t)$ is that for sales rate. Retailers tend to carry those products that sell well. Nuttal [10] has shown this dramatically in the case of candy, using a measure of availability that consists of the percent of stores stocking the brand. In general, let

$v(t)$ = consumer sales rate at reference retailer activity as a fraction of reference sales (index)

From (5.1)

$$v(t) = \prod_{i \in I_E \cup I_M} e(i,t) \quad (5.6)$$

The long run response of availability to the inherent consumer sales rate might appear as in Figure 5.2. Habit is strong and existing levels will tend to carry-over. Suppressing the activity label k , let

$r(v)$ = long run response of availability measure to sales rate (index)

α = carry-over constant (fraction/period)

$e(t)$ = effect of sales rate on availability measure (index)

We take

$$e(t) = \alpha e(t-1) + (1-\alpha) r(v(t)) \quad (5.7)$$

Turning to other distribution variables, we observe that trade promotion usually brings about substantial retailer activity. The in-store manifestations may include special display, lower price, and the posting of point-of-sale advertising. Although data collection of these items is possible, the effects of trade promotion are sufficiently dramatic and short-term that they can usually be measured by sales itself. Therefore, instead of going through the two-step process of defining a retail distribution measure and a function relating it to sales, as in (5.2), we shall retain the submodel developed earlier except that it will be now considered part of the retailer set I_R . In a formal sense (5.3) and (5.2) have been coalesced into a single submodel.

Price is treated similarly. The retailer sets price but often the process is fairly mechanical so that the manufacturer is still in a dialog with the final customer. If so, the previous submodels can be reused but considered part of I_R in (5.1). Sometimes, however, a brand can become positioned as a special attraction or, oppositely, finds itself priced extra high so that a house brand can look like a good buy. Such effects can be handled by a further direct index in the I_R part of (5.1). Media advertising by retailers is generally considered to have rather a small effect on brand sales (although it may have an important effect on store patronage) and so it too can be treated in the same way.

6. Calibration

By calibration is meant finding a set of values of input parameters to make the model describe a particular market. A first question is: how accurately must the market be described? Our answer is: better than the company has been able to do before. Clearly, instant perfection is unlikely. Because science and computers have such a popular image of precision and infallibility, care is sometimes necessary to avoid unreal expectations. However, it is not difficult to start better than the existing situation and improve.

Certain inputs are state data, i.e., are numbers which describe the market as it stands. Examples are reference values of share, product class sales, advertising and promotion. These are usually straightforward to obtain. So are seasonality and trend. A more difficult type of input is response data, i.e., how sales and other performance measures depend on marketing control variables like price or advertising, and so the discussion here will focus on them. However, it should be kept in mind that most of the calibration is founded on current operations. If control variables are held at reference values, the model will project forward in the manner of a conventional forecast.

A five step process is suggested for determining response information when none has existed before: (1) judgement, (2) historical analysis, (3) tracking, (4) field measurement, and (5) adaptive control.

Judgement. People who make decisions about marketing budgets, prices, package designs, etc. are implicitly making judgements about response. At a minimum, therefore, we can calibrate response functions with their judgements and be at least as well off as before. Usually, we shall be better off because we obtain the judgements in an organized way and can obtain them from more than one person.

As it turns out, individuals working closely with a product often make surprisingly similar response estimates. They may, of course, be similar but wrong. It seems likely, however, that their day-to-day efforts to improve sales leave them with a rather good impression of what can and cannot be achieved.

The task of drawing out judgements from experts has received considerable attention in recent years. Our own procedures have been quite simple. A group of knowledgeable people is assembled. The definition of the response to be estimated is discussed in detail. If a response curve is wanted, a table of control variable values is provided along with blanks for the corresponding response values. Each person fills in his estimates. The results are then displayed on a blackboard in anonymous form and discussed. People usually identify their own estimates and a lively discussion follows as to why certain values were picked. Sometimes misunderstandings about what was to be estimated are uncovered. People may introduce considerations that lead others to change their values. Finally, a consensus position is proposed, perhaps modified, and then adopted.

Figure 6.1 shows a share response to advertising curve developed in this way. Each light line represents a different person in the group. The heavy line is the curve finally adopted. Clearly there is a range of opinions, including a particularly extreme case. Yet the differences are fruitfully explicit. The final curve is understood by all participants. It forms a good starting point to which later information can be added. The curve shown is one of a set developed to apply to different geographical regions. (It has been rescaled to protect the original data.)

A particularly interesting application of judgmental methods arises in calibrating the sales response curve in the salesman submodel. Field

SHARE RELATIVE
TO
REFERENCE SHARE

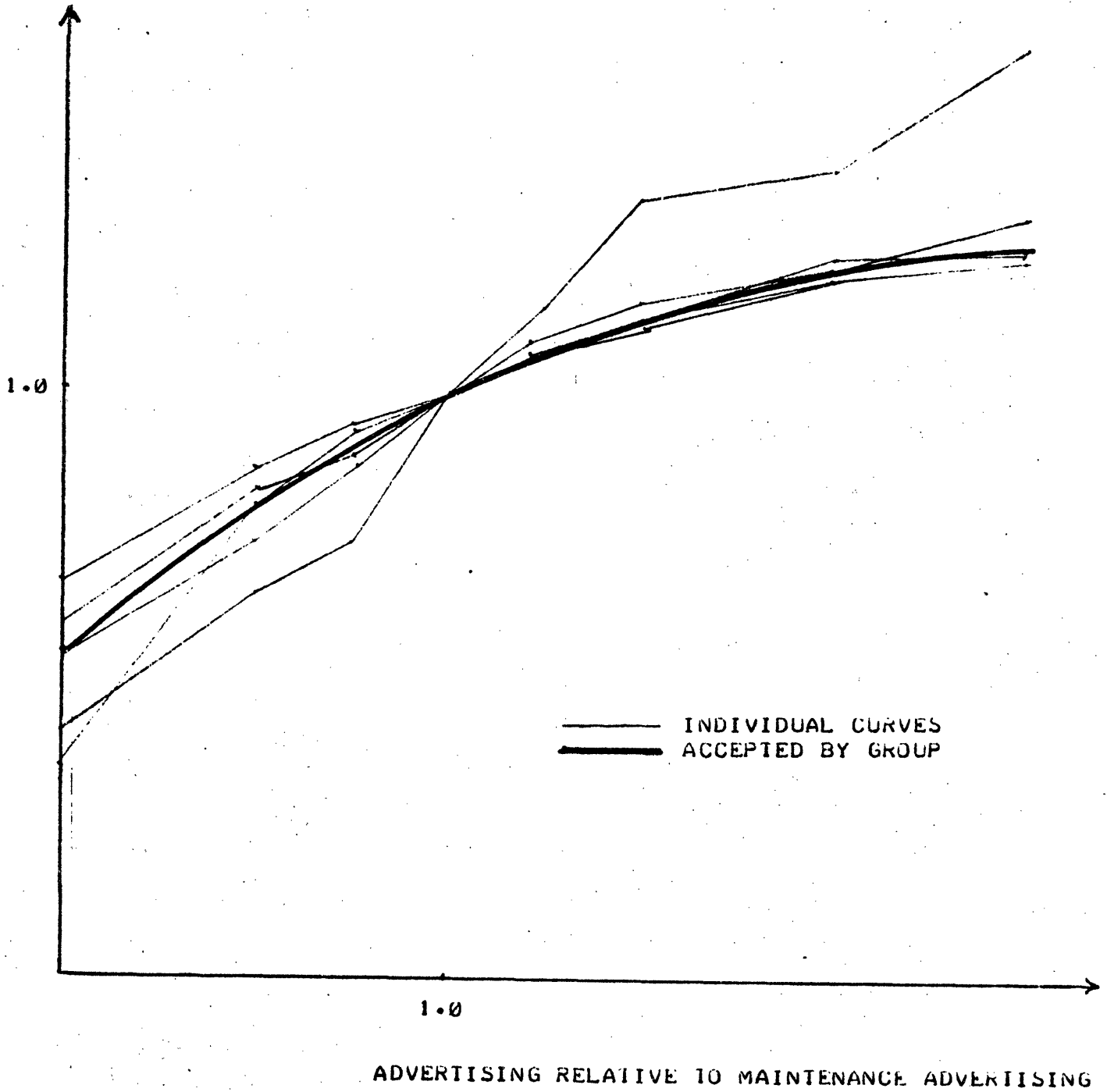


FIGURE 6.1. A JUDGEMENTALLY DETERMINED CURVE OF LONG RUN SHARE RESPONSE TO ADVERTISING RATE.

measurement is difficult because of the inherent variance in sales, although an early study by Brown et al [19] had some success. An encouraging new approach has emerged as a spinoff from Lodish's individual salesman call planning system [17]. Each salesman judgmentally appraises the sales response to additional calls for each of his own customers. This information is kept up to date by him for his own use. However, by aggregating our customers and salesmen, an overall curve of sales response to sales effort for the company can be developed. Although such a curve may initially have biases, they can quite possibly be learned and allowed for. This method of determining sales response has the promise of bringing new, rather detailed information to bear on a long standing and very important problem.

Historical Analysis. The next step is to learn as much as possible from the statistical analysis of available data. Plots and cross tabulations can be made. Time series and cross-section regressions can be run on sales or share vs. price, promotion, or advertising. As many independent views of response as can sensibly be devised should be generated. Examples of this type of analysis abound. See, for example, the review of Parsons and Schultz [2].

Several comments about historical analysis can be made. First, we wish to distinguish between a statistical model and a decision model. A statistical model is a functional form plus a hypothesis about random errors which together form a basis for statistical estimation. A decision model is a relationship between performance measures and control variables. In the present case both would be descriptions of the market and a person can reasonably ask why they would not be the same. The main reason is that most statistical models are not robust.

A linear relationship between sales and advertising, for example, may be statistically reasonable in the sense that the range of available data may make estimation of nonlinear effects pure rubbish. Yet from a decision point of view the linear model is equally rubbish. A solution to the dilemma is to set upper and lower bounds on response by other methods and set the slope at the current operating point by a statistical estimate. A predetermined functional form can fill in the rest of the curve.

Sometimes historical analysis leads to useful response estimates, sometimes it does not. One of the reasons for starting with judgmental numbers is to prevent people from over-interpreting historical analyses, which invariably are based on a limited time period and a limited set of variables. Statistical results sometimes take on too great an air of authority because of their seeming objectivity. In developing inputs for BRANDAID, experience has usually been good with the analysis of promotions of the price-off variety and with studying brand and competitive price changes. Experience has usually been poor in studying advertising.

Tracking. One of the most illuminating steps in calibrating a model is to run it on past data. Response data are put in, along with past values of the control variables, and the model is run. Predicted sales are compared to actual. Deviations are shown to the brand manager and almost always lead to discussions of previously unconsidered marketing phenomena and to new inputs for the model.

Good tracking does not by itself guarantee that the model is well calibrated. A critic can legitimately argue that the model contains enough constants so that almost any past history could be fit. Various protections exist against abuse of this flexibility. First, the user himself should be involved in the calibration and so monitor the process.

Second, one standard technique that can be employed is to calibrate the model on one set of data and test it on another. Third, the model is used for prediction and so will be tested and updated as time passes.

In appraising the results of tracking, we should relate them to our calibration goal, namely to improve on the company's previous description of the market. When the above steps produce a model that tracks well, this is likely to have been done: A set of sub-descriptions will have been constructed which (1) make sense to the manager as explicit statements about the market and (2) fit together to play back sales when the model is run.

An example of tracking will be given in the case study of Section 7.

Field experiments. Unlike an astronomer who must watch the skies for what happens and analyze after the fact, the businessman can experiment in the market place. Frequently this is done. There are many forms of experiment each suitable for certain measurement objectives. Some examples are Floyd and Stout [20], Cox [21] and Rao [22].

Adaptive control. The market changes with time, and so, presumably, does the response to the control variables. Monitoring systems are needed. Ongoing tracking and diagnosis do this, but the process can be substantially assisted by continuing measurement programs. Some companies, in effect, do this now. For a discussion of a formal model of an adaptive control system, see Little [23].

7. Case Study: GROOVY

A report on a live application will illustrate how the model fits into the brand management process. GROOVY is a pseudonym for a well-established brand of packaged goods sold through grocery stores.

Figure 7.1 shows GROOVY sales (warehouse shipments) by month for 1966-68. Sales appear to be highly volatile.

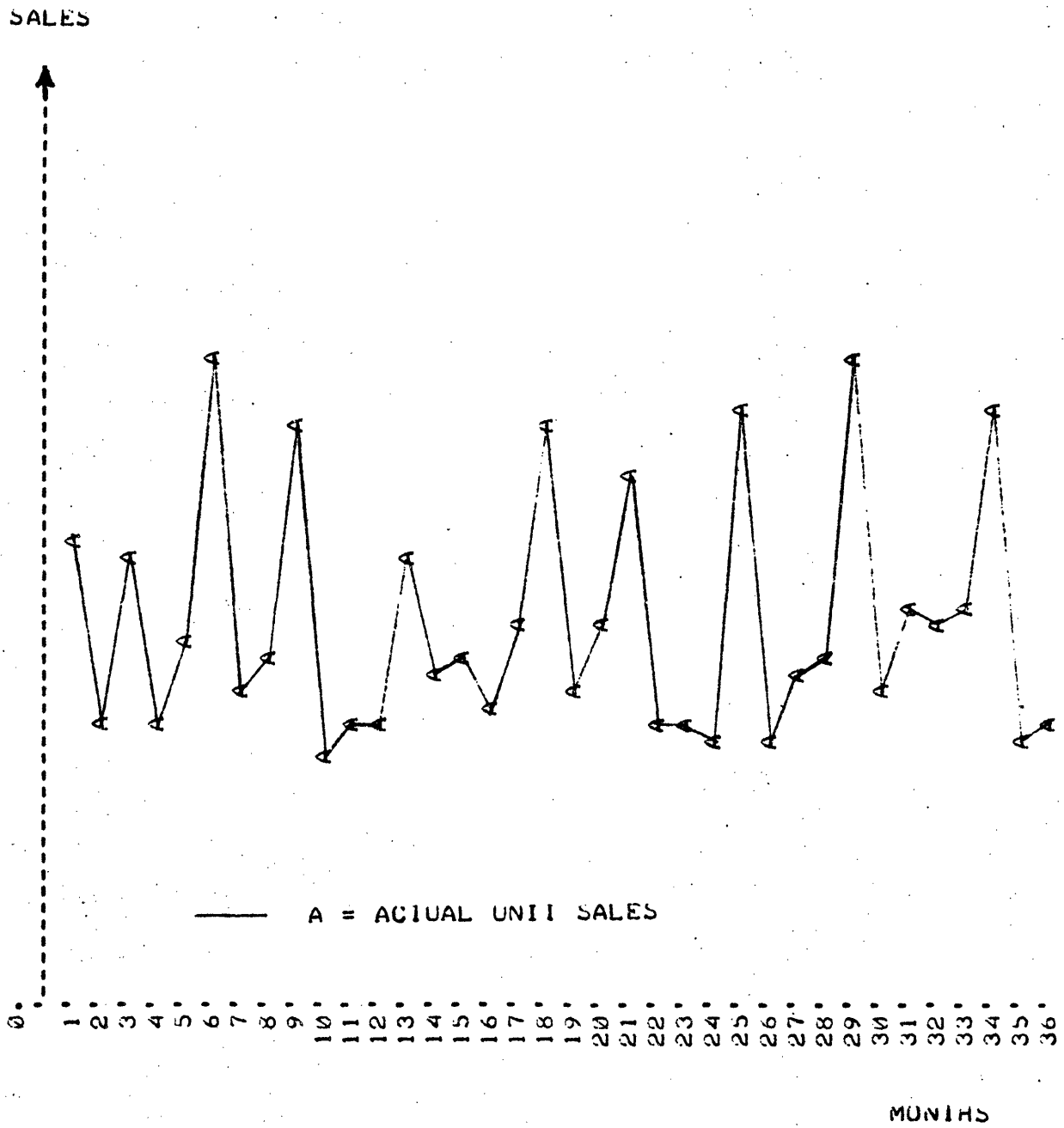


FIGURE 7.1. GROOVY SALES FOR 1966-68

Model implementation can be divided into introductory and on-going periods. The introductory period includes orienting management, forming a team, selecting and formulating a problem, calibrating the model, and initial use. The on-going period includes firefighting, tracking and diagnosis, updating, and re-use.

The introductory period for GROOVY started with a seminar for management on the application of management science in marketing. Subsequently, a team led by the GROOVY brand manager was formed to bring up BRANDAID to analyze marketing strategy and assist in the annual brand planning. Other members of the team were individuals with skills in marketing research, advertising, sales analysis, and management science, the latter being a models specialist.

In selecting a problem, the main emphasis was put on brand planning, especially on setting advertising and promotion budgets, and allocating them over time. In addition, the intention was to produce a month by month forecast of GROOVY sales for the planning year.

With respect to problem formulation, the model was chosen to be national in scope without further segmentation and a basic time period of months was selected. Advertising was treated as a single variable expressed in dollars, since most of the money was in a single medium, television. Advertising and promotion were to be handled by response curves. Seasonality was to be considered. Competitive effects were not to be modeled at this time. A data base was then put together. It contained past sales and marketing expenditures from company records plus various share and product class data derived from Nielsen.

The major calibration of the model took place over about three calendar months with the team meeting on the average of about a half a day per week. The work started by setting reference conditions. 1969 was chosen as a base year. A Nielsen share figure was accepted and,

knowing brand sales from company records, a reference product class sales was established.

The advertising calibration began with a judgemental response curve developed by the advertising-knowledgeable members of the team. Then historical time series data were analyzed by regression with advertising and promotion as the principal independent variables. Promotional effects came through very strongly. Contrary to usual experience, advertising effects came through rather well, too. This was due, at least in part, to the high variance in historical advertising rates. The regressions were discussed by the team, which then adjusted the advertising response curve in the direction of the regression results. The promotional response as estimated by the regression was quite similar to that which company analysts had previously come up with and so this response estimate was considered to be in rather good shape.

Once the model was calibrated, initial brand planning began. Several different budget levels and allocation schemes were tried out. These gave rise to others until quite a variety of different plans were formally evaluated for profitability. Table I shows the results of five of them in coded form. They and several others were presented by the brand manager to higher level management along with his recommendations. Relative to the plan currently under consideration, his recommendation called for one additional promotion and increased advertising with the advertising allocated differently over the year. Management felt, rightly or wrongly, that the advertising response information was shaky and so the final decision was to hold back on the advertising but go ahead with the promotion. At the same time, however, a field measurement program in advertising was authorized.

Several observations can be made about the implementation up to this

point. First, the model did what it was supposed to, namely it related sales and profit to the control variables and could be operated easily to evaluate spending strategies. Second, the marketing decisions about the brand, particularly the overall budget levels, interacted with the decisions for other company products. Thus company guidelines stated that marketing expenses should not exceed a given percentage of sales. Therefore, spending on one brand meant not spending on another. Similarly the company's brands compete with each other for sales to some extent so that profitability for one may be partially at the expense of another.

These considerations are not built into the single brand model nor are they entirely within the assigned responsibility of the brand manager. One conclusion could be that a model of a single brand cannot do what is needed because the real decisions are more complex and at a higher level. An obvious step would be to model these higher level problems and, indeed, this is being done. However, we believe the brand model is a correct tool. The brand manager system is an advocacy system built around the idea of profit responsibility, and the brand model is an appropriate planning aid to support that system. However, users must realize that the optimum point as viewed from the brand may not be the right point for the firm as a whole. This is an example of a general observation that many decisions are affected by considerations outside the model at hand. Even in the above situations, however, the model exposes critical profit tradeoffs.

One consequence of the involvement of higher levels of management in brand decisions is that they need to understand what the model does and does not do. This usually takes a planned effort, built around using the model on specific marketing problems.

Another observation is that, although the demands of calibrating and operating the model are not large, they are competing for managerial time

with many other pressing issues. A model may be viable as a straight overload but for efficiency it is best to move it gradually into planning and forecasting, to replace parts of the current system. Furthermore, a model definitely requires staff support from individuals with management science skills. The brand manager can use the calibrated model by himself because it is on-line and easy to use, and the fact that he can is quite important. However, direct operation by the manager is ordinarily not the best use of his time. A management scientist who has helped formulate and calibrate the model is able to use it more efficiently and can help greatly in formulating questions and interpreting output.

Returning to the chronology of GROOVY, after an initial brand planning push, the on-going period of implementation was entered. Tracking studies were started. These turned out to be very illuminating. Discrepancies between predicted and actual immediately showed up a promotion missing in the historical data. More interesting, a period of low sales in the brand history was identified by the product manager as a period of increased price difference between GROOVY and its competitors. Historical price data were dug out and put into the earlier regressions with good results. After this addition, the three major marketing variables of the brand, price, promotion, and advertising, were handled in the model by response curves.

We would like to emphasize the simplicity of the model as used in GROOVY. The number of options available within BRANDAID tends to obscure the uncomplicated nature of most applications. Figure 7.2 shows the individual indices that multiply together with reference share and product class sales to give predicted brand sales. The advertising calibration considers sales persistence only and promotion considers only two periods of effect. The price model considers both

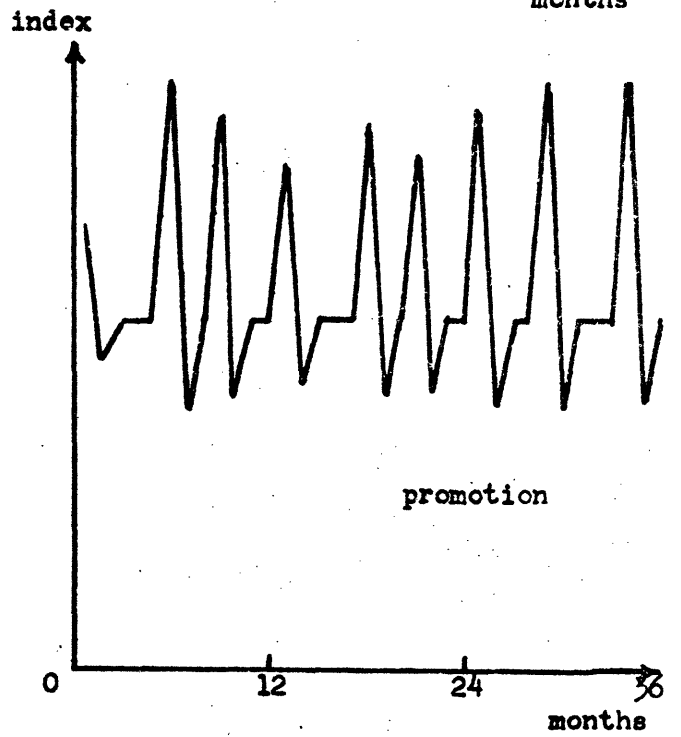
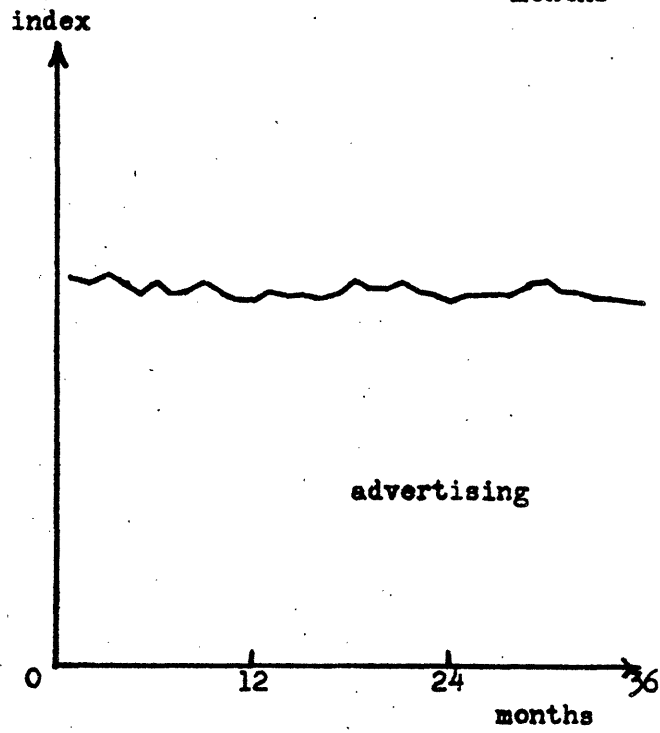
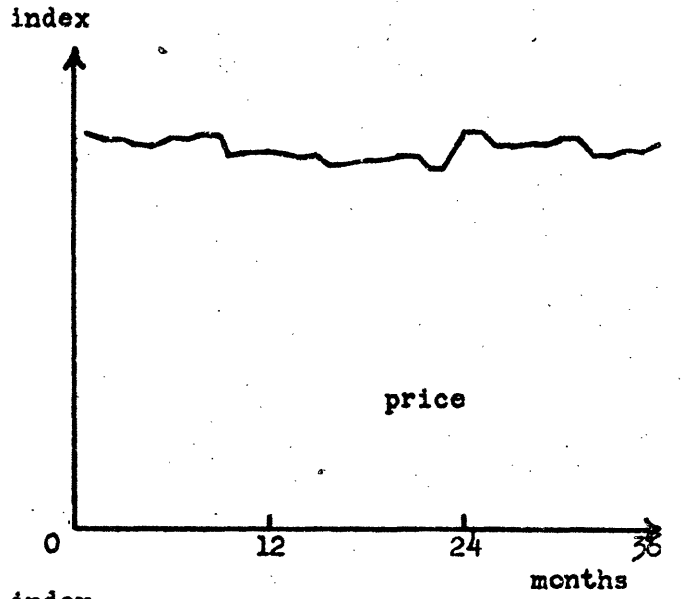
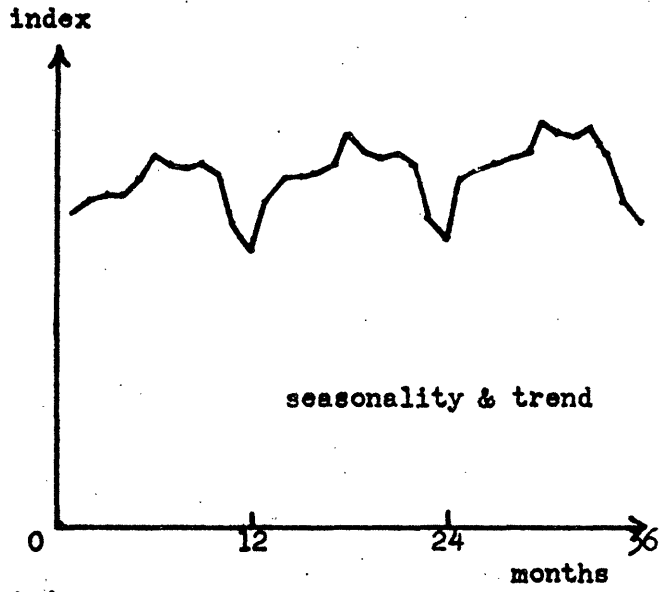


Figure 7.2 The individual effect indices.

company and competitive price. The final tracking shown in Figure 7.3 is remarkably good. (The discrepancy in March 1966 is the missing promotion, which we have never gone back to correct.)

Although Figure 7.3 looks fine, we must ask how well the predictions will hold up in a time interval which has not been used to calibrate the model. The answer, in part, is Figure 7.4.

Disaster seems to have set in. Close inspection, however, is revealing. First of all, there is a "normal period" at the start where the predictions are very close. Then if the model is continued on with the same calibration, the screws seem to come loose. What is occurring in the market is a variety of events not included in the model and, although the point is completely obvious, this illustrates that the model will predict only those phenomena that are built into it. The new phenomena are a strike and a new package size. The package size effect was estimated in advance by marketing research. The results with the updated model are shown in Figure 7.5. We have taken the liberty of modeling the strike retrospectively using the production constraint. As may be seen, it appears that the new package was more successful than anticipated. On the whole, however, the model predictions were considered good and since then the model has continued to track well.

Several firefighting episodes have occurred since the model came into use. These include price changes, proposed advertising changes, the dropping of a promotion, and its subsequent reinstatement. In each case evaluations of the immediate and long run consequences of these moves with the model became parts of the input to the decision. In some cases the strategies suggested by the model were overruled by other considerations but in many cases they were chosen.

The question is sometimes asked whether there have been any clear-cut instances in which use of the model resulted in an action which would

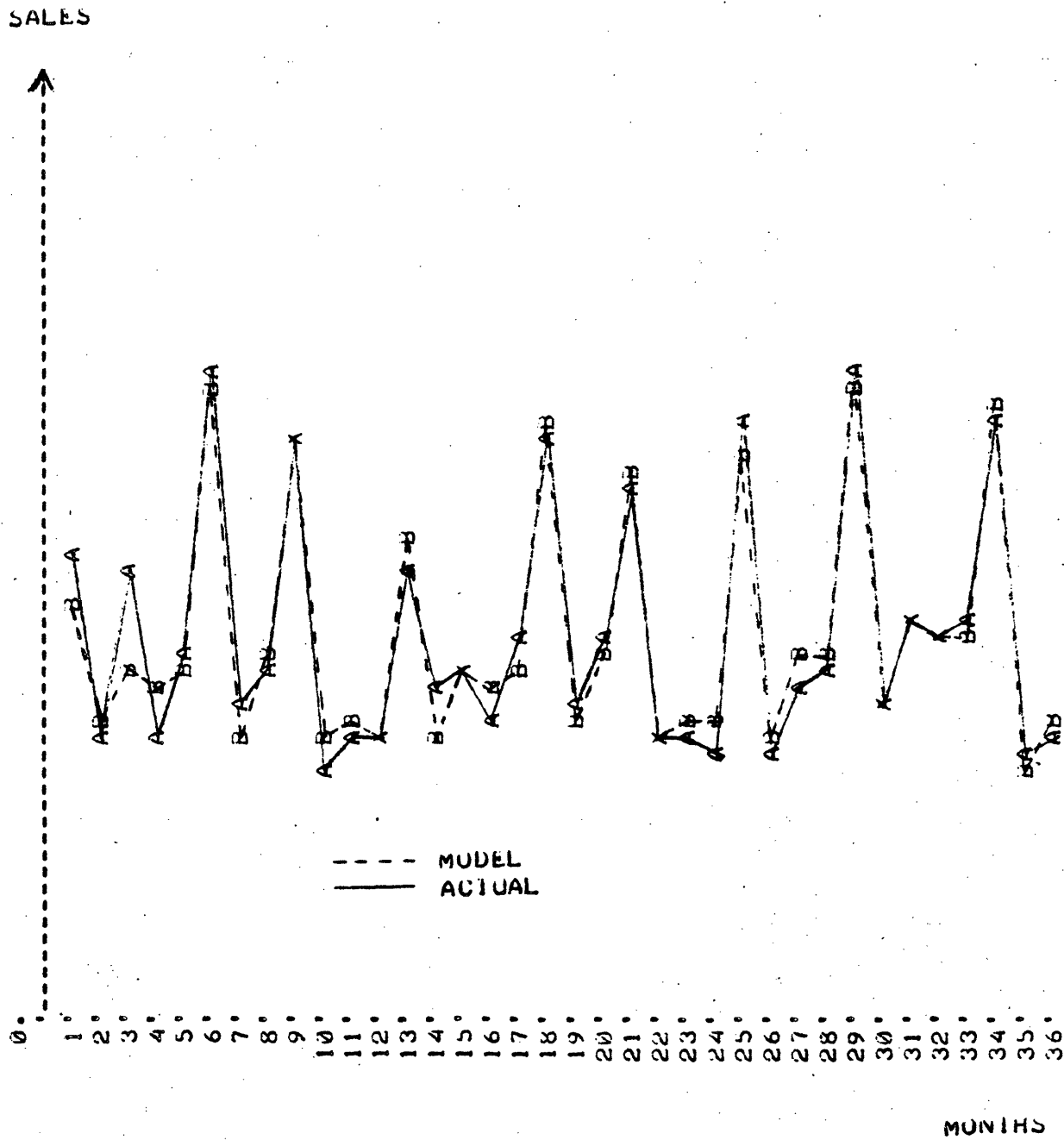


FIGURE 7.3 FINAL TRACKING OF CALIBRATED MODEL 1966-68.

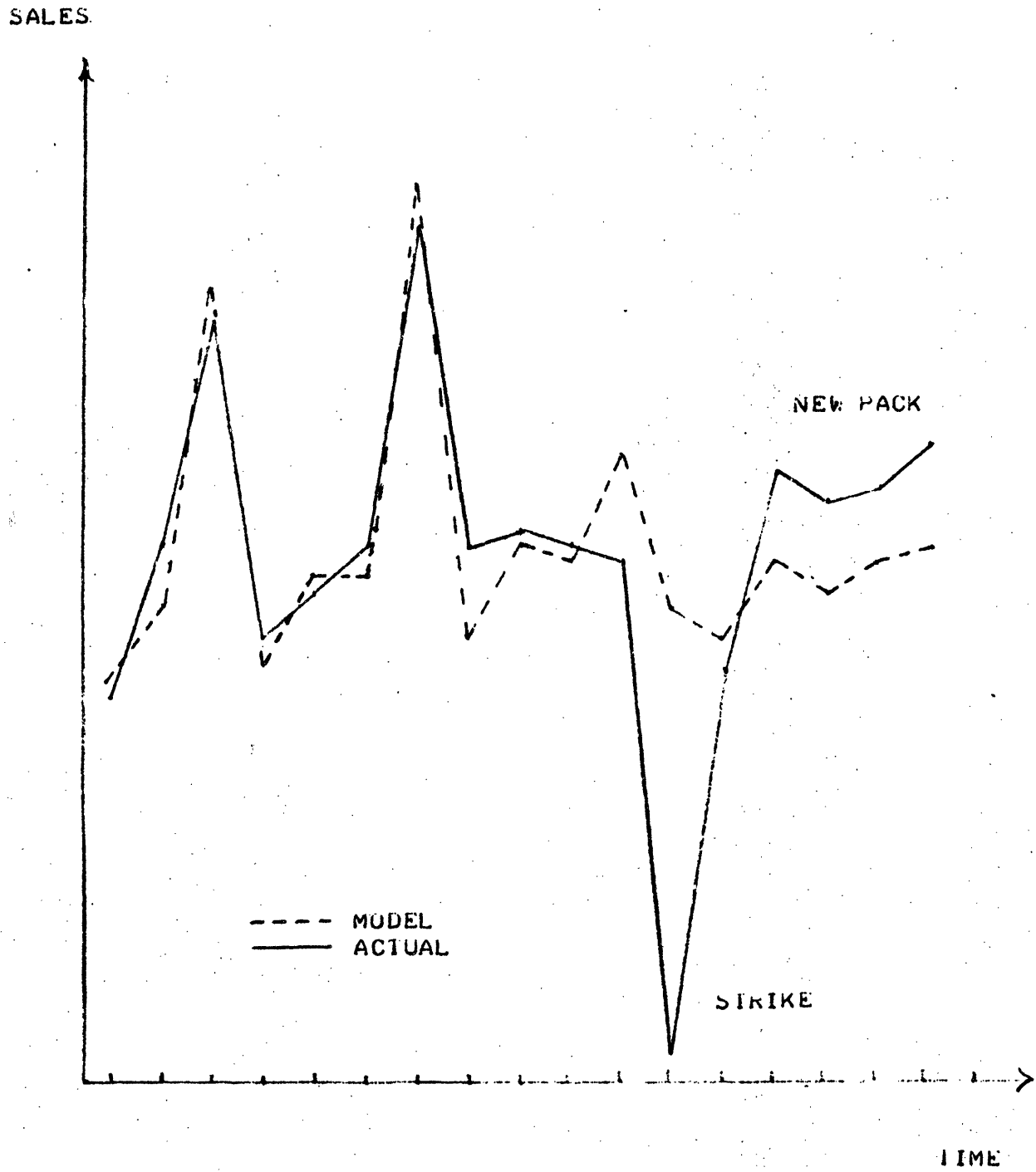


FIGURE 7.4. TRACKING OF THE MODEL WHEN THE CALIBRATION OF FIGURE 7.3 IS CONTINUED INTO 1969.

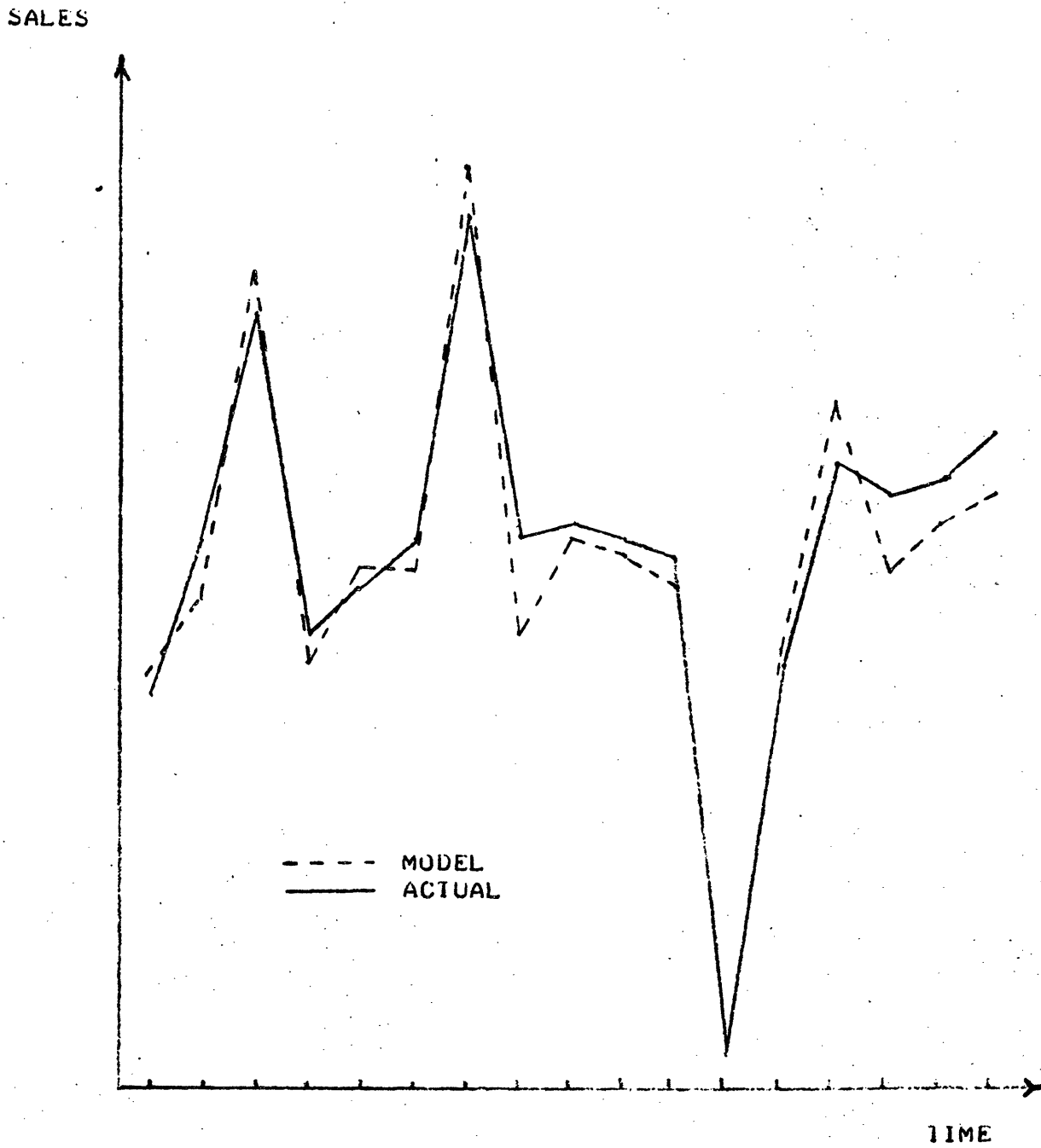


FIGURE 7.5. TRACKING AFTER UPDATING CALIBRATION BY A PRODUCTION CONSTRAINT FOR THE STRIKE AND A MARKETING RESEARCH PRIOR ESTIMATE OF THE NEW PACK EFFECT.

not otherwise have been taken. An example of this type happened in June 1971. At that point the year-to-date sales of the brand were substantially ahead of the previous year. Thus, by one of the most commonly accepted criteria of performance, sales looked good. However, the brand manager suddenly announced the brand was in trouble. Why?

The brand team had been doing regular tracking and analysis of performance. They became aware of important differences between this year and last. A promotion had been run in January of the current year but not in the previous year. In addition, during March of the current year, price has been increased. However, its effect as a depressant on sales was masked by a large corporate TV special and coordinated promotion in which the brand, among others, had been featured. Close study indicated a greater loss in sales occurred than would be expected from a normal price effect. This led to a scrutiny of auxiliary marketing research data and the discovery of a price-ending effect. The median shelf price of a major pack of the brand had moved from 49¢ to 52¢ in the stores. As a result the team modified the model to include the price-ending phenomenon.

Reruns then made it clear that, although year-to-date sales were good, after the model took into account that much of the promotional activity was over, much of the advertising money had been spent, and the price had been increased, the sales picture for the rest of the year was bleak. The brand manager therefore proposed an additional promotion and, on the strength of his case, the management accepted the recommendation. Here, then, is a good example of an action which almost certainly would not have been taken without the tracking and forecasting of the model. By the time the losses would have been detected in actual sales, it would have been very difficult to plan and execute the promotion.

Since that time the model has been used regularly for brand planning and has been frequently called into play for firefighting. Other brands within the company have been brought up on the model. BRANDAID has also been used in a variety of other companies in applications involving a wide range of complexity and marketing detail.

8. Discussion

We are learning how to develop useful marketing-mix models and install them in companies. Simple, standardized pieces are emerging which can be put together in a variety of ways to represent different marketing environments. Implementation involves education, working up applications, demonstrating payoffs, and letting people assimilate what models can and cannot do. The process is not one of sudden breakthroughs, but of modest advances, which together bring about gradual integration of new techniques into the existing system. Unexpected effects arise. Certain issues that a model seems well equipped to handle turn out, on close inspection, to be non-problems. Others initially thought to be peripheral contain high payoffs.

A successful application is almost always coupled with a strong data support system. A good system should be on-line, have powerful manipulation commands, and permit easy application of a variety of statistical packages. Such a system should also permit simple communication between data, models, and statistical methods and be easy to extend along each of these dimensions. One characteristic of using a model is that it focuses data requirements and stimulates a variety of analyses and small models which often take on independent interest and grow in value. Powerful computer software to support such activities is beginning to become available.

One unexpected result of applying BRANDAID to forecasting and

planning has been its emergence as a de facto part of the marketing control system. The situation is depicted in Figure 8.1. Initially, we conceived the principal use of the model to be in constructing the annual plan. Each important marketing action in the brand plan would be related to a model input. Trial plans would be evaluated and, after taking into account any important constraints outside the model, a best plan would be selected. This process is shown in Figure 8.1 by the circuit from PLANNING to MODEL EVALUATION and back. The final plan was seen as a bible which determined marketing actions for the year. It also set sales and profit goals based on a model-developed forecast. Presumably, after completing the plan, brand management would turn its attention to carrying it out. The model would then be put on the shelf until the next year, when it would be dusted off, updated, and used again.

This has not been the case. We have found that tactical changes in which the model can be of assistance occur frequently, although somewhat unpredictably. This is how we learned that the model should be ready to go on a moment's notice. (For example, in one instance a brand manager heard a rumor that his advertising budget would be cut in half. By 5 o'clock he had a complete analysis of what he felt the effects of this would be on this year's and next year's sales and profit for his brand.) Usually the trigger for action is a discrepancy between actual and forecast sales or profit at some level within the company. The process is shown on Figure 8.1 as the feedback of goals vs. actual into ongoing OPERATIONS. A circuit of trial and evaluation develops new strategies which modify the original marketing plan.

The most unexpected result, however, is the new feedback loop stimulated by tracking. Periodically, the marketing actions actually taken, including notable competitive moves, are put into the model. Any discrepancy between

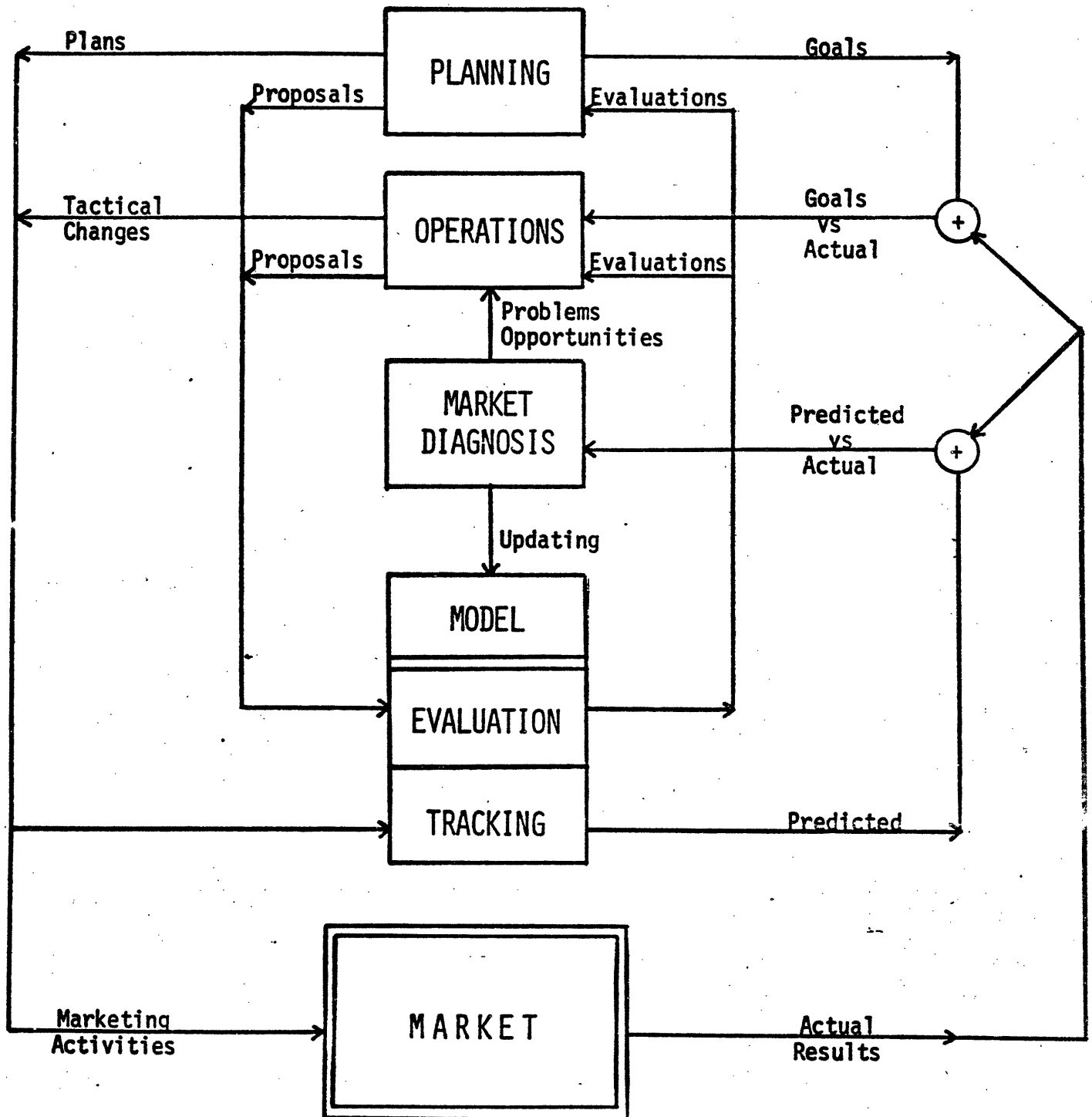


Figure 8.1 THE ROLE OF A MODEL IN THE MARKET CONTROL SYSTEM

predicted and actual quickly confronts the models team. The pressure to understand the reason is great. Not to understand is to say that the model is wrong, which, in effect means the team does not understand what is going on in the market. Prior to the model, the issue was much easier to avoid because the standard of comparison was less explicit. The forecast or previous year's sales might serve as a standard but, usually, enough things have happened since last year or since the construction of the forecast that loose explanations suffice. The model, on the other hand, sets up a requirement for isolating effects and placing numbers against them. These numbers constitute measurements which, although sometimes crude, are usually quite valuable and often form the starting point of new marketing action. The sequence of activities is shown in Figure 8 .I by the feedback of predicted vs. actual into MARKET DIAGNOSIS which generates problems and opportunities for OPERATIONS and updating for MODEL.

A final comment can be made about the value of the diagnosis step. Models are inherently inward looking; that is, by themselves they suggest only those actions that are encompassed within the model structure. The diagnosis step opens up people's thinking and invites new marketing ideas and their representation in the model for better decision-making.

Acknowledgment

Many people have contributed to the ideas presented here. In particular the author wishes to acknowledge his debt to Charles E. Allen of Nabisco, Inc. and Robert L. Klein of Management Decisions System, Inc.

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Appendix A

Model Summary

The pieces of the model are here assembled in one place. The sales influences shown in the market system of Figure 2.1 are listed and numbered in Table A.1. In the text below the basic sales model is first presented; then it is expanded to include retail distribution explicitly; and finally the overall cost and profit expressions are developed.

A.1 Basic Sales Model In general

$$s_b(t) = s_{ob} \prod_{i \in I} e_b(i,t) \quad (A.1)$$

where $s_b(t)$ is the sales rate of brand b in time period t , s_{ob} is its reference value $e_b(i,t)$ is the effect index for sales influence i , and I is the set of sales influences. In this section $I = I_M \cup I_E$, where I_M refers to manufacturer control variables, and I_E , environmental influences.

The submodels for advertising and salesmen have the same form.

For $i \in \{M3, M6\}$

$$e_b(i,t) = \alpha_b(i) e_b(i,t-1) + [1-\alpha_b(i)] r_b(i, \hat{a}_b(i,t)) \quad (A.2a)$$

$$\hat{a}_b(i,t) = \beta_b(i) \hat{a}_b(i,t-1) + [1-\beta_b(i)] a_b(i,t) \quad (A.2b)$$

$$a_b(i,t) = h_b(i,t) k_b(i,t) x_b(i,t) / h_{ob}(i) k_{ob}(i) x_{ob}(i) \quad (A.2c)$$

Here α is the carry over constant for product loyalty; r is the long-run response function for advertising or salesman effort; \hat{a} is the effective effort rate at t , including remembered effects; β is the carry-over constant for remembered effort; a is the actual effort at t ; x is the dollar spending rate, k is the coverage efficiency in terms

SALES INFLUENCES	Model Options	
	direct index	response submodel
<u>Manufacturer's Control Variables</u>		
M1. product characteristics	✓	
M2. price	✓	✓
M3. advertising	✓	✓
M4. consumer promotion		
(a) price-off	✓	✓
(b) sampling	✓	✓
(c) coupons	✓	✓
(d) premiums	✓	✓
(e) other	✓	
M5. trade promotion		
(a) price-off	✓	✓
(b) other	✓	
M6. salesman effort	✓	✓
M7. package		
(a) graphics and function	✓	
(b) assortment	✓	
M8. production capacity	✓	✓
M9. other	✓	
<u>Environmental Influences</u>		
E1. seasonality	✓	
E2. trend	✓	✓
E3. other	✓	
<u>Retailer Activities</u>		
R1. availability	✓	✓
R2. price	✓	
R3. promotion	✓	
R4. advertising	✓	
R5. consumer sales at fixed distribution		✓
R6. other	✓	

Table A.1 Principal sales influences and their treatment in the model.
Any sales influence can depend on brand, pack, time, segment,
or combination of these.

of calls or exposures per dollar; and h is the message effectiveness per call or exposure. The subscript o denotes reference conditions.

If several types of advertising are considered, (A.2c) is replaced by

$$a_b(i,t) = \frac{\sum_j w_b(i,j,t) h_b(i,j,t) k_b(i,j,t) x_b(i,j,t)}{\sum_j w_{ob}(i,j) h_{ob}(i,j) k_{ob}(i,j) x_{ob}(i,j)} \quad (\text{A.2d})$$

where j ranges over advertising types, each of which is given a weight w .

The promotion submodel applies to $i \in \{M4a,b,c,d\}$:

$$e_b(i,t) = e_{ob} \left\{ 1 + \sum_{p \in P_b} \lambda_p r_p(a_p(i,t_p)) [q_p(t-t_p) - 1] (1-b_p) \right\} \quad (\text{A.3a})$$

$$a_b(i,t) = h_b(i,t) k_b(i,t) x_b(i,t) / h_{ob}(i) k_{ob}(i) x_{ob}(i) \quad (\text{A.3b})$$

where P_b is the set of promotions run by brand b ; λ is the fraction of the line promoted; r is the response as a function of the normalized promotional intensity a ; t_p is the time period in which promotion p is run; $q(\cdot)$ is the time pattern of the promotion; and b is the cannibalization. In (A.3b) h is the coverage efficiency of the promotion; k is its consumer effectiveness, and x is the promotional intensity, say, in dollars/sales unit or dollars/customer. The cost of the promotion will be calculated in section A.3

The price submodel occurs for $i = M2$.

$$e_b(i,t) = \psi_b(x(i,t)) r_b(i, a_b(i,t)) \quad (\text{A.4a})$$

$$a_b(i,t) = x_b(i,t) / x_{ob}(i,t) \quad (\text{A.4b})$$

Here x is the manufacturer's price, ψ is the price-ending effect function; r is the sales response function for price, and a is the normalized price.

Several sales influences we handled by direct index, including $\{M1, M4e, M7, M9, E1, E3\}$. Any other influences can be simplified to a direct index, if desired, and custom models can be developed to replace a given term. An option for trend, $i = E2$ is the growth model

$$e_b(i,t) = e_{ob}(i) \prod_{\tau=1}^t [1.0 + r_b(i,\tau)] \quad (A.5)$$

where r is the growth/period as a function of time.

If competitive effects are to be treated, the submodels above hold but are considered to generate $e'_b(i,t)$ as their left hand side for any i handled competitively. Then the sales effect index effect for use in (A.1) is

$$e_b(i,t) = e'_b(i,t) - \sum_{k \neq b} [s_{ok}/s_{ob}] \gamma_{bk}(i) [e'_k(i,t) - 1] \quad (A.6)$$

where γ is the source of sales matrix.

Production capacity constraints on sales rate, if applicable, enter at $i = M8$ and take the form

$$e_b(i,t) = \min \{ 1.0, M_b(t) / [s_{ob} \prod_{i \neq M8} e_b(i,t)] \} \quad (A.7)$$

where $M_b(t)$ is the production capacity of brand b for period t .

Market share and product class sales are computed in a straightforward manner:

$$\zeta(t) = \sum_b s_b(t) \quad (A.8)$$

$$m_b(t) = s_b(t) / \zeta(t) \quad (A.9)$$

A.2 Retail Distribution Explicit

The effect indices of (A.1) are now expanded to include I_R , a set of retail activities. Furthermore, manufacturer activities, I_M , may enter directly as modeled above or indirectly by influencing retail indices or possibly (but not usually) both. For present purposes we assign price and trade promotion to work through the intermediary of the retailer by setting

$$e_b(R2,t) = e_b(M2,t) \quad (A.10a)$$

$$e_b(R3,t) = e_b(M5,t) \quad (A.10b)$$

Thus, in effect, we adopt the previous models for these manufacturer activities but acknowledge that they work through the retailer.

On the other hand, the effect of availability is handled by a new submodel. For the retail activity $i = R1 \in I_R$ with associated variable d ,

$$e_b(i,t) = f_b(i,d_b(i,t)) \quad (A.11a)$$

$$d_b(i,t) = d_{ob}(i) \prod_{k \in D(i)} e_b(k,i,t) \quad (A.11b)$$

The function f gives the sales response to availability d . In turn d is determined by a reference value d_0 and effect indices $e(k)$ for $k \in D$, where $D = \{R5, M6, E1\}$ and possibly other influences if appropriate. The submodels for salesmen, $k = M6$, and seasonality, $k = E1$, are as in the previous section. The submodel for the effect of consumer sales rate on availability, $k = R1$, is

$$e_b(i,k,t) = \alpha_b(i,k)e_b(i,k,t-1) + [1-\alpha_b(i,k)]r_b(i,k,v_b(t)) \quad (A.12a)$$

$$v_b(t) = \prod_{j \in I_M \cup I_E} e_b(j,t) \quad (\text{A.12b})$$

Here, α is the carry-over constant; r is the availability response to consumer sales rate and v is the normalized consumer sales rate at reference retailer activity.

For $i \in \{R4, R6\}$, retail advertising and miscellaneous other other retail activities direct indices are used.

A.3 Cost and Profit Models. The basic profit rate, $p(t)$ is expressed by

$$p_b(t) = g_b(t) s_b(t) - \sum_{i \in I_c} c_b(i,t) \quad (\text{A.13})$$

where I_c is the set of activities for which costs are considered explicitly. To take a general case, suppose that the model application involves market segments (e.g., geographic areas) and that all costs considered are either incurred by segments or allocated to them. Let the units of p be dollars/customer/year. The total profit for the brand (or contribution to profit, if not all costs are included) in a planning interval from T_1 to T_2 is

$$\Pi_b = \sum_j \sum_{t=T_1}^{T_2} N(j,t) p(j,t) \Delta \quad (\text{A.14})$$

where j ranges over segments, N is the number of customers in a segment at t and Δ is the length of a time period in years.

In (A.13)

$$g_b(t) = x_b(M2,t) - c_b(M2,t) \quad (\text{A.15})$$

where x is the price/unit and c the cost/unit. For $i \in \{M1, M3, M6, M7, M9\}$

$$c_b(i,t) = x_b(i,t) \quad (\text{A.16})$$

i.e., spending is an explicit dollar rate. This may sometimes be true for promotion, $i \in \{M4, M5\}$, but more often promotional cost is in dollars per unit and the total depends on the units sold. In particular,

$$c_b(i, t) = \sum_{p \in P_b} c_{fp}(t) + \sum_{p \in P_b} \{x_p\} l_p s_b(t) [e_{ob}/e_b(i, t)] [1 + [q_p(t-t_p)-1] (t-t_p)^{\varepsilon} [\tau_1, \tau_2] r_p(a_p(i, t_p))] \} \quad (A.17)$$

where $c_f(t)$ is the fixed cost rate of promotion p and the remaining notation is described in section A.1.

Appendix B

Implementation

A model is not productive until people use it and take different and better actions because of it. Experience has shown that considerable time is needed to introduce a model, customize it, calibrate it, build confidence in it, and have it used efficiently. Initial problems have been treated usefully in 4-6 months, but usage may continue to evolve and deepen over two or more years. We shall describe a sequence of implementation steps for a models application.

At the outset we should observe that successful implementation depends much on the attitudes and interests of the people concerned. The best successes have involved: (1) An internal sponsor who is a senior person on the company staff. This is a person interested in innovation who sees potential company benefit from the project. (2) An appropriate marketing manager. In one case we have worked with a former model builder. More often a good person is someone who likes the style of thinking represented by a model and sees opportunities in the project for his brand and himself. (3) A models man on location. He understands models and computers, believes they can help, and has a substantial block of his own time officially committed to the project. (4) A top management umbrella. If high executive levels display interest in the project and believe it has potential payoff, then lower levels tend to participate creatively.

Implementation can be divided into an introductory period and an on-going period.

1. Introductory period.

(1) Management orientation. A one or two day seminar for management on the state of the art in marketing models, information systems,

and management science in marketing will go a long way to clarify what models can and cannot do and to setting the stage for the project.

(2) Forming a models team. Implementation is a team effort. The team leader should be a marketing manager with decision-making responsibility in the area being modeled. Another key person is a models specialist who will live with the application, assist the problem formulation, help on data analysis, and perform an educational function for the rest of the team. The teams also need someone from marketing research with knowledge about available data. Finally it needs people with skills in individual areas of model focus, e.g., advertising or promotion.

(3) Problem selection and formulation. Ideally a problem is selected which is of current concern to the company, but still manageable in size. The model is best started simply and later expanded. One good starting place is a national model to be used for developing marketing budgets for the brand plan. Other possibilities are the geographic allocation of advertising, the analysis of pricing strategies, or the planning of promotional strategies. Once a problem area has been selected, the brand manager and other experienced marketing people describe the important factors bearing on the problem, and how they think the market works. Data needs and availability are ascertained. The general model is customized to the situation at hand. Market segmentation, if any, is decided on. Units are chosen. The basic time period is selected as is the time horizon of the model.

(4) Calibration. Key historical data are assembled. The data is put on line for easy retrieval and manipulation. Reference conditions are specified. Judgements and statistical analysis of data

Appendix C

Relation of Advertising Submodel toSasieni and Vidale-Wolfe Models

Sasieni [14] discusses a general class of advertising models of the form

$$\dot{s} = g(s, a, t)$$

where s is sales rate, a is advertising rate, $\dot{s} = ds/dt$, and t is continuous.

The Vidale-Wolfe [24] model is a special case:

$$\dot{s} = \rho a(1 - \gamma m) - \lambda s \quad s \in [0, m]$$

where ρ, m , and λ are non-negative constants

The advertising submodel of this paper is in discrete time and is

$$s(t) = s_0 e(t)$$

$$e(t) = \alpha(a(t)) e(t-1) + [1 - \alpha(a(t))] r(a(t))$$

We can put this into continuous form by introducing a variable time unit, h , presumed to be small, and letting $\alpha = 1 - \bar{\alpha}h$.

Then
$$\dot{s} = \lim_{h \rightarrow 0} [s(t) - s(t-h)]/h$$

or
$$\dot{s} = s_0 \bar{\alpha}(a) r(a) - \bar{\alpha}(a) s$$

This is a special case of Sasieni's form but not exactly the Vidale-Wolfe case. The latter would be achieved if $\bar{\alpha}$ were made constant and $r(\cdot)$ made a function of e as well as a , namely

$$r(a(t), e(t-1)) = (\rho/s_0 \alpha) a(t) [1 - \frac{s_0}{m} e(t-1)]$$

This advertising submodel could be added as an optional substitute to

(31) without much difficulty.

If the advertising remembrance model is added, the result will not be of Sasieni's form. To see this, we note that wherever $a(t)$ appears above, $\hat{a}(t)$ is substituted with

$$\hat{a}(t) = \beta \hat{a}(t-1) + (1-\beta)a(t)$$

or, in the continuous case,

$$d\hat{a}(t)/dt = -\bar{\beta}\hat{a}(t) + \bar{\beta} a(t).$$

This has the explicit solution.

$$\hat{a}(t) = e^{-\bar{\beta}t} \hat{a}(0) + \bar{\beta} e^{-\bar{\beta}t} \int_0^t e^{\bar{\beta}s} a(s) ds$$

which does not work into Sasieni's form.

are used by the team to develop response curves. An input book summarizing parameter values and other data along with a brief explanation of their sources can usefully be put together. Tracking runs are made and lead to refinement of the model.

(5) Initial Use. Strategies for the problem at hand are proposed and evaluated. The reasons for results coming out as they do are investigated until it is clear to the team not only what the model says but why it says it. Sensitivity analyses are made to show the effect of uncertain inputs on the results. Then the results are presented to management. Strategies accepted for implementation are used in the model to forecast the details of sales and share over the planning horizon.

B.2 Ongoing Period

(1) Firefighting. As unexpected marketing events occur the brand's situation is analyzed with the model. New actions are proposed, evaluated and carried out.

(2) Tracking and Diagnosis. As the future becomes the present, actual sales are compared with model predictions. Explanations are sought for discrepancies. This means examining auxiliary marketing research data and perhaps initiating new data collection. The discrepancy may arise because of poor model calibration, or possibly inappropriate model structure, but, most often, the reason is some phenomenon not heretofore included in the model. The magnitude of the effect can often be estimated by size of the discrepancy and new marketing insight obtained.

(3) Updating and evolution. The team may desire to expand the scope of the model and improve its inputs. New decision areas are

introduced. Special field measurements are undertaken. Phenomena uncovered in tracking are added to the model.

(4) Re-use. As the original planning problem recurs, it is attacked again with the improved model.

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