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Exceptional Paper

ADVISOR 2: MODELING THE MARKETING MIX DECISION FOR INDUSTRIAL PRODUCTS*

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This paper reports the results of the ADVISOR 2 study, aimed at providing an understanding of and guidance for marketing mix decisions for industrial products. The study involved 22 companies and 131 products. Although cross-sectional in nature, justification is presented for using the descriptive results as guidelines for marketing mix decisions. Models are presented for advertising expenditures, marketing expenditures, marketing budget allocations, year-to-year changes in advertising spending and for selection of distribution channels.

The level of marketing expenditures and the split of marketing into advertising and personal selling are shown to be affected by a few, general product and market characteristics of which product sales and the number of customers are key. It is shown that it is fruitful to study the advertising budget as advertising = (advertising/marketing) × marketing; i.e., a marketing budget is set and then a split of that budget into personal and impersonal communications is made. This two-stage view clarifies the role of different product and market characteristics in the models.

The change in advertising spending is related to changes in market share, changes in product plans and changes in the number of competitors modified by the number of customers, their concentration and the size of the advertising budget.

The decision to use a direct channel of distribution (primarily salesforce) is affected by the size of the firm, the size of an average order, the stage in the product's life cycle, the complexity of the product, the fraction of the product's sales made-to-order and the purchase frequency of the product.

A discussion of the use of the ADVISOR models both for marketing decision making and for marketing researchers and model builders is included.

(MARKETING–ADVERTISING/PROMOTION; MARKETING–MIX; INDUSTRIAL MARKETING)

1. Introduction

Management Science, by nature, is normative. We seek models and measurement procedures that improve or optimize the operation of management systems. Our major tools are so designed: mathematical programming, control theory, the development of response surfaces, etc.

Yet many complex or transient systems do not fit the optimization mode. Consider a price change. If controlled experimentation is not possible, one may not be able to model the effect of a price change that occurs in conjunction with competitive pricing response, a new product introduction and at the beginning of a recession.

But decisions get made: when faced with developing an operating rule in a dynamic situation, managers often rely on guidelines, rules of thumb, coefficients of industry behavior. There are at least two arguments to support this approach. The first deals with the concept of shared experience. Managers dealing with similar problems over a period of time may develop some equilibrium behavior which appears to be reasonable.

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Bowman [3] suggests that, through experience, managers learn what the critical variables are that affect their decisions and acquire reasonable implicit models of these problems. However, in a specific decision situation, they may respond selectively to particular information clues and organizational pressures. Thus, Bowman argues that experienced managers make good decisions on the average but may display considerable variance in behavior. It therefore follows that managers' decisions could be improved by making them more consistent.

In a series of studies Bowman [3] and Kunreuther [7] show that significant cost savings can be realized by consistently applying decision rules from the managers' own past behavior.

A second, related argument takes a Darwinian view of management practice. By and large, those products in place have survived: they are managed successfully. Efficient market theory suggests that marketing behavior, on average, will be pushed toward optimal behavior or the enterprise will fail.

The ADVISOR studies, aimed at industrial marketing problems (the marketing of goods and services to industrial, commercial or government markets for consumption or resale) are aimed at a situation where Bowman's concepts apply. Certainly, doubts and uncertainty about the impact of industrial marketing spending (see [13] for a review of what is known about industrial advertising) suggest that these decisions are subject to substantial variability. Like Bowman, the goal of this work is "pragmatic rather than utopian, in that it offers one way of starting with the managers' actual decisions and building on them to reach a better system" [3, p. 310].

This paper presents the results of those studies. Models are developed, describing the influences on advertising spending, marketing spending, marketing budget allocations, annual changes in advertising spending and selection of distribution channels. The budgeting decisions are shown to be affected by a few general product and market characteristics; among these, product sales and the number of customers are the most important. The results are valuable as a description of industry practice. More importantly, they provide an independent benchmark against which industrial product managers can check their plans and actions.

2. Background of the ADVISOR Studies

As Webster [16] points out, industrial marketing has long been the neglected step-child of quantitative marketing analysis: consumer marketing has been the main focus. This neglect has resulted from the fact that in industrial markets, potential customers are often few in number (statistical inference often does not apply) and that product-markets are often more limited, with large diversity in both the size (a five-man shop and General Motors may both be customers) and complexity (many different people with different backgrounds and responsibilities interact in the buying process) of the purchase decision. Much of the quantitative analysis appropriate for consumer markets is not directly transferable and few successful developments exist.

In 1973, in response to this lack of quantitative guidance, twelve companies with heavy involvement in the marketing of industrial products, together with the Association of National Advertisers and researchers from MIT, began a study of the industrial marketing mix. The base of the study was extensive product, market and customer data for a wide range of products supplied by the participating companies. This program—ADVISOR 1 (see [9], [12] for a review of the results)—established that the factors involved in marketing budgeting for industrial products are quite general.

This cross-sectional approach was partially motivated by the success of the PIMS program (see Schoeffer et al. [15]). PIMS, Profit Impact of Marketing Strategy, began as an internal study of General Electric business and, through the initial support of

TABLE 1
ADVISOR 1 *and* ADVISOR 2 *Operating Ratios*

	MEDIAN			
	ADVERTISING / SALES	ADVERTISING / MARKETING	MARKETING / SALES	SAMPLE SIZE
ADVISOR 1 (1973 data)	0.6%	9.9%	6.9%	66
ADVISOR 2 (1975 data)	0.7%	10.0%	7.0%	131

TABLE 2
Principal Product Category

Machinery and Equipment	21.1%	Partially Processed Material	6.5%
Raw Material	3.3%	Chemical	11.4%
Fabricated Material	39.0%	Other	1.6%
Component Part	17.1%		

the Marketing Science Institute, expanded to include over 250 participating companies and nearly 2000 businesses.

(The relationship of PIMS and ADVISOR is discussed in Section 6.1.).

Early in 1977 a larger study—ADVISOR 2—began with 22 companies participating (including AT&T Long Lines, DuPont, General Electric, Goodyear, International Harvester, International Paper, 3M, Norton, Owens Corning, Union Carbide, U.S. Steel and others). The objectives of the study were to investigate and try to confirm the results of ADVISOR 1 with a larger data base and to extend the range of the study by looking at several years of data and analyzing budgeting changes.

A questionnaire was developed and distributed to participating companies with an industrial "product" as the basis for its completion. A total of 131 questionnaires were returned, of which 125 were received early enough to be considered for complete analysis. Table 1 compares some operating ratios in ADVISOR 1 with those in ADVISOR 2.

(Here Marketing is defined as Advertising plus Personal Selling plus Technical Service spending. Advertising includes all impersonal marketing communications: trade and technical press, exhibitions and trade shows, sales promotions, etc.)

Table 2 gives the principal product category, pointing to the diversity of the data.

ADVISOR 2 is thus based on extensive product and market data. These data; collected 2 years after and on a completely different set of products than ADVISOR 1, reflect a clear consistency in some key measures of marketing importance.

3. ADVISOR 2 Model Development: Norm Models

ADVISOR 1 [9] proposed linear additive models of Advertising/Sales (A/S), Advertising/Marketing (A/M), and Marketing/Sales (M/S). These variables were ranked by size (from 1 = smallest ratio to 66 = largest ratio) and then related to dichotomous independent variables (high and low scores) on market share, purchase frequency and other key independent variables. There are some significant limitations in those models:

(1) They assume A/S and M/S are independent of sales level. This implies constant returns to scale for industrial marketing activities, an assumption that should be checked empirically.

(2) New products, without a sales history, should not be included in A/S and M/S analyses.

(3) Products with no advertising or marketing spending should be analyzed separately from those with positive spending for several logical and statistical reasons ([11]).

Careful analyses of the budgeting decision process suggests that the models should

(a) incorporate the effect of interactions between product characteristics;

(b) allow product characteristics to reflect *proportional* changes in the marketing level;

(c) check the form of the relationship between marketing spending and sales (Is M/S constant?).

The level of advertising (or marketing) spending is dictated primarily by the "size" of the product (as measured by last years' sales) and by the number of customers the marketing effort must reach. That spending is then modified by such factors as stage in the life cycle of the product, customer concentration, technical complexity of the product, etc.

A simple structure that reflects these concepts is log-linear:

$$\text{Marketing}_t = \beta_0 \text{Sales}_{t-1}^{\beta_1} \text{Users}^{\beta_2} \prod_i C_{\text{var}_i}^{\beta_i} \prod_j \beta_j^{D_{\text{var}\,j}} \tag{1}$$

where

Marketing = Marketing Spending,

Sales = Sales dollars,

Users = Number of customer-individuals the marketing program must reach,

C_{var_i} = Continuous, independent variable i, transformed to be greater than 1,

D_{var_j} = 0-1 indicator for discrete, independent variable j.

Two things should be noted about this postulated log-linear form. First, the coefficient of sales (β_1) allows a check on the ADVISOR 1 model structure. Secondly, it extends the ADVISOR 1 analysis by incorporating continuous independent variables. If we postulate a multiplicative error term of lognormal form, we can then use ordinary least-squares on the logarithm of equation (1).

As we are concerned with both Advertising and Marketing, we can investigate advertising budgeting as a two-step process: first setting a marketing budget and then determining advertising's rule in that budget. This suggests we investigate the advertising to marketing ratio as well, noting that

$$\text{Advertising} = \frac{\text{Advertising}}{\text{Marketing}} \times \text{Marketing}. \tag{2}$$

Equation (2) suggests that we should expect some structural consistency between the models we estimate independently, for Advertising, Advertising/Marketing and Marketing.

Products with significant amounts of missing data and products with inconsistent data (where product sales were greater than industry sales, where alternate measures of market share did not match, etc.) were eliminated from the analysis. Products in the introductory stage of the life cycle, and zero-advertising products were also excluded. In addition, products in which no marketing spending other than advertising took place were not included in the calibration of the A/M model. (The A/M model uses a logistic transformation, log((A/M)/(1-A/M)), to yield a dependent variable distribution that is approximately normal and that leads to predictions between 0 and 1, a desirable property.)

In total, 11 "good" data points were excluded from the analysis because they were in the introductory stage of the life cycle or had no advertising. The fact that these products should not *and* do not conform to our analysis here suggests important areas for future research (see §8).

TABLE 3

Norm Model Results

	Continuous Variables						Dichotomous Variables					
Dependent Variable	Sales (LSLS)	No. of Users (LUSERS)	Customer Concen- tration (LCONC)	Fraction of sales made to order (LSPEC)	Prospect Customer Product Attitude Differ- ence (DIFF)	Sales Direct to Users (LDIR- USER)	Stage in Life Cycle (LCYCLE)	Product Plans (PLANS)	Product Complex- ity (PROD)	Constant	R^2 / F	SEE / N
Advertising (LADV)	+ 0.618 (9.1)	+ 0.104 (3.6)	− 1.881 (3.1)	− 1.989 (4.4)	•	•	− 0.892 (3.7)	+ 1.503 (6.0)	•	− 0.651	0.59 / 25.0	1.12 / 110
A/M (Logit (A/M))	− 0.232 (4.5)	•	•	•	+ 0.383 (2.0)	− 0.255 (2.1)	•	•	− 0.230•• (1.2)	+ 0.544	0.24 / 7.5	0.91 / 100
Marketing (LMKTG)	+ 0.712 (12.6)	+ 0.082 (3.1)	− 1.633 (3.1)	− 0.993 (2.8)	− 0.305 (1.7)	+ 0.194•• (0.6)	− 0.424 (2.0)	+ 0.809 (3.9)	+ 0.528 (2.5)	+ 0.185	0.72 / 28.2	0.91 / 110

• variable insignificant and logically irrelevent

•• variable retained for logical consistency

Notes: · t-statistics in (·)

· variable names, keyed to Appendix 1, in (·)

· all equations significant at $\alpha < 0.001$

The main variables that are important in these equations (see Appendix 1 for complete definitions) were identified by prior correlation analysis as guided by ADVISOR 1 and a careful qualitative review of the budgeting process in participating companies. Table 3 gives the results of the regressions.

Let us examine Table 3 one column at a time.

SALES: Both advertising and marketing are strongly and positively related to sales. The nonobvious relationship is that with A/M: as sales goes up, advertising gets less of the marketing dollar. This may result from a limit on possible media spending because the number of trade journals is limited, while no such limit exists on the sales force. We also note that the coefficient of advertising (0.618, standard error = 0.07) is significantly less than 1, as was implicit with our ADVISOR 1 model results. Thus, our analysis rejects the form of the ADVISOR 1 model; we significantly improve it here.

USERS: The more users, the more money is spent on marketing and on advertising. There is no readable effect on the A/M ratio.

CONC: The more concentrated the purchases (the greater the fraction of sales to the three largest customers), the *less* is spent in advertising and in marketing. The more concentrated are sales, the less is required for marketing expenditures. The A/M ratio is unaffected.

SPECIAL: If a large proportion of a product's sales is special (i.e., made to order) both the advertising and marketing budgets are lower. A "special" product is most likely a design-item, and marketing communications is secondary to customer generated need. Once again, we see little effect on the A/M ratio.

LCYCLE: At the growth stage in the life cycle of the product, more is spent in advertising and in marketing than when the product is in the mature stage. Little effect is seen on the A/M ratio.

PLANS: This variable reflects high "aggressiveness" of company plans for the product (increase market share, for example). Under these circumstances both advertising and marketing expenditures are increased and A/M is unaffected.

PROD: If a product is fairly complex (such as machinery) and has a technical story to tell, more must be spent marketing it (positive effect on marketing). Personal selling, then, is more frequently used to communicate the message. We see little effect on the level of advertising.

DIFF: This variable is positive if current customers rank product quality higher than do prospective customers. This is often a situation where a company is not aggressively marketing the product. This seems to reflect a lowering in the level of selling effort. Marketing is lowered and the advertising/marketing ratio increases, with no effect on advertising.

DIRUSERS: If the proportion of sales direct to users is high, a high level of personal selling is often needed. This leads to effects that are the reverse of those for DIFF: negative effect on A/M, positive on M, no effect on A.

These models seem to fit well and to give results that are intuitively understandable and internally consistent. It is most important to note in Table 3 that only sales level affects all three equations: all other equations balance, with each variable affecting only two of the equations.

4. Change Models

The primary concept of the ADVISOR change models is that year-to-year changes in the marketing budget (advertising, in particular) are primarily the result of changes in the internal or external environment, modified by the level of certain key variables. We should not expect change models to fit as well as norm models; the change models aim at, essentially, residual variation (change in the norms).

The change model was developed as follows:

Define

$$\Delta \mathrm{ADV} = \frac{\mathrm{ADV}_t - \mathrm{ADV}_{t-1}}{\mathrm{ADV}_{t-1}} .$$

Suppose ΔADV has a (logical) upper limit of U and a lower limit of L. (These were determined to be 1.0 and -0.55 respectively, as logical break-points from frequency plots). Then

$$\Delta^* = \frac{\Delta \mathrm{ADV} - L}{U - L} , \tag{3}$$

which lies in the region (0, 1). Assume we then take

$$\mathrm{logit}(\Delta^*) = \log\left(\frac{\Delta^*}{1 - \Delta^*} \right)$$

and postulate that

$$\mathrm{logit}(\Delta^*) = a_0 + a_1 x_1 + a_2 x_2 + \cdots + a_n x_n,$$

where $x_1, \ldots, x_n$ are key independent variables. This transformation will produce the desired relationship, it is a multivariate logistic function:

$$\Delta \mathrm{ADV} = L + \frac{U - L}{1 + \exp(-(a_0 + a_1 x_1 + a_2 x_2 + \cdots + a_n x_n))} . \tag{4}$$

A correlation analysis and in-depth discussion with project participants led to a model specification indicated in Table 4.

The results here indicate that an increase in the aggressiveness of product plans, a decrease in market share or an increase in the number of competitors are associated with an advertising increase. In addition, the proportional change is greater when the number of customers is high and they are not highly concentrated, and when the prior year's advertising level is low. An advertising level indicator was included to reflect the fact that a large proportional change on a large base was less likely than on a small base.

As expected, the fit here is not as good as for the norm models: the models are simple and do not explain a great deal of data variance. Several more complex model forms were tried with no significant improvement in model fit; scattergrams do not

TABLE 4
Advertising Change Model

Dependent Variable	Change in Plans (CPLANS)	Change in Market Share (CSHR)	Change in No. of Competitors (CCOMP)	Customer Concentration (CONC)	No. of Customers (LCUSERS)	Advertising Level Indicator (ADVDUM)	Constant	R^2 / F	SEE / N
logit (Δ^*)	+ 2.124 (4.0)	− 1.390 (3.0)	+ 1.172 (1.8)	− 1.147 (2.0)	+ 0.029** (0.8)	− 0.532 (2.1)	− 0.193	0.39 / 6.9	1.03 / 72

** Included for logical model consistency
Note: · t-statistics in (·)
· variable names, keyed to Appendix 1, in (·)
· equation significant at $\alpha < .001$

reveal patterns of nonlinearity. However, the effects are of the right sign, are consistent, and do provide a level of understanding about the dynamics of industrial marketing budgeting not previously available.

Details of the analysis as well as an indication of the types of media most affected by advertising change and a marketing change model are found in [11].

5. Distribution Channels Model

The data collected in ADVISOR 2 include measures of directness of channels of distribution. Using the same motivation, we seek a relationship between product, market and environmental characteristics and the distribution channel selection decision. Our objective is to develop norms to guide that decision.

A manufacturer must assess channel alternatives to determine if they meet established objectives and fit well with the company, product, competitive environment, and users. Normally, firms need only analyze a subset of all possible channel structures as being feasible.

Figure 1 depicts the six most common channels for industrial products (adapted from Hass [6, p. 153]). Diamond's [5] study of 167 industrial manufacturers in 220 product lines found that these six basic channels accounted for all sales in his sample. Note that of the six basic channels, three represent "captive" or company-internal channels (paths 1, 2 and 6), while the remaining three use industrial distributors as an intermediary. This distinction points up a primary question: should the distribution channel be composed of captive or independent units?

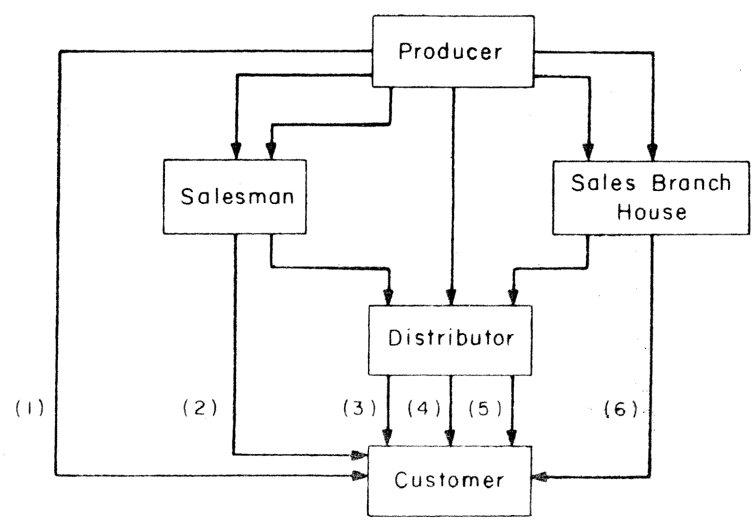

FIGURE 1. The Six Most Common Industrial Channels.

We propose a simple, hierarchical approach to analyzing the channel decision-making process. In the first stage, a decision is made about whether a product's distribution should be handled by captive or independent channel members. If captive, a choice must be made between a client sales force or some form of captive intermediary (sales branch). The third stage is the choice of a specific channel structure. This is particularly relevant if an indirect channel is chosen.

Our analysis deals with the first stage only. The ADVISOR 2 data yielded too few company-owned resellers to allow for meaningful analysis of stage 2. And, as Lewis [8] and Haas [6] point out, the choice of a specific mode of distribution channel is often constrained by legal, competitive and other environmental constraints; often the marketer has no choice.

To perform the analysis at stage 1, we are interested in discriminating between a captive channel and an independent channel of distribution. Discriminant analysis was used for this purpose as the distribution of captive channels was bimodal. Trying to predict "percentage captive" through regression would not be as reasonable as trying to classify a product as primarily captive or not. Linear discriminant analysis assumes, for optimality, that the discriminating variables have a multivariate normal distribution and that the covariance matrices of the two groups are equal (Morrison [14]). However, the technique is quite robust; as an applied decision-making tool, as in this instance, discriminant analysis can provide useful descriptive information.

To develop the discriminant function, two groups were designated as those products that had at least 90 percent of their distribution handled through captive (group one) or independent (group two) channels. This yielded group memberships of fifty-five and thirty-five, respectively. The remaining thirty-five cases, which exhibited more of a balanced distribution strategy, were held out of the analysis. The results of the discriminant analysis are described in Table 5 (Barefoot [1] gives the literature review process that led to the selection of these variables).

The canonical correlation associated with the discriminant function is 0.518. This measure of association explains how closely the discriminant function and a dummy variable that defines the group membership of each case are related.

A summary of the discriminant function and key associated statistics can be found in [11].

The classification phase of the discriminant analysis revealed that 70 percent of the cases used in the development of the discriminant function were correctly classified. This represents a success rate of prediction significantly greater than that expected by chance.

A predictive test was performed classifying the thirty-five products that were held out of the original analysis. This is a severe test of the model's classification abilities, as the majority of cases in this subset have at least 30 percent of their distribution going through the *secondary* channel mode. Twenty-two of the thirty-five cases in the subsample were correctly classified, yielding a rate of 62.9 percent successfully predicted, significantly better than chance at $\alpha = 0.06$.

We interpret the results in Table 5 as follows:

SIZE OF FIRM has the largest positive contribution to the discriminant score (which corresponds to captive distribution as the dependent variable). This means that as a firm grows larger, it is better able to support a company-owned distribution system.

SIZE OF AVERAGE ORDER also exhibits a positive effect on captive distribution. Thus, as the average order size increases, the captive (essentially direct) option becomes more economical.

TECHNICAL-PURCHASE COMPLEXITY also contributes positively. This variable is based on the manufacturer's impression of the importance of technical service in the product category and on the perceived amount of analysis that the buyer must perform prior to purchasing the product. The more important technical service is to a product's success and the more important the buyer views the purchase, the more likely a manufacturer will be to sell it through company-owned distribution channels.

TABLE 5

Standardized Distribution Channel Analysis Discriminant Function

$$\begin{aligned} D = & +0.531 \text{ (size of firm)} \\ & + 0.402 \text{ (size of average order)} \\ & + 0.228 \text{ (technical-purchase complexity)} \\ & - 0.534 \text{ (stage in product life cycle)} \\ & - 0.261 \text{ (degree of standardization)} \\ & - 0.155 \text{ (purchase frequency)} \end{aligned}$$

STAGE IN PRODUCT LIFE CYCLE is important: the negative sign indicates that as the product goes from growth to maturity, captive distribution becomes the more appropriate strategy. Thus, a new or growing product is more likely to use a captive form of distribution than one that has leveled off in sales.

DEGREE OF STANDARDIZATION also has a negative effect. This variable is derived from the fraction of a product's sales that is standard or carried in inventory. A product that is complex, unique, or made-to-order, is more frequently sold through direct means than through independent middlemen.

PURCHASE FREQUENCY has a negative effect too, indicating that as purchase frequency increases, the likelihood of using captive distribution channels decreases. As a product becomes more of a common purchase item, with less personal selling necessary to secure a sale, it becomes advantageous for a manufacturer to sell through distributors or other convenient outlets.

In order to use these results, we need a classification function, which gives the likelihood of a particular mode of distribution given the discriminant score.

If we let:

D = our discriminant score $=\sum a_i x_i$ where $\{a_i\}$ are the coefficients and x_i are the discriminating variables,

q_1 = prior probability of captive,

$q_2 = 1 - q_1$ = prior probability of independent channel,

$P_r(D/\text{Captive})$ = empirical ordinate of the (likelihood) density function of D, given a captive channel, then the classification problem is to find $P_r(\text{Captive}/D)$, which, by Bayes rule, is

$$P_r(\text{Captive}/D) = \frac{P_r(D/\text{Captive})q_1}{q_1 P_r(D/\text{Captive}) + q_2 P_r(D/\text{Independent})}.$$

6. Assessment

6.1. ADVISOR 1 *and* PIMS

The PIMS study, larger and older than ADVISOR, is much better known. How do ADVISOR and PIMS relate? PIMS was developed as a study of general business strategy and its impact on profitability. As such, most reported results deal with profitability as the dependent variable, a different focus than ADVISOR. PIMS collected more general data to focus on a "business," rather than a "product." PIMS studied a mixture of industrial and consumer business; ADVISOR focuses on industrial product marketing. As such ADVISOR measures a subset of those items addressed in PIMS but measures them in more detail.

The only published report of a study of PIMS data that is comparable to the ADVISOR study was made by Buzzell and Farris [4]. Both ADVISOR and Buzzell-Farris (BF) focus on product-market factors that affect industrial marketing cost ratios. However, ADVISOR concentrates on major determinants of industrial marketing budgets while BF aim at comprehensiveness. They thus include a number of variables that are intercorrelated and not statistically significant. After careful analysis, we find that inconsistencies between ADVISOR and BF can be explained by

Measurement Differences. Most of the questions were worded differently, and few variables in the two studies are directly comparable.

Differences in Modeling Philosophy. Examination of the BF correlation matrix (confirmed with a RIDGE regression analysis) shows that multicollinearity in the equations is quite important, and, thus, coefficient-estimate variance is large. Problems with unstable coefficients arise mainly with those variables that are statistically significant. It thus appears that the BF models could be simplified with little loss of predictive accuracy.

Differences in Products Selected. The BF criterion was that less than 50% of the business' sales could be to households, a much less stringent criterion than that used in ADVISOR.

In total, aside from some philosophical and data differences, the results of the Buzzell-Farris [4] study on the PIMS data and the results of ADVISOR 1 are quite consistent.

6.2. ADVISOR 1 *vs.* ADVISOR 2

We compare the ADVISOR 2 norm models with the results of ADVISOR 1. Due to the larger data base, we found more variables significant in ADVISOR 2.

We found consistent results with life cycle and customer concentration. Customer growth rate was related to and found better represented in ADVISOR 2 by product plans and the number of users (a large number of users and positive product plans relate closely to growth in the customer base). Quality and product uniqueness is also associated with company plans (support is given for those products that a company feels are unique).

Purchase frequency was found to be ambiguous. In ADVISOR 2 (and probably in ADVISOR 1) there was confusion between the number of times a product is *ordered*/year and the frequency of *purchase decision*. For this reason the variable was excluded from analysis in ADVISOR 2.

Finally, market share, which was a strong variable in ADVISOR 1, was not found to have an effect in ADVISOR 2. We resolve this seeming inconsistency as follows.

In ADVISOR 1, A/S was related to market share negatively: $A/S \sim 1/D$ where $\sim$ means "is related to" and D represents market share. The relationship shows that as share increased, A/S decreases.

In ADVISOR 2, $A \sim S^{0.6}$ or $A/S \sim 1/S^{0.4}$. Some simple data analysis showed that market share was closely related to sales, as $D \sim S^{0.2}$. Using this result we get $A/S \sim 1/D^2$ in ADVISOR 2.

Thus, we see from the above relationship that the implication of the ADVISOR 2 model is that A/S *is* related to market share in a similar way as in ADVISOR 1.

Thus, market share was included in the ADVISOR 1 model as a correction factor to compensate for the assumption that A/S was modeled as a constant. This was a model mis-specification. The inverse relationship with market share served to deflate that ratio when sales got larger. Our exponent of sales, less than 1 in ADVISOR 2, serves the same purpose and does it directly.

Thus we conclude that ADVISOR 2 generally confirms while reinforcing and improving upon ADVISOR 1 (and the associated effort by Buzzell and Farris).

6.3. *Discussion*

A key variable that is missing from all the analyses is product profitability. Relationships with product profitability are marginal at best. This may suggest two conflicting effects. Some products spend more, trying to capitalize on high margins. Others may have low margins because of low volume and correspondingly high allocations of fixed costs; thus they spend more when their margins are low to boost volume (and, thus, margins). We feel the problem is treated in the PLANS variable for predictive purposes, although the issue is not completely clear.

In order to assess the importance of this work and the relevance of some other variables that are, perhaps, missing we must ask if the effects are, indeed, real.

It should be noted that the experienced managers involved in this study generally agree that the major variables included here do, in fact, affect budget decisions in an aggregate, industry-average way. However, their limited experience does not permit them to say to what degree. ADVISOR 2 refines this situation. It puts magnitudes and ranges on the effects of a number of key variables. This is new knowledge. The results do what they were intended to: they carefully reflect business practice and identify significant effects that can be used as norms and guidelines by industrial marketing managers.

Our data base is not exhaustive and we must distinguish between the accuracy of measuring an effect and the accuracy of prediction. If we had four times as many products, our measurements of the contribution of significant variables would be about twice as accurate, and we would almost certainly measure more variables successfully.

On the other hand, we would probably not be able to improve our prediction very much. This is because there are specific factors—changes in management, for example—that would not be accounted for by any reasonable set of variables.

Thus we conclude that real effects have been measured. The measurements must be interpreted in the context of this specific analysis, but they represent a significant addition to our understanding of the determinants of industrial marketing budgets.

7. Uses

The results of the ADVISOR project can be used in a variety of ways to help support industrial marketing decision-making. A key use is as a tool for managerial control. Here characteristics for an existing product are collected and input to a computer program. The program feeds back budgeting guidelines that are then compared with the actual budget. (Table 6 gives part of a sample par report. The center is the point prediction and the ranges are prediction intervals with a user-specified tolerance limit.) If the guidelines agree with the budget, no further analysis is performed. If they disagree, reasons for the differences are sought. Here, the model acts as a control procedure for exception analysis—to find those product cases most in need of more detailed review.

Another mode of use deals with developing spending levels for products with no sales history. If a sales potential-projection can be made, then this, along with other characteristics can be entered into the ADVISOR program to generate marketing guidelines for the new product.

Most companies develop long range product plans each year. ADVISOR allows one to generate communications programs consistent with those plans. Product and market forecasts can be developed as ADVISOR input, helping to generate consistent spending projections.

There are many other possible uses of ADVISOR such as determining which key market variables to monitor as indicators of communications budget changes; assessing the relative or joint effect of several variables on marketing budgets; and allocating scarce marketing resources over a multi-product line.

An important thing to note is that the ADVISOR study uses, detailed above, were developed by project-participants. These are ways that participating companies *are currently using the results*. Each participating company has a computer program in house that automatically generates ADVISOR norms, taking a set of 19 key questions as input.

ADVISOR results are being used by marketing researchers in another context. Industrial markets do not have the same set of audits of competitive marketing activities as do consumer markets. ADVISOR allows the researcher to predict competitive marketing spending levels in markets where that information is not otherwise available. Among other uses, these competitive ADVISOR predictions can be used as "Them" in Us/(Us + Them) models of market response. (Note that the number and sales-distribution of competitors have important impact on the predicted level of marketing spending; the model must be used carefully.)

TABLE 6

Sample Portion of Par Report

	ACTUAL	INDUSTRY NORMS	
	BUDGET	CENTER	RANGE
ADVERTISING (K$)	20.000	24.000	19.200– 28.800
ADVERTISING/MARKETING	0.020	0.025	0.020– 0.030
MARKETING (K$)	1000.000	950.000	760.000–1140.000

8. Conclusion

The ADVISOR 2 study provides new understanding of the marketing budget process for industrial products that can be used to support and improve management practice. New guidelines are now available against which current decisions can be checked. It is significant that these norms are both quantitative and situation-specific —that is, they recognize the key underlying product and market characteristics, and their underlying interrelationships. (Product class indicators and company indicators when included in the models did not improve them by any significant degree. Our results are thus quite general).

A number of areas deserving further attention have become apparent during the study. First, our norm-model analysis is based on historical sales and is thus inappropriate for new products. A fruitful area for further work would be an ADVISOR type model for new products. Similarly, an analysis discriminating between products that do advertise and products that don't advertise would resolve questions about when zero advertising seems appropriate. A special sample would need to be created for such an analysis.

An alternative approach to studying marketing mix development is to group products with similar marketing mixes and then determine differences between these groups (sort of a reverse ADVISOR analysis). The results of such an effort (Bolshon, Fitchet and Hansen [1]) are largely consistent with those presented here.

Another direction of current work is aimed at finding out not what industrial marketers are doing, but determining what they *should do*. Here we collect time series data on products going through a period of transition (changes in marketing or in the environment) and infer the sales response to changes in the market. This response model can then be used to develop profit-improving marketing plans. Initial results look encouraging and will be the subject of later publications.

There are clearly other related areas of study. For example, duplication of ADVISOR in a non-U.S. environment, (i.e., Europe) is currently underway and could be an important step toward establishing the cross-cultural generality of the results. The ADVISOR studies to date, however, have been an important first step in providing quantitative tools to support the industrial marketing budget-setting process. They draw upon an infrequently tapped source of quantitative information—the combined experience of a wide cross section of decision-makers—to provide quantitative support for management decisions. We feel this approach, although frequently difficult to implement, will be increasingly recognized as an important way and, in some cases, the only way, to address a variety of decision-problems.[1]

Appendix 1. Variable Definitions

(Norm and Change Models)

Variable Name	Description	Models
1. ADV	Total amount of money spent on advertising and sales promotion for this product, including production, in 1000's	
2. ADVDUM	= 0 if advertising budget < sample median 1 otherwise	

[1] This paper represents the results of efforts by many people. Professors Jean-Marie Choffray of ESSEC, John Little and Alvin Silk of MIT were all influential in motivating this analysis. In addition, Jessie Abraham, Donald Barefoot, Barbara Bolshon, Sandy Fitchet, Gregory Resker and Mary Ann Ritter contributed to developing these results. We are indebted to Donald Gluck of DuPont for stimulating the start of the ADVISOR Project, to Harry Darling of ANA for helping it to prosper and to all of the representatives from the participating companies for their time, support and creative input.

3.	CCOM	$\dfrac{\text{(No. of major competitors (over 1\% market share) year-1} - \text{No. of major competitors year-2)}}{\text{No. of major competitors year-2}}$	CHANGE-ADV
4.	CONC	Fraction of industry dollar sales purchased by industry's three largest customers	CHANGE-ADV
5.	CPLANS	Change in product plans from current year to year-1. (Variable constructed from change in weighted average of possible product plans possibilities in original questionnaire).	CHANGE-ADV
6.	CSHARE	$\dfrac{\text{Dollar Market Share}_{t-1} - \text{Dollar Market Share}_{t-2}}{\text{Dollar Market Share}_{t-2}}$	CHANGE-ADV
7.	DIFF	Difference between how current customers and prospective customers perceive product quality relative to industry average. = 0, prospective customers perceived quality higher than current customers = 1, otherwise	NORM-A/M MKTG
8.	DIRUSER	Fraction of sales volume made direct to users + fraction of sales volume made to users via company owned resellers + 1.	NORM-A/M
9.	LADV	LN(ADV)	
10.	LCONC	LN (1.+CONC)	NORM-ADV, MKTG
11.	LCUSER	LN (No. of industry downstream specifiers year-1 + No. of industry users year-1 + No. of industry independent resellers year-1)	CHANGE-ADV,
12.	LCYCLE	Stage in product life cycle = 0, growth = 1, maturity Missing, introduction or decline	NORM-ADV, MKTG
13.	LDIRUSER	LN(DIRUSER + 1.)	NORM-MKTG
14.	LMKTG	LN(MKTG)	
15.	LSLS	LN(Product $ sales) (Lagged 1 year in 1000)	NORM-ADV, A/M MKTG
16.	LSPEC	LN(SPEC + 1.) (see definition of SPEC)	NORM-ADV, MKTG
17.	LUSERS	LN(No. of industry downstream specifiers + No. of industry users * No. of usual decision makers in user's organization + No. of industry independent resellers * No. of usual decision makers in reseller's organization)	NORM-ADV, MKTG

18.	MKTG	PSTS + ADV	
19.	PLANS	= 1, if product plans are "positive" i.e., if respondent indicated increase in market as an objective, say = 0, otherwise	NORM-MKTG, ADV
20.	PROD	Product complexity— = 1, if the product is machinery and equipment, or component part. = 0, otherwise	NORM-MKTG, A/M
21.	PSTS	Total amount of money spent on Personal Selling and Technical Service for the product (including applicable overhead)—in the current year, in 1000's.	
22.	SPEC	Fraction of product's volume sales produced to order	

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