This paper presents a comparative analysis of the findings of two field studies and three recent laboratory experiments that assessed the efficacy of judgment based models in aiding marketing decision making. This analysis indicates factors that may affect the effectiveness of these models. The implications of the findings for users of judgment based marketing decision models as well as model builders are discussed, and suggestions are made for future research to improve the models' effectiveness.

JUDGMENT BASED MARKETING DECISION MODELS: PROBLEMS AND POSSIBLE SOLUTIONS

Introduction

Many marketing decisions are made in complex environments where numerous variables affect decision outcomes; market response to these variables is frequently nonlinear and incorporates carryover effects. Since decision making under these conditions is a difficult cognitive task, managers often rely on simple heuristics such as setting advertising budgets as a fixed percentage of sales instead of structuring the problem to analyze and evaluate alternative courses of action (e.g., Howard and Morgenroth 1968, March and Simon 1958).

While model based approaches have great potential for improving decision making in these situations, it is also difficult to construct and operationalize valid models of these environments. The models tend to be either too simple so they are not valid representations of the real world or so complex that the manager does not understand the models and, consequently, does not use them. To circumvent these problems, Little (1970) suggested a model building approach, which he termed Decision Calculus. This approach seems to have had a major impact on model building in marketing, since over 20 models based on this approach have appeared in the literature, many of which are sold commercially.

In his original article, Little (1970) identified six model design criteria that have since been translated into a four-step procedure for the development and implementation of marketing decision models (Montgomery and Weinberg 1973). In the first step, the manager verbalizes his implicit model of the situation to be analyzed, specifying the variables that affect the criterion variable as well as the general relationships between these variables. In the next step, the model builder translates this verbal description into a formal mathematical model. Although each model has unique features, the market

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response functions in many decision calculus models often have the same general form. For these models the criterion variable is postulated to be a function of two types of effects: (a) the current effect of the control variable, which is usually modeled with monotonically increasing functions that are either S-shaped or strictly concave, and (b) a term that captures the lagged influences of all other factors (e.g., carryover effects of past marketing efforts) and the current effects of other variables (Mitchell and Morton 1976). Mathematically, this general model form may be represented as:

$$Y_t = g(\cdot) + f(x_t)$$  \hspace{1cm} (1)$$

where $Y_t$ is the value of the criterion variable (e.g., sales) at time $t$, $g(\cdot)$ represents the level of $Y_t$ in the absence of the control variable, $x_t$ is the level of the control variable at $t$ (e.g., advertising expenditures), and $f$ is the functional form of the current effects of $x_t$ on $Y_t$.\(^1\)

The third step involves the estimation of the parameters of the model, while in the fourth step an interactive computer program is developed to enable the manager to examine alternative decisions. This procedure and the design criteria suggested by Little, result in models that are claimed to be simple, robust, and complete, as well as easy to understand and use (Little 1970, Montgomery and Weinberg 1973).

The use of this approach, however, has some potential limitations. For example, making a model robust frequently means that information beyond the normal operating range of the firm is required to estimate some of the parameter values. Also, the completeness criterion frequently causes the models to be overparameterized (i.e., the models have a large number of parameters relative to the amount of data available). Thus, more than one set of parameters often can adequately reproduce the available data. These problems, plus the complexity of the resulting models (e.g., nonlinearities and multicollinearity among the critical variables usually preclude the use of statistical procedures to obtain direct estimates of all the parameters. Instead, most decision calculus models rely at least in part on managerial judgment for parameter estimation. Specifically, parameters values are often inferred by asking the manager for judgmental estimates of outcomes, $Y_{t+1}$, for specific values of the control variable, $x_{t+1}$ (e.g., estimates of $Y_{t+1}$ if $x_{t+1}$ were cut to zero, increased by 50% over $x_t$, etc.).\(^2\)

In order to augment managerial judgment, Little (1970, 1975) suggests using data from market tests as well as statistical analysis where possible. Secondly, he also suggests that the veracity of the model and the judgmental estimates should be assessed by seeing how well they replicate historical data. If the model does not replicate the data accurately, the model and/or the judgmental estimates may be revised. However, with over parameterized models this procedure may not provide good diagnostic information for accessing the veracity of the model and its parameters (Chakravarti, Mitchell, and Staelin 1977).

Managerial judgment is an essential element of the development and implementation process for this type of model. Consequently, the efficacy of judgment-based models relies heavily on the manager’s cognitive abilities to specify the critical variables and their interrelationships, and to provide valid judgments for inferring parameter estimates. Recent research in psychology, however, suggests that humans may have trouble providing valid estimates for the required inputs. Simon (1957), for instance, has suggested that in order to make a complex situation more manageable, individuals tend to construct simplified models. Consequently, a manager’s model may be overly simple and, thus, incorrectly specified. Moreover, numerous studies have demonstrated that human judgments are frequently subject to systematic biases (e.g., Tversky and Kahneman 1974). These biases are influenced

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1 Most decision calculus models use one of the following forms:

a) $Y_t = a + f(x_t)$
where $a$ is a constant,

b) $Y_t = a_t + f(x_t)$
where $a_t$ is a time-subscripted constant,

c) $Y_t = a_t + h(Y_{t-1}) + f(x_t)$
where $h(Y_{t-1})$ is a function of past marketing efforts, or
d) $Y_t = a_t + k(z_x) + f(x_t)$

where $z_x$ is a measure of goodwill and $k(x_t)$ is some function of goodwill. In each case, these models can be represented by equation (1). In models of the form (a), $g(\cdot)$ is a constant base level to which $Y_t$ falls in the absence of the control variable in any time-period. In (b), $g(\cdot)$ may be thought of as current period effects of all other marketing variables except $x_t$. In (c) and (d), $g(\cdot)$ represents both current and carryover effects, the only difference being that the functional forms $h$ and $f$ are modified by $k$ in (d).

Examples of decision calculus models with these functional forms are CALLPLAN (Lodish 1971), which is of the form (a) or (b); ADBUDG (Little 1970), which is of the form (c); and DETAILER (Montgomery et al. 1971), which has the form specified by (d).

2 This parameterization procedure should be contrasted with Bayesian approaches that also use subjective estimates from managers. The Bayesian approach explicitly attempts to capture the decision maker’s uncertainty about sales forecasts or model parameters and to take this uncertainty into account in decision making. The decision calculus approach, however, requires managers to provide deterministic estimates, and unlike the Bayesian approach, does not incorporate the uncertainty in these estimates into either the model building or the parameterization procedures.
by such factors as the wording of the question and the type of extraneous information available. Thus even if the manager's model is correctly specified, the parameters required to operationalize the model may be inaccurate if derived judgmentally.

Given these limitations and the importance of managerial judgment in the development and implementation of these models, it is essential to understand the effects of potential judgmental biases on the ability of these models to aid managerial decision making. As will be discussed, understanding these potential biases is important in designing decision support systems. This paper presents the results of a series of experiments that represent some initial work in the area. The next sections discuss alternative approaches for examining the effect of judgmental bias on the efficacy of these models, along with the methodology and results of these experiments. Finally, the paper presents the implications of the results for both managers and model builders.

Examining The Efficacy of Judgment Based Models

Research evidence from other areas may be used to address the efficacy of judgment based models. For instance, proponents of judgment based models appeal to two different streams of research when discussing the potential advantages of this approach (e.g., Little 1970, Montgomery et al. 1971). The first is a series of studies that show predictions from regression models based on an individual's previous judgments frequently outperform the individual's future judgments. These results, termed bootstrapping (Goldberger 1970), have been found in a number of diverse situations (e.g., Bowman 1963, Sawyer 1966). The second is the finding that individuals can provide better predictions when an aggregate forecasting problem is decomposed into a series of simpler component predictions (Armstrong 1978).

However, neither of these research streams are directly relevant for assessing the value of judgment based models (Chakravarti, Mitchell, and Staelin 1979, 1980a). First, the bootstrapping model uses regression analysis of past judgments to obtain parameter estimates of a paramorphic representation of an individual's judgmental process, while judgment based models use one shot subjective judgments to obtain parameter estimates of the manager's implicit model of the environment. Second, decomposition improves predictions only when the component estimates meet certain conditions (e.g., Armstrong 1978, Staelin and Turner 1973), and these are not necessarily satisfied with judgment based models. Thus, claims regarding the efficacy of judgment based models should not rest on these results but on empirical evidence that the models help managers to make better decisions, after other sources of variation in managerial performance have been carefully controlled.

Laboratory and field experiments are two different approaches that may be used to address these issues. A field study by Fudge and Lodish (1977) used 10 matched pairs of United Air Lines sales representatives. The group that developed their account strategy using the CALLPLAN (Lodish 1971) model, averaged 8.1% higher sales than the 10 representatives in the control group. In another instance Edelman (1965) reported that a bidding model based on managerial judgments was able to outperform the manager in terms of more profitable and yet competitively successful bids.

Although both studies provide evidence that judgment based models may help managers perform better, neither provides much insight into why and under what general conditions one might expect positive results. For example, it is not clear whether the models helped the manager process available information in a more consistent fashion, or whether formally interacting with the computer based model and examining its output improved the manager's understanding of market response. Since these issues affect the type of decision support systems that need to be developed, a systematic understanding of exactly how a model complements a manager is required.

The Laboratory Experiments

Three recent studies (Chakravarti, Mitchell, and Staelin 1979, 1980a, McIntyre 1980) have used laboratory experiments to examine the validity of parameter estimates based on managerial judgments and the efficacy of judgment based models. The studies examined these issues in situations where the managers' understanding of the market was based primarily on the outcomes of their prior decisions by simulating the use of judgment based models in a lab setting. For example, Chakravarti, Mitchell, and Staelin (CMS) asked middle and upper level managers to make a number of advertising expenditure decisions for a hypothetical firm first without and then with a judgment based model. However, instead of letting the marketplace determine decision outcomes (as in the field studies), the researchers used a predetermined function of the form in equation (1) with known parameters
to generate the decision outcomes. Generating decision outcomes with a known function gave the researchers two capabilities that were not available in the field studies, namely to make objective evaluations of the accuracy of the manager’s judgmental forecasts of decision outcomes used as the inputs for parameterization, and objective comparisons of the decisions made by the managers against the known best (optimal) decisions in the given situations.

General Description of Studies

The two studies by Chakravarti, Mitchell, and Staelin (1979, 1980a) used a simplified version of the ADBUDG model. This model was selected because Little (1970) used it to present the decision calculus approach and claimed that it incorporated all the model building criteria that he advocated. Also, Larreche and Montgomery (1977) had experts compare 14 marketing decision models on 16 dimensions and reported that their experts rated ADBUDG best on 11 of these dimensions and second or third on three others. 3 McIntyre’s choice of a simplified version of the CALLPLAN model seems to have been based on his desire to have a stable and static environment generate the data (McIntyre 1980).

In the first CMS study, subjects had to set an advertising budget for a single territory, while in the second experiment subjects had to allocate a fixed budget over either three or six territories. The task in the McIntyre study was identical to the task in the second CMS study.

Each of the three experiments followed the same general format. First, subjects (either experienced managers or MBA students) were given scenarios that described the nature of the industry they were operating in, the current levels of the marketing control variable of interest as well as the current market position and profit position of their firm. Next, subjects were asked to make a series of expenditure decisions for the market(s) under his/her control, and provide an estimate of the market outcome associated with each decision. In the notation of equation (1), each subject made decisions on $x_i$ and provided $\hat{Y}_i$, where $\hat{Y}_i$ represents the subject’s estimate of $Y_i$ associated with $x_i$. The predetermined response function used to generate the actual market outcome $Y_i$ corresponding to $x_i$. These $Y_i$ values along with associated one period profit data were given to the subject as feedback after each decision. Thus the subjects had an opportunity to learn the nature of the relationship between their $x_i$ decisions and the market outcome $Y_i$ and profits.

After making a number of decisions, the subjects received classroom instruction concerning the use of models in decision making and a description of the general form of the model generating the data. For example, in the CMS studies subjects were informed that the one period market response to advertising was probably S-shaped and that there was a carryover effect from period to period.

Although the subjects were told about the general form of the model generating the data, they were not told the exact form of the curve (i.e., the parameter values were not indicated). In fact, a major goal of each study was to examine how well the subject could assess the shape of this curve based on the data generated by their decisions prior to being introduced to the model. This was done by asking subjects to estimate $Y_{i+1}$ for a series of specific settings of $x_{i+1}$. These judgments were similar to the ones normally used to parameterize decision calculus models.

After providing these judgmental estimates, the CMS subjects were given access to an interactive computer model that had a response function that was structurally identical to the model generating their decision outcomes. They were allowed to use the model to assess the validity of and modify their judgmental estimates on the basis of replicating the outcomes of their previous decisions. The interactive model also included an optimization procedure that determined the best decisions based on the judgmental estimates. In McIntyre’s study, subjects were only given the output of an optimization procedure. Since the models used in all three studies for optimization were identical to the models used to generate decision outcomes, the optimization programs would yield the true optimal decision if the subjects provided the correct judgmental estimates.

Following exposure to the interactive model, subjects made another series of expenditure decisions. At this stage, however, the decision model’s predictions were available to help them. Extent of model usage in this phase of decision making was monitored for each subject and taken into account in the analyses.
Comparative Analyses of Results

There were significant contrasts in the findings of the above studies. In the two CMS studies, the subjects did not make better decisions when they used the model and, in fact, made poorer decisions on the average. In the McInntyre study, as in the two field studies, subjects' decisions improved on the average following use of the model.

The major difference between the CMS studies and the three other studies was in the type of the response function used to generate the feedback data provided to the subjects. In McInntyre's study, the response function did not have any carryover effects. Consequently, the subjects could get an excellent idea of the shape of the response function by plotting the feedback data and then judgmentally extrapolating these for values outside the available range. Theoretically, at least, the same was true of the Fudge and Lodish (1977) study, since the environment was felt to be almost identical to that in the McInntyre experiment. The Edelman (1965) study required managers to specify judgmentally a univariate cumulative probability function for bid award over a set of competitive bid price differentials. Even though the true function was not known (as in the Fudge and Lodish study), there is no reason to suspect dynamic carryover effects in this situation. Thus, in each case where judgment based models helped decision makers, the data generating environment seems to have been fairly stable and simple.

In contrast, the two CMS studies used a more complex response function to generate the data. This response function included a carryover effect over and above the nonlinear current effects in the other three studies. In such situations, the decision makers seem to have been unable to provide response estimates that were accurate enough to enable the model to help them make better decisions than they could without the model.

The difficulty in judgmental estimation of outcomes in dynamic environments seems to stem from the fact that the carryover effect causes the response function to shift from period to period (see Figure 1). Thus the data points that subjects saw in the two CMS experiments did not lie along a single response function but came from different members of a family of response functions. Hence, as shown in Figure 1, a simple plot of market outcomes \( Y_t \) against the \( x_t \) values would lead subjects to mis-specify the relationship between \( Y_t \) and \( x_t \), because the plot suppresses the time dimension. Extrapolation, therefore, leads to obvious errors unless the manager can disentangle the carryover effect from the current effect judgmentally. In the CMS studies it seemed that the subjects had difficulty doing this.

These problems with estimation ability are even clearer upon detailed examination of the two CMS studies yielding almost identical findings. Some of the more relevant findings are as follows:

- Subjects improved their predictions of market outcomes (\( \bar{Y}_t \)) associated with their advertising decisions as they repeated the task. However, the sizes of their estimation errors increased as they made larger changes in their decisions. The accuracy of these estimates did not improve with exposure to the model and parameterization process.

- In the aggregate, subjects made larger errors in their estimates of market response for decision variable settings that were further away from their current position (e.g., zero and saturation advertising) relative to settings near their current position. Two factors seemed to contribute to this aggregate effect. Subjects showed a systematic tendency to provide estimates that were too close to their current market positions. This bias resembles the anchoring phenomenon (Tversky and Kahneman 1974). Secondly, after controlling for the anchoring bias, subjects tended to overestimate market response associated with advertising increases and underestimate...
market response associated with advertising cuts. The subjects were most accurate when estimating outcomes close to their current position.

- Exposure to the model, classroom instruction, and the parameterization exercise did not help the subjects provide better judgmental estimates. This finding was also reported by McIntyre.

- Subjects were less confident, on the average, in their outcome estimates for decisions further away from their current position relative to those close to their current position.

- When subjects' judgmental estimates of market response were used to parameterize the model and predict market outcomes for their earlier decisions, these predictions were less accurate on the average than their direct intuitive estimates. In other words, combining a set of decompositional judgments to arrive at the aggregate forecast performed no better than the subjects' direct intuitive estimates.

- Subjects predicted market outcomes better when they were operating on the linear portions of the response function than when they were in the concave or convex regions near the asymptotes.

- Subjects made better (closer to optimal) decisions over time. In other words, they were able to adapt to their environment. McIntyre also reported this finding.

- Subjects in the second CMS study made relatively larger errors in their judgmental estimates and also learned at a slower rate than their counterparts in the first study. This was manifested in terms of slower improvements over time both in decision optimality and in the accuracy of their estimates of market outcomes associated with their decisions. This was probably because the second study subjects had to stay within a budget constraint and thus could not experiment by varying their expenditure allocations as much as subjects in the first study.

- The complexity of the decision task that was manipulated by varying the number of territories over which allocations were to be made (either three or six) did not affect the results either for estimation accuracy or for decision optimality. McIntyre, who used an identical manipulation of task complexity, however, reported a small negative effect on decision optimality as the number of territories increased. However, he too did not find any model usage by task complexity interactions.

**Implications of Findings**

The findings reported above have important implications for the development and implementation of judgment based marketing decision models. However, while the use of the laboratory approach provided the researchers with the capability of making objective evaluations of managers' performances in the experimental setting, it may have also placed limitations on the external validity of the results. These limitations are discussed before the implications are presented.

**Limitations**

First, many of the subjects had little prior experience making advertising budgeting decisions. While this may have caused them some initial difficulty in performing the task, we found no direct evidence that this affected the results. Also, all the subjects were experienced decision makers (senior and middle management executives), and as discussed earlier, their estimates indicated very few inconsistencies and their decisions improved over the course of the experiment. Thus, the results should be generalizable to a broader group than those sampled.

Secondly, the specific models used (ADBUDG and CALLPLAN respectively) may have influenced the results. For example, if the ADBUDG response function did not correspond to a manager's general understanding of advertising effects on market share, he/she may have been confused while trying to use the feedback provided to discern the nature of the data generating function. However, during the classroom sessions CMS tried to elicit from the subjects their implicit model of advertising effects on market share. This discussion led to the structural form that was actually being used to generate the data (the ADBUDG response function). The subjects did not question the correctness of this structural form or propose any alternative structures. Also, during these sessions the relationships between the judgmental estimates and the model's parameters were carefully explained so that there was considerable agreement and a generally good understanding of the S-shaped advertising response function and the parameterization approach at the end of the classroom session.

The interaction between the manager and the model builder in these studies may have been less than in commercial applications. However, in the two CMS studies, subjects spent 90 minutes and 3 hours, respectively, in classroom sessions and
in addition, the average subject spent 2.3 and 4.9 hours respectively in the on-line parameterization tasks, with some subjects spending 6.5 and 15 hours in the respective studies.

Finally, the experimental studies may not have provided all the information that a manager may have in some real world situations. In some situations a manager may have exogenous information that enables him/her to estimate the outcomes of decisions outside his/her normal operating range. For example, in industrial selling situations, a manager may know that a client firm has a policy of keeping purchases from a specific supplier within some maximum or minimum bounds. This information may help in developing estimates for the effects of saturation sales call levels. While in these specific instances it may be possible to obtain good judgmental estimates, exogenous information is not always available. Even when such information is available, managers may draw biased inferences from it (e.g., Ross 1977, Tversky and Kahneman 1974). The results of these studies may not be valid for group decision making situations.

Implications for Users of Judgment Based Models
The findings presented here demonstrate that in order for a decision model to aid managers in decision making, the market response function must be correctly specified and parameterized. If the decision environment is complex (e.g., incorporates carryover effects) and reliable exogenous information is not available, managers may have difficulty providing the judgmental estimates necessary to parameterize the response function. At the same time, McIntyre's findings show that managerial judgments may be fairly accurate in stable and simple decision environments. It follows, therefore, that judgment based models are most likely to improve decisions when the environment is stable and simple. The presence of this condition can be assessed during the initial stages of model building when the manager verbalizes his/her implicit model of the situation and may be used as an indicator of when managerial judgments may be relied upon.

A corollary of the above is that use of the model seems to improve decision making primarily by enabling the manager to process available information better and to examine possible decision alternatives more completely, rather than by helping the manager learn more about market response through interaction with the model. This is substantiated by all three studies where subjects were unable to provide better judgmental estimates following exposure to the model. Even in the Fudge and Lodish field study, subjects systematically underestimated market response as revealed by actual sales outcomes. Fudge and Lodish, however, attributed these discrepancies to subjects attempting to adjust for the risks inherent in changing sales call policies.

When judgmental parameterization is necessary in more complex environments, users of decision models should be aware of the following. Managers seem best at providing estimates within the normal operating range of the firm. Outside this range (e.g., for estimates of market share associated with zero or saturation advertising) the manager has little prior basis for making assessments, managerial estimates incorporate considerable uncertainty and may be subject to large errors and systematic biases (e.g., the effects of anchoring). Although model predictions within the normal operating range of the firm may not be substantially affected by these errors (particularly if tracking is used), the optimal decision recommended by the model may deviate considerably from the true optimal. This is because obtaining a valid optimal solution requires a valid model over the range of possible decisions. Also, when the model is being used for allocating resources across units (e.g., territories, branches, etc.), errors in the estimates of the response function parameters for one unit normally will affect the model's recommended allocation in all units. Although caution should be used in implementing the recommendations of judgment based models whenever the environment is complex, the more worrisome situations are those where the recommendations fall outside the firm's normal operating range.

Caution should be observed in using judgment based models even if tracking is used to validate the parameter estimates. CMS (1977) showed that in situations where the number of parameters is large relative to the number of data points available, an overparameterized model may (a) reproduce past data with a number of different parameter sets which may have different decision implications, and (b) produce reasonable future predictions irrespective of the value of the control variable. Managers who are unaware of this may gain undue confidence in a set of parameter values or in the model structure because of fits obtained to past data.

The CMS results also show that in complex decision environments, decomposing the response function estimation problem into a series of component estimates did not yield better forecasts of decision outcomes than the manager's direct estimates. This is not surprising since the component estimates included those for zero and saturation advertising in which the errors were likely to be
larger than the errors in direct estimates of decision outcomes within the normal operating region. Hence the advantages claimed on the basis of decomposition for judgmentally parameterized models are unlikely to be realized in practice, since the conditions required for decomposition to work are not met.

All three studies indicated that subjects made more accurate judgmental estimates when they gained experience, particularly when they made decisions over a wide range of their response functions as against when they made repetitive decisions within a limited range. As discussed before, subjects in the second CMS study experimented less since they had a budget constraint. Consequently, these subjects learned about their response functions at a slower rate and also made larger errors in their judgmental estimates, relative to the subjects in the first study who did not have budget constraints and, hence, were able to experiment more. This indicates the importance of broadening the range of managerial experience, possibly through market experimentation, when using judgment-based models.

The need for market experiments to provide information about market response to control variables has been emphasized before by many authors, most notably Little (1966, 1970, 1977, 1979). However, the practical use of field experimentation is often limited by organizational constraints (Ackoff and Emshoff 1975), and by problems with the quality of data that real world market tests generate (Little 1980). The design and use of adaptive control procedures (Little 1967, 1977, Pekelman and Tse 1980) that explicitly address the cost benefit trade-offs in market experimentation may be the most useful long run approach to addressing these problems.

The results provide some evidence that the complexity of the decision task in and of itself probably is not a reliable gauge of the potential benefits of using judgment-based models for marketing decision making. Both the CMS and McIntyre studies did not find any marked effects of varying the number of allocation units from three to six territories on the ability of the model to improve decision making. On the other hand, the complexity of the judgment task involved in parameterizing the market response function may be the more important determinant of the efficacy of a judgment-based model.

Finally, situational factors (e.g., the firm’s specific location on the market response function) seemed to affect the accuracy of the subjects’ judgmental estimates. The direction of such influences may vary over situations. However, since such factors will probably have an impact in most actual usage situations, model users should consider them in assessing the potential value of a model in the particular situation.

Implications for Model Builders

Given the implications drawn in the preceding section, it is necessary to consider future directions that model builders may consider in order to circumvent some of the problems that were identified. Several possible directions may be considered.

First, since judgmental inputs and consequently model recommendations outside the normal operating of the firm may be invalid, it may not be advisable to use judgment-based models to determine the optimal level of the decision variables. Instead, model usage might be restricted to assessing the marginal effects of small changes in the decision variables. Effort then would be directed at obtaining a more efficient rather than the optimal deployment of the firm’s resources. Interestingly, if judgment-based models are used only in this manner and if the response function is stable and simple, there may be some question as to the incremental benefits that these models provide, since econometric approaches should outperform managerial judgments in determining the slope of the response function, unless the latter incorporate valid exogenous knowledge. This is especially true if multiple control variables affect the decision outcome.

An alternative approach would be to look for procedures to improve the parameter estimates required for such models. This might be accomplished in two ways. First, estimation procedures might take into account the uncertainty associated with model predictions at different levels of the decision variables along with some measure of the manager’s loss function. Unfortunately, the existing deterministic models do not permit the inclusion of such factors. However, by adding error terms to the models, statistical procedures could be used to obtain parameter estimates along with indications...
of the amount of uncertainty associated with a particular estimate.

Another approach (CMS 1980b) utilizes a specific combination of statistical methods and judgmental estimation to parameterize models of the form in equation (1). The basic idea is to decouple the carryover effect from the current effect using econometric techniques. Specifically, if \( g(·) \) and \( f \) are reasonably independent (statistically), the parameters of \( g(·) \) can be estimated fairly accurately using regression analysis. Subtracting the estimated \( g(·) \) effect from the observed \( Y_t \) values yields an estimate of the current effect \( f = Y_t - \hat{g}(·) \). The parameters of \( f \) then can be determined by a combination of curve fitting and judgmental estimation. Preliminary tests of these procedures on data bases generated in the first CMS study produced estimates that had an average absolute error of 6.2% as compared to the 20% average error in the managerial estimates. The stability of the procedures is being investigated further by the authors.

Analytical expressions showing both individual and joint effects of the errors in the various judgmental estimates on model predictions can be obtained by successive partial differentiation, first of the model parameters with respect to the judgmental estimates, and then of the criterion variable with respect to the model parameters. Chakravarti (1979) shows such a sensitivity analysis for the ADBUDG model. While the details are beyond the scope of this paper, these analysis are useful for assessing whether or nor decomposition is likely to help improve the aggregate predictions of a model in a given situation.

**Future Research**

Future research should be directed at understanding the causes of the biases involved in judgmental parameter estimates. While research in cognitive and social psychology (Ross 1977, Slovic et al. 1977, Tversky and Kahneman 1974) provides some insights, this research needs to be extended so the findings pertain directly to judgmental estimation of market response. Such research may provide predictions as to the direction and magnitude of bias that may be expected in the judgmental inputs required for parameter estimation. If this bias could be predicted or estimated, it may be possible to adjust managerial judgments to improve the validity of model parameters and thus augment the model’s ability to aid and improve marketing decisions.

Another important area for future research concerns the role of exogenous information in managerial judgments. The lab studies reviewed earlier did not provide subjects with information beyond formal outcome feedback. However, in the real world, managers may have a repository of exogenous information with which to make inferences about market response. While in some situations this information may be fairly specific and reliable, in many situations the information may be soft, not necessarily pertinent, and even misleading. In these latter situations, the resulting inferences may be subject to bias due to the use of heuristics such as availability, representativeness, and anchoring, which have been identified by psychologists (e.g., Ross 1977; Slovic et al. 1977; Tversky and Kahneman 1974).

Finally, the degree to which managers can correctly specify the underlying data-generating model is also of potential research interest since judgment based models seem to work best when the market response function is fairly simple. One approach might be to have managers given data and informal cues about a data-generating function known to the researchers and then asked to provide descriptions of the critical variables and their relationships. The model description methodology of Gaver and Geisel (1973) could be used to examine the resultant descriptions. The findings would indicate the extent to which managerial judgment can be relied upon in the model specification.

**Conclusion**

This paper has reviewed two field studies and three laboratory studies that assessed the usefulness of judgment based marketing decision models. It is argued that there is a need to understand and take into account the cognitive abilities of managers in designing marketing decision models and their support systems. The resulting models and support systems should draw upon the managers’ cognitive strengths and compensate for their weaknesses. Failure to take these limitations into account may result in models that do not improve decision making.

The research results discussed in this paper represent an initial step in this direction. While these laboratory studies have external validity limitations, they are able to provide a detailed understanding of the biases contained in judgmental estimates and situational factors affecting these estimates. Understanding these biases and situational factors should, in turn, lead to improved decision support systems. For instance, although Little (1970, 1975) has suggested the use of statistical analysis to augment managerial judgments, he has not indicated how and when it should be used. The results of the
studies reported here indicate situations when statistical analysis may be particularly useful and indicates which parameters should be estimated with these techniques. For example, the studies show that a smart statistician may be able to augment managerial judgments in dynamic market response environments by disentangling the carryover effect from the current effect statistically (CMS 1980b).

This leaves the manager with a significantly simpler judgmental task that he/she may be able to perform fairly accurately.

Finally, it is hoped that the problems discussed in this paper will stimulate additional research aimed at improving the procedures for the development and implementation of marketing decision models.

REFERENCES


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