

MARKETING DECISION SUPPORT MODELS

The Marketing Engineering Approach

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Marketing managers make ongoing decisions about product features, prices, distribution options, sales compensation plans, and so on. In making these decisions, managers choose from among alternative courses of action in a complex and uncertain world. Like all decisions that people make, marketing decision making involves judgment calls. Most traditional marketing decision making, while sometimes guided by the concepts of our literature, has been largely based on managers' mental models, intuition, and experience.

In many cases, such mental models, perhaps backed up by market research data, may be all that managers need to feel psychologically comfortable with their decisions. Yet, mental models are prone to systematic errors (Bazerman, 1998). While we all recognize the

value of experience, that experience is unique to every person and can be confounded with responsibility bias: Sales managers might choose lower advertising budgets in favor of higher expenditures on personal selling, while advertising managers might prefer larger advertising budgets.

Consider an alternative approach to the mental model for a decision involving setting advertising expenditures: Managers might choose to build a spreadsheet decision model of how the market would respond to various expenditure levels. They could then use this model to explore the sales and profit consequences of alternative expenditure levels before making a decision. The systematic translation of data and knowledge (including judgment) into a tool that is used for decision support is what we call marketing engineering. In contrast, relying solely on the mental

model of the particular decision maker without using any support system is what we refer to as conceptual marketing. A third option would be to automate the decision process. For example, CoverStory (Schmitz, Armstrong, & Little, 1990) automatically analyzes scanner data. If a marketer would directly follow CoverStory's recommendations, we would call this automated marketing. Bucklin, Lehman, and Little (1998) foresee considerable opportunities for the computer taking over many of the traditionally human tasks associated with marketing decisions. However, given the intrinsic complexity of marketing problems (many instruments; a large number of environmental factors, including competition; and substantial uncertainty in each of these factors), for many marketing decisions, a combination of marketing support tools and the judgment of the decision maker provide the best results. We call approaches that systematically combine judgment with formal models as the marketing engineering (ME) approach. More specifically, we define ME as a systematic approach to harness data and knowledge to drive marketing decision making and implementation through a technology-enabled and model-supported interactive decision process.

The ME approach relies on the design and construction of decision models and implementing such decision models within organizations in the form of marketing management support systems (MMSSs). In this chapter, we focus primarily on describing the marketing engineering approach and its potential benefits, as well as illustrating how some leading companies use ME. Specifically, we (a) summarize the major trends shaping the environment for marketing decision making; (b) outline the benefits associated with the ME approach; (c) provide an overview of the ME approach, focusing particularly on describing various market response models that form the core of marketing models; (d) offer managerial suggestions for implementing ME; and (e) sketch future developments regarding ME deployment and use. Chapter 31 by Van Bruggen and Wierenga in this book provides a broad perspective on the various types of MMSSs (ranging from optimization-focused systems to creativity enhancement systems) and explores the success factors associated with MMSS.

THE EMERGING MARKETING DECISION ENVIRONMENT

Although there have been attempts to employ aspects of ME in organizations since the 1950s, the pace has accelerated in the past decade because of the range of technologies that have made the approach not only feasible but, increasingly, an imperative in competitive markets. Past attempts to engineer marketing generally led only to short-lived successes, not because of poor models but generally because of the lack of technology to embed that success in the fiber of the organization. Within the past decade, technology has advanced to a stage where it now makes it possible for model-based decision making to be an integral part of the repertoire of skills of the marketing manager.

For several decades, researchers and practitioners have developed and implemented powerful systems that facilitate decision making in real-world marketing settings (for case studies and examples, see Assad, Wasil, & Lilien, 1992; Lilien, Kotler, & Moorthy, 1992; Little, 1970; Wierenga & Van Bruggen, 2000). Yet, until recently, much of the knowledge about marketing decision models resided primarily in specialized academic journals or required considerable technical expertise to use, thus making it available only with the help of specialized consultants. Major changes began with the development of stand-alone models to support marketing analytics, embedded within the hundreds of commercially available canned software packages. With the advent of enterprise-wide systems for resource planning (ERP) and customer relationship management (CRM), marketing analytics have increasingly become an integrated aspect of the decision-making architectures that leading firms employ. As an indication, an IDC report in 2005 projected annual growth of 4.5% in marketing automation applications for the years 2004–2009 (IDC, 2005).

Figure 12.1 shows how the ME approach transforms objective and subjective data about the marketing environment into insights, decisions, and actions. Figure 12.2 sketches how ME can become an integral part of the information and decision architectures supporting marketing decision making.

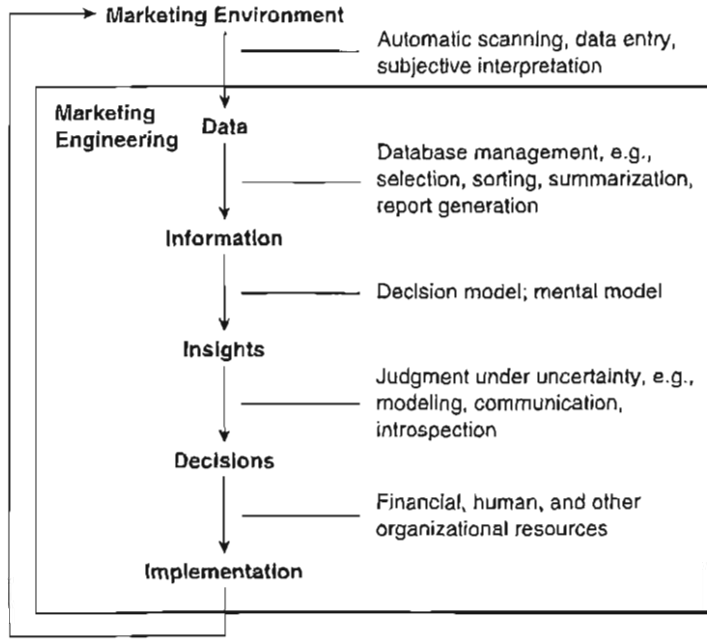


Figure 12.1 Marketing Engineering Approach to Decision Making

Note: The marketing engineering approach to decision making helps transform objective and subjective data about the marketing environment into decisions and decision implementations.

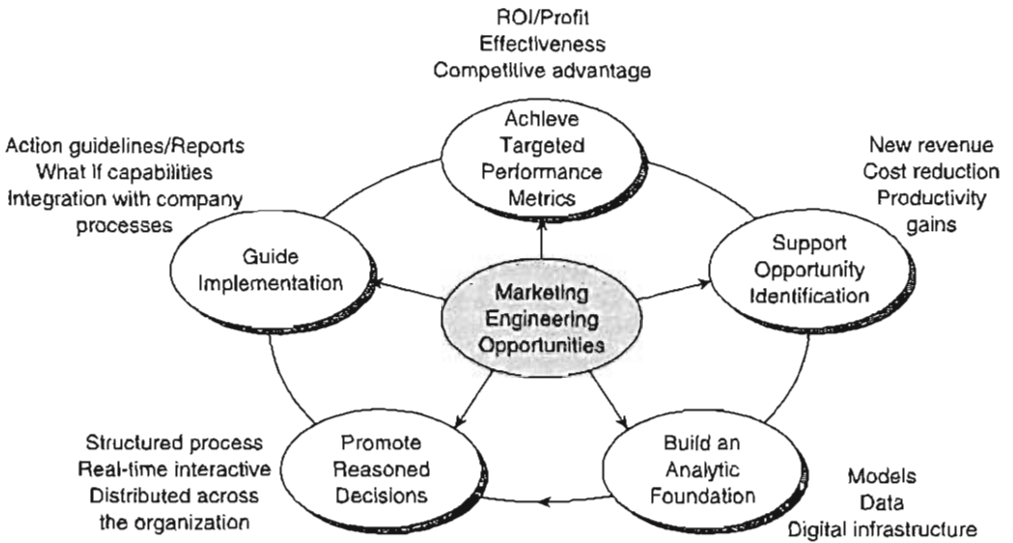


Figure 12.2 Marketing Engineering as an Integral Part of the Information and Decision Architectures Supporting Marketing Decision Making

Note: The marketing engineering (ME) approach offers several opportunities for using information technologies to architect the marketing decision environment throughout an organization. It supports identification of new business opportunities, offers a common analytic foundation for driving marketing decisions, incorporates the latest insights and practices associated with a particular area of marketing decision making (e.g., segmentation), and integrates actions with decisions, all of which can serve to enhance strategically important metrics.

Table 12.1 Degree of Correlation With the True Outcomes of Three Types of Models, Showing That Even Subjective Decision Models Are Superior to Mental Models but That Formal, Objective Models Do Far Better

<i>Types of Judgments Experts Had to Make</i>	<i>Mental Model^a</i>	<i>Subjective Decision Model^b</i>	<i>Objective Decision Model^c</i>
Academic performance of graduate students	.19	.25	.54
Life expectancy of cancer patients	-.01	.13	.35
Changes in stock prices	.23	.29	.80
Mental illness using personality tests	.28	.31	.46
Grades and attitudes in psychology course	.48	.56	.62
Business failures using financial ratios	.50	.53	.67
Students' ratings of teaching effectiveness	.35	.56	.91
Performance of life insurance salesman	.13	.14	.43
IQ scores using Rorschach tests	.47	.51	.56
Mean (across many studies)	.33	.39	.64

Source: Russo and Shoemaker (1989, p. 137).

a. Outcomes directly predicted by experts.

b. Subjective decision model: outcomes predicted by subjective linear regression model, formalizing past predictions made by experts.

c. Objective decision model: linear model developed directly from data.

Although marketing engineering could encompass all the elements shown in Figures 12.1 and 12.2, in this chapter, we focus more narrowly on how marketing engineering helps transform data, information, and insights into decisions. This aspect has traditionally been the realm of marketing academia, and it continues to be the core component where academic contributions have the potential to improve both theory and practice.

Several trends, both on the supply side and demand side, favor the wider acceptance of the marketing engineering approach:

1. High-powered personal computers connected to networks are everywhere.
2. The volume of data is exploding.
3. Firms are reengineering marketing such that marketing managers are increasingly dealing directly with market information and using computers to do tasks that were once done by staff support people.
4. Marketing is being held to higher standards of accountability.

Marketing engineering is a way to capitalize on the above trends that favor both the supply

and demand for marketing analytics. ME enables us to capture the essence of marketing problems in well-specified models, and it improves our ability to make decisions that influence market outcomes. For example, with the large number of installations of Microsoft Excel (about 300 million users in 2005), Java applets, and other software components, companies can easily integrate ME into their information and decision architecture. That integration will increase managers' ability to gather, process, and share information and to apply marketing models at the point of decision making.

Next, we briefly outline the potential benefits that firms gain by adopting and using marketing analytics. At the outset, note that the mere availability, or the use, of marketing analytics need not necessarily significantly affect managerial or organizational performance; it is far more important to make analytics a part of the company's basic capability in managerial decision making. In Table 12.1, we present summaries of studies that have evaluated the impact of models in improving managers' prediction accuracy in various decision contexts.

Consider the first row of Table 12.1, where the formalized intuition of experts captured in a simple linear model outperforms the experts

themselves. Accuracy here improved from 19% correlation between direct expert judgments of student performance to 25% correlation using a linear, descriptive model relating past judgments to the data available to make those judgments. An explanation for this improvement is that the decision model more consistently applies the expertise of the experts to new cases.

The third column in Table 12.1 lists the accuracy of an "objective" linear regression model. For the academic performance study, the independent variables for the regression model were the same factors used by the experts, but the dependent variable was a known measure of the academic performance of the graduate students. The predictions in this case were based on a holdout sample of data to which the objective model was applied. For this model, the correlation of predictions with true outcomes was 54%. Table 12.1 also shows the average correlations between predictions and true outcomes across several studies. We see that subjective decision models had an average correlation of 39% with true outcomes as compared to 33% for the intuitive mental models

These results point to a few interesting conclusions: (a) When managers can build an objective model based on actual data, they will generally predict the best. However, in many decision situations, we do not have data that show the accuracy or the consequences of past decisions made in the same context. In such cases, the next best option is to codify the mental model that decision makers use into a formal decision model. The calibrating of response models using the decision calculus method (Little, 1970) is a way to formalize the mental models of decision makers. (b) Among these three types of models, the least accurate is the mental model. However, on average, all three types of models had a positive correlation with the truth, while a model with random predictions would have zero correlation with the truth. (c) Managers should focus their attention on finding variables useful for prediction but should use decision models to combine the variables in a consistent fashion.

Managers recognize that models are incomplete, and therefore, they correctly believe that model results cannot be implemented without being modified by judgments. If model results

are to be tempered by intuitive judgments, why not rely on judgments in the first place? The latter conclusion, however, does not follow from the first. As Hogarth (1987) notes, "When driving at night with your headlights on you do not necessarily see too well. However, turning your headlights off will not improve the situation" (p. 199).

Decision support tools and mental models should be used in conjunction, so that each works to strengthen the areas where the other is weak. Mental models can incorporate idiosyncratic aspects of a decision situation, but they also overfit new cases to old patterns. On the other hand, decision models are consistent and unbiased but underweight idiosyncratic aspects. In a forecasting task, Blattberg and Hoch (1990) found that predictive accuracy could be improved by combining the forecasts generated by decision models with forecasts from mental models. Furthermore, they reported that a 50-50 (equal weighting) combination of these two forecasts provided the highest predictive accuracy.

Marketing engineering can be both data driven and knowledge driven. A data-driven support tool can answer "what-if" questions, based on a quantified market response model. A knowledge-driven decision support tool captures the qualitative knowledge that is available about a particular domain. An example is the ADCAD expert system for advertising design (Burke, Rangaswamy, Wind, & Eliashberg, 1990). Other knowledge-driven decision support technologies relevant for marketing include case-based reasoning, neural networks, and creativity support systems (see Wierenga & Van Bruggen, 2000).

There are other benefits to the marketing engineering approach. Managers using this approach could explore more decision options, consider decision options that are farther away from "historical norms," more precisely assess the relative impact of different marketing decision variables, facilitate group decision making, and enhance their own subjective mental models of market behavior. In essence, the marketing engineering approach can lead to better and more systematic marketing decision making.

Several well-documented examples have demonstrated that companies can derive substantial benefits from the application of the marketing engineering approach to decision

making: see ABB Electric (Gensch, Aversa, & Moore, 1990), Marriott Corporation (Wind, Green, Shifflet, & Scarbrough, 1989), Syntex Laboratories (Lodish, Curtis, Ness, & Simpson, 1988), The German Railroad Corp. (Dolan & Simon, 1996), and Rhenania (Elsner, Krafft, & Huchzermeier, 2004).

Each of the above examples involves a complex and unstructured decision problem, a model, some data, managerial judgment, and a successful, profitable outcome for the firm. Staelin (1999) and Lilien and Rangaswamy (2001) provide many additional examples in areas such as sales promotion planning, movie scheduling, industrial product line development, sales force management, product design, and forecasting new product diffusion.

TOOLS FOR MARKETING ENGINEERING: MARKET RESPONSE MODELS

The wide availability of spreadsheet software, such as Excel, has made it easier to work with mathematical representations of marketing phenomena. For example, marketing spreadsheets typically include planned marketing expenditures and the associated gross and net revenues. However, in most cases, the model developer does not establish a relationship, within the spreadsheet, between marketing inputs (e.g., advertising) and sales revenues. Thus, marketing inputs only affect net revenue as a cost item. We refer to such spreadsheets as “dumb” models. They make little sense as marketing models because they are silent about the nature of the relationship between marketing inputs and outputs. For the spreadsheet model to make sense, the model developer must define objectives and variables explicitly and specify the relationships between variables. In a “smart” model, an equation or “response model” will be embedded in the spreadsheet. The manager can then look at the effect of advertising on both sales and revenues to see if increases or decreases in advertising can be justified. Hence, the design environment (knowledge, software, and data) facilitates marketing engineering.

In this section, we explore the nature of market response models, which provide the basic tools for marketing analytics (i.e., the ingredients

that can transform a dumb spreadsheet model into a smart model). Response models are critical for systematically addressing many recurring strategic and tactical decision problems in marketing, such as marketing budgeting and mix allocations, customer targeting, and product/company positioning. Without models that describe how customers and markets might respond to various marketing actions, it is very difficult to fully assess the opportunity costs of the decision at hand. *Marketing Engineering* (Lilien & Rangaswamy, 2004) provides additional details about how response models are integrated into various marketing decision models. That book also includes an extensive set of software tools to gain a hands-on learning of these models.

Market response models require that the following be made explicit:

Inputs: The marketing actions that the marketer can control, such as price, advertising, selling effort, and the like—the so-called marketing mix—as well as noncontrollable variables, such as the market size, competitive environment, and the like

Response model: The linkage from those inputs to the measurable outputs of concern to the firm (customer awareness levels, product perceptions, sales levels, and profits)

Objectives: The measure that the firm uses for monitoring and evaluating those actions (e.g., the level of sales in response to a promotion, the percentage of a target audience that recalls an ad)

Response models function within the framework of marketing decision models (Figure 12.3). A firm’s marketing actions (Arrow 1) along with the actions of competitors (Arrow 2) and environmental conditions (Arrow 3) combine to drive the market response, leading to key outputs (Arrow 4). Those outputs are evaluated relative to the objectives of the firm (Arrow 5), and the firm then adapts or changes its marketing actions depending on how well it is doing (Arrow 6)—the decision-modeling link.

In this chapter, we will focus first on the simplest of the model types: aggregate response to a single marketing instrument in a static, noncompetitive environment. Then we will

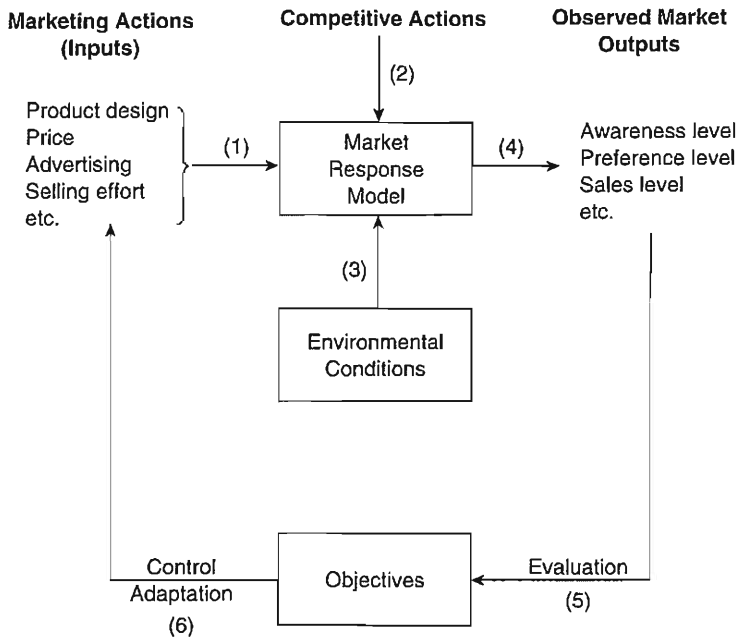


Figure 12.3 Market Response Models

Source: Russo & Schoemaker (1989). Used by permission of Doubleday, a division of Random House, Inc.

Note: Market response models translate marketing inputs, competitive actions, and environmental variations into observed market outputs within the framework of a marketing decision model—Arrow 6, the decision-modeling link.

introduce additional marketing instruments, dynamics, and competition.

We use several terms to denote the equation or sets of equations that relate dependent variables to independent variables in a model, such as *relationship*, *specification*, and *mathematical form*.

Parameters are the constants (usually the *a*'s and *b*'s) in the mathematical representation of models. To make a model form apply to a specific situation, we must estimate or guess what these values are; in this way, we infuse life into the abstract model. Parameters often have direct marketing interpretations (e.g., market potential or price elasticity).

Calibration is the process of determining appropriate values of the parameters. You might use statistical methods (i.e., estimation), some sort of judgmental process, or a combination of approaches.

For example, a simple model is

$$Y = a + bX. \quad (1)$$

In Equation (1), *X* is an independent variable (advertising, say), *Y* is a dependent variable

(sales), the model form is linear, and *a* and *b* are parameters. Note that *a* in Equation (1) is the level of sales (*Y*) when *X* equals 0 (zero advertising), or the base sales level. For every dollar increase in advertising, Equation (1) says that we should expect to see a change in sales of *b* units. Here, *b* is the slope of the sales/advertising response model. When we (somehow) determine that the right values of *a* and *b* are 23,000 and 4, respectively, and place those values in Equation (1) to get

$$Y = 23,000 + 4X, \quad (2)$$

then we say we have calibrated the model (given values to its parameters). See Figure 12.4.

Some Simple Market Response Models

In this section, we provide a foundation of simple but widely used models of market response that relate one dependent variable to one independent variable in the absence of competition. The linear model shown in Figure 12.4

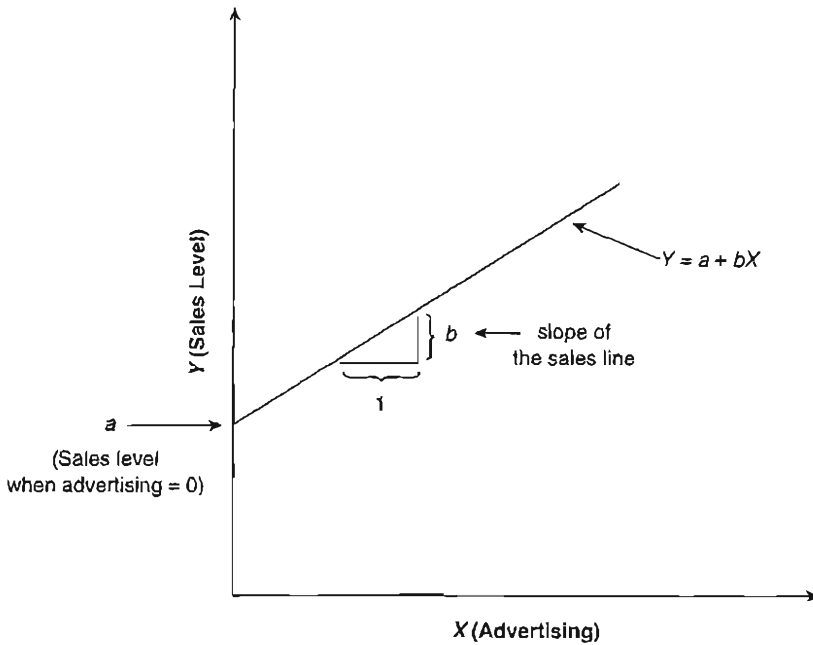


Figure 12.4 Interpreting the Coefficients of a Linear Response Model

is used frequently, but it is far from consistent with the ways markets appear to behave.

Saunders (1987) summarizes the simple phenomena that have been reported in marketing studies and that we should be able to handle using our toolkit of models (Figure 12.5). In describing these eight phenomena here, we use the term *input* to refer to the level of marketing effort (the X or independent variable) and *output* to refer to the result (the Y or dependent variable):

- P1. Output is zero when input is zero.
- P2. The relationship between input and output is linear.
- P3. Returns decrease as the scale of input increases (every additional unit of input gives less output than the previous unit gave).
- P4. Output cannot exceed some level (saturation).
- P5. Returns increase as scale of input increases (every additional unit of input gives more output than the previous unit).
- P6. Returns first increase and then decrease as input increases (S-shaped return).

P7. Input must exceed some level before it produces any output (threshold).

P8. Beyond some level of input, output declines (supersaturation point).

The phenomena we wish to incorporate in our model of the marketplace depend on many things, including what we have observed about the market (data), what we know about the market (judgment or experience), and existing theory about how markets react. We now outline some of the common model forms that incorporate these phenomena.

The Linear Model

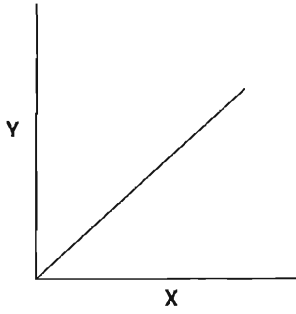
The simplest and most widely used model is the linear model:

$$Y = a + bX. \quad (3)$$

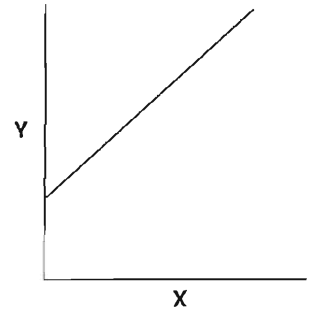
The linear model has several appealing characteristics:

- Given market data, one can use standard regression methods to estimate the parameters.
- The model is easy to visualize and understand.

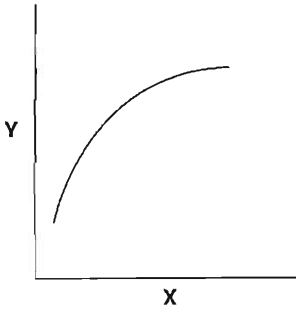
P1: Through origin



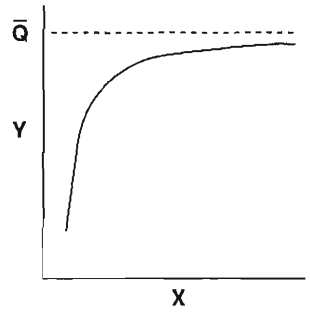
P2: Linear



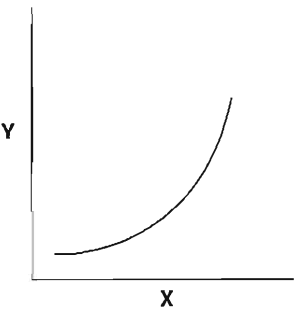
P3: Decreasing returns (concave)



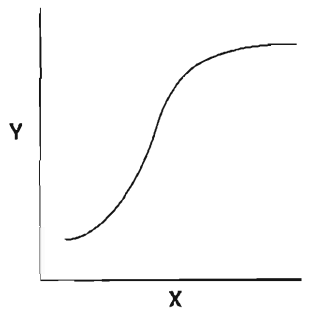
P4: Saturation



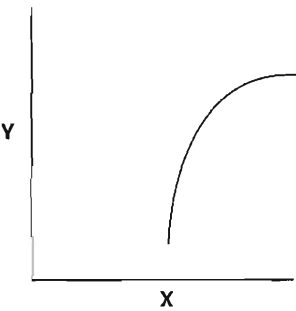
P5: Increasing returns (convex)



P6: S-shape



P7: Threshold



P8: Super-saturation

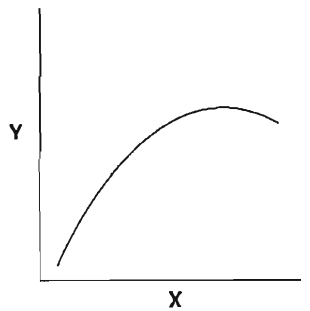


Figure 12.5 Pictorial Representation of Saunders's (1987) Response Model Phenomena

- Within specific ranges of inputs, the model can approximate many more complicated functions quite well—a straight line can come fairly close to approximating most curves in a limited region.

It has the following problems:

- It assumes constant returns to scale everywhere (i.e., it cannot accommodate P3, P5, or P6).
- It has no upper bound on Y .
- It often gives managers unreasonable guidance on decisions.

On this last point, note that the sales slope ($\Delta Y/\Delta X$) is constant everywhere and equal to b . Thus, if the contribution margin (assumed to be constant, for the moment) is m for the product, then the marginal profit from an additional unit of spending is bm . If $bm > 1$, more should be spent on that marketing activity, without limit—that is, every dollar spent immediately generates more than a dollar in profit! If $bm < 1$, nothing should be spent. Clearly, this model is of limited use for global decision making (it says: spend limitless amounts or nothing at all!), but locally the model suggests whether a spending increase or decrease is appropriate.

Linear models have seen wide use in marketing, and they readily handle phenomena P1 and P2. If X is constrained to lie within a range ($\underline{B} \leq X \leq \bar{B}$), the model can accommodate P4 and P7 as well.

The Power Series Model

If we are uncertain about the nature of the relationship between X and Y , we can use a power series model. Here the response model is

$$Y = a + bX + cX^2 + dX^3 + \dots, \quad (4)$$

which can take many shapes.

The power series model may fit well within the range of the data but will normally behave badly (becoming unbounded) outside the data range. By selecting parameter values appropriately, the model may be designed to handle phenomena P1, P2, P3, P5, P6, and P8.

The Fractional Root Model

The fractional root model,

$$Y = a + bX^c \text{ (with } c \text{ prespecified)}, \quad (5)$$

has a simple but flexible form. There are combinations of parameters that give increasing, decreasing, and (with $c=1$) constant returns to scale. When $c = 1/2$, the model is called the square root model. When $c = -1$, it is called the reciprocal model; here, Y approaches the value a when X gets large. If $a = 0$, the parameter c has the economic interpretation of elasticity (the percent change in sales, Y , when there is a 1% change in marketing effort X). When X is price, c is normally negative, whereas it is positive for most other marketing variables. This model handles P1, P2, P3, P4, and P5, depending on what parameter values you select.

The Semilog Model

With the functional form

$$Y = a + b \ln X, \quad (6)$$

the semilog model handles situations in which constant percentage increases in marketing effort result in constant absolute increases in sales. It handles P3 and P7 and can be used to represent a response to advertising spending where, after some threshold of awareness, additional spending may have diminishing returns.

The Exponential Model

The exponential model,

$$Y = ae^{bX} \text{ where } X > 0, \quad (7)$$

characterizes situations where there are increasing returns to scale (for $b > 0$); however, it is most widely used as a price response function for $b < 0$ (i.e., increasing returns to decreases in price) when Y approaches 0 as X becomes large. It handles phenomena P5 and, if b is negative, P4 (Y approaches 0, a lower bound here).

The Modified Exponential Model

The modified exponential model has the following form:

$$Y = a(1 - e^{-bX}) + c. \quad (8)$$

It has an upper bound or saturation level at $a + c$ and a lower bound of c , and it shows decreasing returns to scale. The model handles phenomena P3 and P4 and is used as a response function for selling effort; it can accommodate P1 when $c = 0$.

The Logistic Model

Of the S-shaped models used in marketing, the logistic model is perhaps the most common. It has the form

$$Y = \frac{a}{1 + e^{-(b+cX)}} + d. \quad (9)$$

This model has a saturation level at $a + d$ and has a region of increasing returns followed by decreasing return to scale; it is symmetrical around $d + a/2$. It handles phenomena P4 and P6, is easy to estimate, and is widely used.

The ADBUDG Model

The ADBUDG model, popularized by Little (1970), has the form

$$Y = b + (a - b) \frac{X^c}{d + X^c}. \quad (10)$$

The model is S-shaped for $c > 1$ and concave for $0 < c < 1$. It is bounded between b (lower bound) and a (upper bound). The model handles phenomena P1, P3, P4, and P6, and it is used widely to model response to advertising and selling effort.

Calibration

Calibration means assigning good values to the parameters of the model. Consider the simple linear model (Equation 3). If we want to use that model, we have to assign values to a and b . We would want those values to be good ones. But what do we mean by *good*? A vast statistical and econometric literature addresses this question, but we will try to address it simply and intuitively.

Calibration Goal

We want estimates of a and b that make the relationship $Y = a + bX$ a good approximation of how Y varies with values of X , which we know something about from data or intuition.

People often use least squares regression to calibrate a model. In effect, if we have a number of observations of X (call them x_1, x_2 , etc.) and associated observations of Y (called y_1, y_2 , etc.), regression estimates of a and b are those values that minimize the sum of the squared differences between each of the observed Y values and the associated "estimate" provided by the model. For example, $a + bx_7$ would be our estimate of y_7 , and we would want y_7 and $a + bx_7$ to be close to each other. We may have actual data about these pairs of X s and Y s, or we may use our best judgment to generate them ("What level of sales would we get if our advertising was 10 times what it is now? What if it was half of what it is now?").

When the data that we use for calibration are actual experimental or market data, we call the calibration task *objective calibration* (or objective parameter estimation). When the data are subjective judgments, we call the task *subjective calibration*.

In either case, we need an idea of how well the model represents the data. One frequently used index is R^2 , or R -square. If each of the estimated values of Y equals the actual value of Y , then R -square has a maximum value of 1; if the estimates of Y do only as well as the average of the Y values, then R -square has a value of 0. If R -square is less than 0, then we are doing worse than we would by simply assigning the average value of Y to every value of X . In that case, we have a very poor model indeed!

Formally, R -square is defined as

$$R^2 = 1 - \frac{\text{(Sum of squared differences between actual } Y\text{s and estimated } Y\text{s)}}{\text{(Sum of squared differences between } Y\text{s and the average value of } Y\text{)}}. \quad (11)$$

Example: Suppose we have run an advertising experiment across a number of regions with the following results:

Region	Annual Advertising (Per Capita), \$	Annual Sales Units (Per Capita)
A	0	5
B	2	7
C	4	13
D	6	22
E	8	25
F	10	27
G	12	31
H	14	33

Let us take the ADBUDG function (Equation 10). If we try to estimate the parameters of the ADBUDG function (a , b , c , d) for these data, to maximize the R -square criterion, we get

$$\hat{a} = 39.7, \hat{b} = 4.6, \hat{c} = 2.0, \hat{d} = 43.4, \text{ with } R^2 = 0.99.$$

Figure 12.6 plots the results, showing how well we fit these data.

In many cases, managers do not have historical data that are relevant for calibrating the model for one of several reasons. If the firm always spends about the same amount for advertising (say 4% of sales in all market areas), then it has no objective information about what would happen if it changed the advertising-to-sales ratio to 8%. Alternatively, the firm may have some historical data, but that data may not be relevant because of changes in the marketplace such as new competitive entries, changes in brand price structures, changes in customer preferences, and the like. (Consider the problem of using year-old data in the personal computer market to predict future market behavior.)

As we pointed out earlier, formal models based on subjective data outperform intuition. To formally incorporate managerial judgment in a response function format, Little (1970) developed a procedure called "decision calculus." In essence, decision calculus asks the manager to run a mental version of the previous market experiment.

Q1: What are our current level of advertising and sales?

Q2: What would sales be if we spent \$0 in advertising?

Q3: What would sales be if we cut 50% from our current advertising budget?

Q4: What would sales be if we increased our advertising budget by 50%?

Q5: What would sales be if advertising were made arbitrarily large?

Suppose that the manager answered Questions 2 through 5 by 5, 13, 31, and 40, respectively; we would get essentially the same sales response function as in the previous example.

Objectives

Consider the role of the objectives in Figure 12.3. To evaluate marketing actions and to improve the performance of the firm in the marketplace, the manager must specify objectives. Those objectives may have different components (profit, market share, sales goals, etc.), and they must specify the time horizon, deal with future uncertainty, and address the issue of "whose objectives to pursue."

Short-Run Profit

The simplest and most common objective (in line with our focus on a single marketing element in a static environment) is to maximize short-run profit. The equation focusing on that single marketing element in a static environment is

$$\text{Profit} = (\text{unit price} - \text{unit variable cost}) \times \text{sales volume} - \text{relevant costs} \quad (12a)$$

$$= \text{unit margin} \times \text{quantity relevant} - \text{costs.} \quad (12b)$$

We can use response models to see how the sales volume in Equation (12a) is affected by our marketing actions. If our focus is on price, then (assuming costs are fixed) as price increases, unit margin goes up and quantity sold generally goes down. If we focus on another marketing instrument, such as advertising, then margin is fixed, quantity goes up, but costs go up as well.

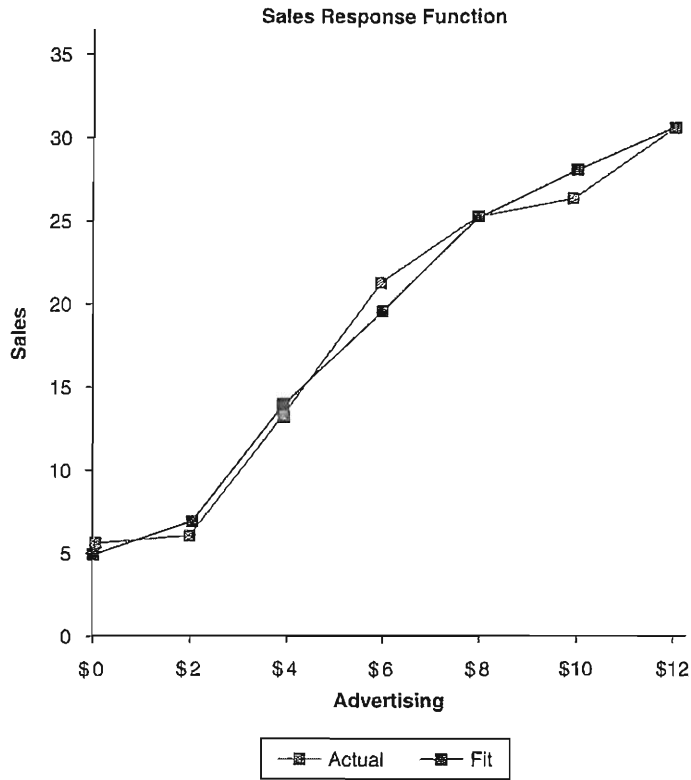


Figure 12.6 Calibration Example Using ADBUDG Function, With $R^2 = 0.99$

Relevant costs generally consist of two components: fixed and discretionary. Discretionary costs are those associated with the marketing activity under study and should always be considered. Fixed costs include those plant and overhead expenditures that should be appropriately allocated to the marketing activity. Allocating fixed costs is thorny and difficult; it keeps accountants employed and frequently frustrates managers of profit centers.

For our purposes, only two questions are relevant concerning fixed costs:

Are the fixed costs really fixed? Suppose that tripling advertising spending leads to a 50% sales increase, leading in turn to the need to increase plant size. These costs of capacity expansion must be taken into account. Normally, fixed costs are locally fixed; that is, they are fixed within the limits of certain levels of demand and shift to different levels outside those regions. As with our response models, as long as we focus locally, most fixed costs are indeed fixed.

Are profits greater than fixed costs? If the allocated fixed costs are high enough, absolute profitability may be negative. In this case, the decision maker may want to consider dropping the product, not entering the market, or some other action.

Long-Run Profit

If a marketing action or set of actions causes sales that are realized over time, we may want to consider profit over a longer time horizon. If we look at the profit stream over time, then an appropriate way to deal with long-run profits is to take the present value of that profit stream:

$$PV = Z_0 + Z_1r + Z_2r^2 + Z_3r^3 = \dots, \quad (13)$$

where Z_i is the profit for period i , and $r = 1/(1 + d)$, with d being the discount rate. The discount rate d is often a critical variable; the closer d is to 0, the more oriented to the long term the firm is, whereas a high value of d (over .25 or so)

reflects a focus on more immediate returns. In practice, the more certain the earnings flow, the lower the discount rate that firms use.

Dealing With Uncertainty

Managers know few outcomes of marketing actions with certainty.

Consider the following example:

Conglomerate, Inc., is considering two possible courses of action: continuing with its current laser pointer, whose profit of \$100,000 for the next year is known (almost for sure), or bringing out a replacement that would yield a profit of \$400,000 if it is successful (likelihood = 50%) or a loss of \$100,000 if it is unsuccessful (likelihood = 50%). What should it do?

If the firm had lots of money and the ability to make many decisions of this type, on average it would make $50\% \times \$400,000 + 50\% \times (\$100,000)$ or \$150,000 with the new product, and so it seems clear that this is the better decision. But if the firm (like capital markets) values more certain returns over less certain ones, then the decision is not that clear. What about a \$310,000 gain versus the \$100,000 loss for an average gain of \$105,000 but a 50% chance of losing \$100,000? Is it worth the risk?

Suppose that Conglomerate's managers would be just indifferent between the 50–50 chance of a \$400,000 profit or a \$100,000 loss and a \$125,000 gain for sure. We call the \$125,000 in this case the certainty monetary equivalent for the risky investment. The difference between the average gain (\$150,000) and the certainty monetary equivalent (\$125,000) is called the *risk premium*.

Either formally through utility theory (Lilien et al., 1992) or informally by applying some combination of high discount rates or risk premiums, Conglomerate's managers should incorporate their attitude toward risk in evaluating potential actions when the outcomes are uncertain.

Multiple Goals

Although profit of some sort is an overriding goal of many organizations, it is not the only factor managers consider in trying to decide among possible courses of action. Managers may say, "We want to maximize our market share and our profitability in this market!" or

"We want to bring out the best product in the shortest possible time." Such statements are attractive rhetoric but faulty logic. For example, one can almost always increase market share by lowering price; after some point, however, profit will be decreasing while market share continues to increase. And when price becomes lower than cost, profit becomes negative even though market share is still increasing!

If a firm has two or more objectives that possibly conflict, how can the decision maker weight those goals to rank them unambiguously? A sophisticated branch of analysis called multi-criteria decision making deals with this problem. The simplest and most common approach is to choose one (the most important) objective and to make all the others constraints; then management optimizes one (e.g., a profit criterion) while considering others to be constraints (e.g., market share must be at least 14%).

A second approach is goal programming, in which managers set targets for each objective, specify a loss associated with the difference between the target and actual performance, and try to minimize that loss. Trade-off analysis (Keeney & Raiffa, 1976) and the analytic hierarchy process (Lilien & Rangaswamy, 2004, chap. 6) are additional procedures for handling multiple objectives and trade-offs among objectives. Ragsdale (2000) provides a nice discussion of how to implement multiobjective optimization in a spreadsheet framework.

Whether you use a simple formal method, such as the approach employing a single goal plus constraints, or a more sophisticated method of dealing with trade-offs among goals, it is critical that you neither ignore nor poorly assess important goals.

After you have specified goals or objectives, the ME approach facilitates the process of decision making—suggesting those values of the independent variables (such as level of advertising, selling effort, or promotional spending) that will best achieve these goals(s) (such as maximize profit, meet target levels of sales, or maximize market share).

Multiple Marketing-Mix Elements: Interactions

In the section on calibration, we dealt with market response models of one variable. When

we consider multiple marketing-mix variables, we should account for their interactions. As Saunders (1987) points out, interactions are usually treated in one of three ways: (1) by assuming they do not exist, (2) by assuming that they are multiplicative, or (3) by assuming they are multiplicative and additive. For example, if we have two marketing-mix variables X_1 and X_2 with individual response functions $f(X_1)$ and $g(X_2)$, then assumption (1) gives us

$$Y = af(X_1) + bg(X_2). \quad (14)$$

Assumption (2) gives us

$$Y = af(X_1)g(X_2). \quad (15)$$

And assumption (3) gives us

$$Y = af(X_1) + bg(X_2) + cf(X_1)g(X_2). \quad (16)$$

In practice, when multiple marketing-mix elements are involved, we can resort to one of two forms: the (full) linear interactive form or the multiplicative form. The full linear interactive model (for two variables) takes the following form:

$$Y = a + bX_1 + cX_2 + dX_1X_2. \quad (17)$$

Note here that $\Delta Y/\Delta X_1 = b + dX_2$, so that sales response to changes in marketing-mix element X_1 is affected by the level of the second variable, X_2 .

The multiplicative form is as follows:

$$Y = aX_1^bX_2^c. \quad (18)$$

Here, $\Delta Y/\Delta X_1 = abX_1^{b-1}X_2^c$ so that the change in the response at any point is a function of the levels of both independent variables. Note here that b and c are the constant elasticities of the first and second marketing-mix variables, respectively, at all effort levels X_1 and X_2 .

Dynamic Effects

Response to marketing actions does not often take place instantly. The effect of an ad campaign does not end when that campaign is over; the effect, or part of it, will continue in a diminished way for some time. Many customers purchase more than they can consume of a

product during a short-term price promotion. This action leads to inventory buildup in customers' homes and lower sales in subsequent periods. Furthermore, the effect of that sales promotion will depend on how much inventory buildup occurred in past periods (i.e., how much potential buildup is left). If customers stocked up on Brand A cola last week, a new promotion this week is likely to be less effective than one a long period after the last such promotion.

Carryover effects is the general term used to describe the influence of a current marketing expenditure on sales in future periods (Figure 12.7). We can distinguish several types of carryover effects. One type, the delayed-response effect, arises from delays between when marketing dollars are spent and their impact. Delayed response is often evident in industrial markets, where the delay, especially for capital equipment, can be a year or more. Another type of effect, the customer holdover effect, arises when new customers created by the marketing expenditures remain customers for many subsequent periods. Their later purchases should be credited to some extent to the earlier marketing expenditures. Some percentage of such new customers will be retained in each subsequent period; this phenomenon gives rise to the notion of the customer retention rate and its converse, the customer decay rate (also called the attrition or erosion rate).

A third form of delayed response is hysteresis, the asymmetry in sales buildup compared with sales decline. For example, sales may rise quickly when an advertising program begins and then remain the same or decline slowly after the program ends.

New trier effects, in which sales reach a peak before settling down to steady state, are common for frequently purchased products, for which many customers try a new brand but only a few become regular users.

Stocking effects occur when a sales promotion not only attracts new customers but also encourages existing customers to stock up or buy ahead. The stocking effect often leads to a sales trough in the period following the promotion (Figure 12.7). The most common dynamic or carryover-effect model used in marketing is

$$Y_t = a_0 + a_1X_t + \lambda Y_{t-1}. \quad (19)$$

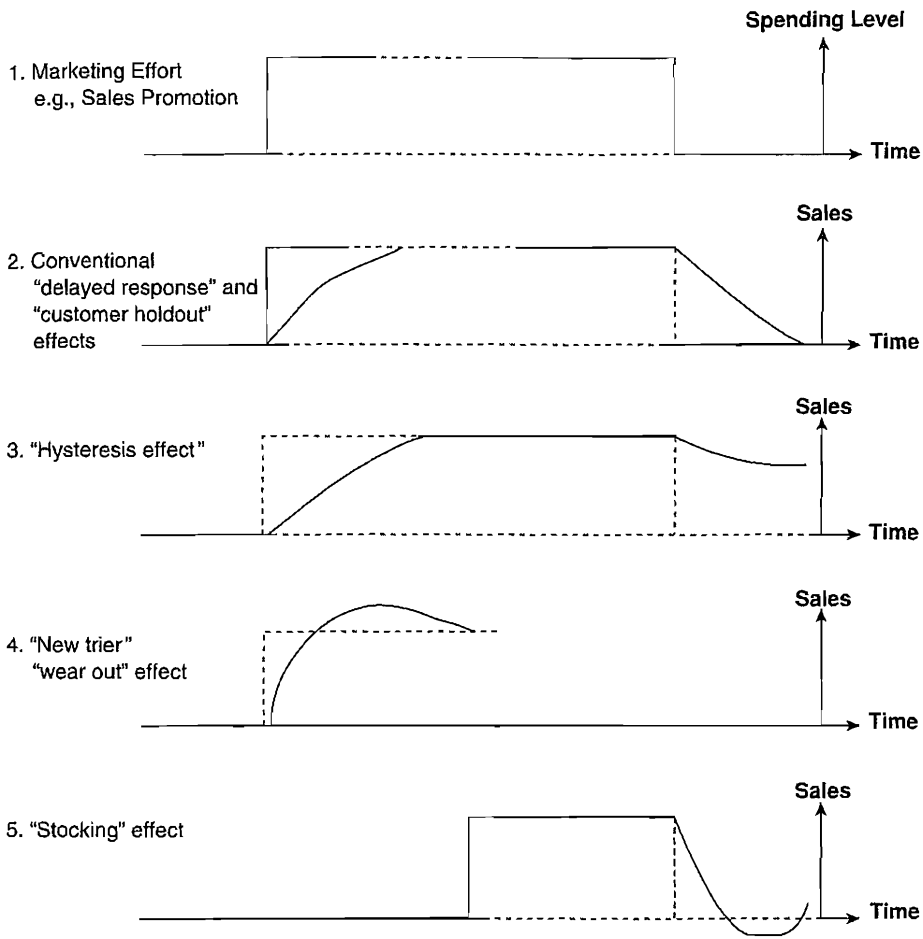


Figure 12.7 Some Types of Dynamic Marketing Responses

Source: Saunders (1987, p. 33).

Equation (19) says that sales at time t (Y_t) are made up of a constant minimum base (a_0), an effect of current activity $a_1 X_t$, and a proportion of last period's sales (λ) that carries over to this period. Note that Y_t is influenced to some extent by all previous effort levels $X_{t-1}, X_{t-2}, \dots, X_0$ because Y_{t-1} depends on X_{t-1} and Y_{t-2} , and in turn, Y_{t-2} depends on X_{t-2} and Y_{t-3} and so on. The simple form of Equation (19) makes calibration easy—managers can either guess λ directly as the proportion of sales that carries over from one period to the next or estimate it by using linear regression.

Market-Share Models and Competitive Effects

Thus far, we have ignored the effect of competition in our models, assuming that product sales result directly from marketing activities. Yet, if the set of product choices characterizing a market is well defined, we can specify three types of models that might be appropriate:

- Brand sales models (Y)
- Product class sales models (V)
- Market-share models (M)

Note that by definition

$$Y = M \times V \quad (20)$$

Equation (20) is a powerful reminder that we obtain our sales (Y) by extracting our share (M) from the market in which we are operating (V). Thus, an action we take may influence our sales by affecting the size of the market (V), our share of the market (M), or both. It is possible that an action of ours may result in zero incremental sales in at least two ways. First, it might have no effect at all. But second, it might entice a competitive response, leading to a gain in total product class sales (V goes up) while we lose our share of that market (M goes down). Equation (20) allows us to disentangle such effects.

Models of product class sales (V) have generally used many of the analytic forms we have introduced earlier, using time-series or judgmental data and explaining demand through environmental variables (population sizes, growth, past sales levels, etc.) and by aggregate values of marketing variables (total advertising spending, average price, etc.). Market-share models are a different story. To be logically consistent, regardless of what any competitor does in the marketplace, each firm's market share must be between 0% and 100% (range restriction), and market shares, summed over brands, must equal 100% (sum restriction).

A class of models that satisfies both the range and the sum restrictions are attraction models, where the attraction of a brand depends on its marketing mix. Essentially, these models say our share = us/(us + them), where "us" refers to the attractiveness of our brand, and "(us + them)" refers to the attractiveness of all brands in the market, including our brand. Thus, the general attraction model can be written as

$$M_i = \frac{A_i}{A_1 + A_2 + \dots + A_n}, \quad (21)$$

where A_i = attractiveness of brand i , and $A_i \geq 0$, and M_i = firm i 's market share.

Attraction models suggest that the market share of a brand is equal to the brand's share of the total attractiveness (marketing effort).

While many model forms of A 's are used in practice, two of the most common are the linear

interactive form and the multiplicative form outlined in the section on interactions of marketing-mix elements. Both of these models suffer from what is called the "proportional draw" property. We can see this best via an example:

Example: Suppose $A_1 = 10$, $A_2 = 5$, and $A_3 = 5$. In a market with A_1 and A_2 only,

$$m_1 = \frac{10}{10+5} = 66\frac{2}{3}\% \text{ and } m_2 = \frac{5}{10+5} = 33\frac{1}{3}\%.$$

Suppose brand 3 enters the market. Then after entry,

$$\bar{m}_1 = \frac{10}{10+5+5} = 50\%, \quad \bar{m}_2 = 25\%, \quad \text{and } \bar{m}_3 = 25\%.$$

$$\bar{m}_1 = \frac{10}{10+5+5} = 50\%, \quad \bar{m}_2 = 25\%, \quad \text{and } \bar{m}_3 = 25\%.$$

Note that Brand 3 draws its 25% market share from the other two brands, $16\frac{2}{3}\%$ from Brand 1 and $8\frac{1}{3}\%$ from Brand 2—that is, proportional to those brands' market shares. But suppose that Brand 3 is a product aimed at attacking Brand 1; one would expect it to compete more than proportionally with Brand 1 and less than proportionally with Brand 2.

Thus, when using simple market-share models, be sure that all the brands you are considering are competing for essentially the same market, otherwise you will need to use extensions of these basic models that admit different levels of competition between brands (Cooper, 1993).

Response at the Individual Customer Level

Thus far, we have looked at market response at the level of the entire marketplace. However, markets are composed of individuals, and we can analyze the response behaviors of those individuals and either use them directly (at the segment or segment-of-one level) or aggregate them to form total market response.

Because information at the individual level is now widely available, researchers are increasingly interested in response models specified at the individual level. The information comes from scanner panels, where a panel of consumers uses specially issued cards for their supermarket shopping, allowing all

purchase information—captured by bar-code scanners—by that consumer to be stored and tracked; database marketing activities, which capture purchase information at the individual level; and other sources such as customer relationship management (CRM) databases and Web logs.

Whereas aggregate market response models focus, appropriately, either on brand sales or market share, models at the individual level focus on purchase probability. Purchase probability at the individual level is equivalent to market share at the market level; indeed, by summing purchase probabilities across individuals (suitably weighted for individual differences in purchase quantities, purchase timing, and the like), one gets an estimate of market share. Hence, it should not be surprising that the most commonly used individual response models have forms that are like Equation (21), our general market-share response model. At the individual level, the denominator represents all those brands that an individual is willing to consider before making a purchase.

The specific functional form most commonly used to characterize individual choice behavior is the multinomial logit model (MNL). This model is derived from a strong theoretical framework, which assumes that each customer i 's utilities for each alternative product varies randomly (according to a well-specified distribution) from one purchase occasion to another but that each customer always chooses the alternative that provides the highest utility on each purchase occasion (see Chapter 14, this volume, for a more complete description of the MNL model). The MNL model has been widely used in various marketing applications.

A simple form of the multinomial logit model is

$$P_{ij} = \frac{e^{A_{ij}}}{\sum_j e^{A_{ij}}}, \quad (22)$$

where

A_{ij} = attractiveness of product j for individual i

$$= \sum_k w_k b_{ijk}, \quad (23)$$

b_{ijk} = individual i 's evaluation of product j on product attribute k (product quality, for example), where the summation is over all products that individual i is considering purchasing; and

w_k = importance weight associated with attribute k in forming product preferences.

Choosing, Evaluating, and Benefiting From a Marketing Response Model

The model forms we have described in this chapter present a number of trade-offs. One model form is not better than another. Each is good in some situations and for some purposes. We need to consider the model's use. Although a number of criteria are useful in selecting a model, here are four we suggest that apply specifically to response models.

Model Specification

- Does the model include the right variables to represent the decision situation?
- Are the variables, as represented, managerially actionable?
- Does the model incorporate the expected behavior of individual variables (e.g., diminishing returns, carryover effects, or threshold effects)?
- Does the model incorporate the expected relationships between variables (e.g., patterns of substitutability and complementarity)?

Model Calibration

- Can the model be calibrated by using data from managerial judgment or historical data or through experimentation?

Model Validity and Value

- Does the level of detail in the model match that in the available data?
- Does the model reproduce the current market environment reasonably accurately?
- Does the model provide value-in-use to the user?
- Does the model represent the phenomenon of interest accurately and completely?

Model Usability

- Is the model easy to use? (Is it simple, does it convey results in an understandable manner, and does it permit users to control its operation?)
- Is the model, as implemented, easy to understand?
- Does the model give managers guidance that makes sense?

When we select a model, we can summarize these criteria in one question: "Does this model make sense for this situation?" That is, does the model have the right form, can it be calibrated, is it valid, and is it useful? If the answers are all yes, then the model is appropriate.

BUSINESS VALUE OF MARKETING ENGINEERING: FROM PROMISE TO REALITY

Marketing engineering succeeds because of sophisticated managers, not because of sophisticated models. Such managers recognize that decisions affect many stakeholders and that people resist change and will not embrace decision processes they do not understand or decisions not favorable to their interests. Therefore, developing good decisions is only half the challenge. It is just as important to make those decisions acceptable to stakeholders within a firm, recalling that model users and decision makers may be different. Models can also help people understand and accept decisions: Models improve communications among the stakeholders.

By clearly stating model assumptions and understanding the results, managers can replace positions with principles: Instead of saying "Let's do X," one might say "I believe that our objective should be A, and based on the model, X is a good way to achieve that objective." If the process of articulating model assumptions is orchestrated well, discussion will focus on the merits of those assumptions rather than on the appropriateness or validity of the model output. Models are particularly useful when they help change mental models by challenging the assumptions or beliefs underlying those mental models. A model also provides an explicit mechanism for including stakeholders in the decision process. For example, at Syntex Labs,

the stakeholders participated by providing inputs to the model and by helping implement model results (Lodish et al., 1988). Managers are more likely to accept decisions resulting from a model if they know their inputs and judgments are part of the process. The following tips and suggestions should help to increase the likelihood of your achieving success with marketing engineering.

Tips and Suggestions

Be Opportunistic

Select problems or issues that have a good chance of rapid and demonstrable success.

Start Simple, and Keep It Simple

It is best to start with problems that are understandable and familiar to the stakeholders.

Work Backward—Begin With the End Goal of the Modeling in Mind

Start with an understanding of the goal of the modeling effort. For example, is it to provide justification for a course of action? Is it to resolve an issue for which judgment seems to be inadequate? Is it to facilitate a team decision?

Score Inexpensive Victories

Look for areas in which the costs of model development are low compared with potential benefits.

Develop a Program, Not Just Projects

One-off projects, though useful, do not have the same impact as a programmatic engagement in marketing engineering.

A Look Ahead

To improve their performance and future prospects, firms are investing heavily in information technology infrastructures linked to communication networks. The marketing function is also undergoing fundamental transformations

because of these technologies: The marketing operations of direct mail firms depend on toll-free telephone systems for sales and support; salespeople keep in touch with customers and headquarters using laptop computers; large retailers cannot survive without online price-lookup systems. Firms today install computers and software everywhere, not just in their back offices. Yet many marketing managers continue to make decisions in the traditional, old-fashioned way, without using the information and decision-aiding technologies that are already available. Some firms have recognized that one of their most important assets is relevant information whose business implications decision makers can interpret in a timely manner. To take advantage of the data and information already available to them, firms are integrating decision-aiding technologies into the fabric of their day-to-day operations and decisions. Many firms now use sophisticated marketing analytics for several types of decisions, including fine-tuning of their direct marketing campaigns, profiling their users/nonusers on an ongoing basis, replenishing their inventories in real time, or identifying cross-sell opportunities. Examples described in the public domain include Wal-Mart ("9/11 Timeline," 2002), Travelocity (Klebnikov, 2001), and Harbor Freight, Inc. (Kitts, Vrieze, & Freed, 2005).

We expect that during the next decade, the major developments in technologies to support marketing decisions will be geared to helping managers process the information that is already available to them: to filter the relevant from the irrelevant and to draw out insights from information. Many large firms are putting together a new corporate activity called Marketing Information Systems (MKIS) to support and enhance enterprise-wide performance using marketing information. Although the concept of MKIS has existed for a number of years (see, e.g., Kotler, 1966), the scope and potential value of the present-day MKIS is far greater than was envisioned in those early days.

MKIS, typically located within the marketing department, is charged with harnessing marketing-related information and distributing and facilitating its use within the firm. Even as the marketing function seems to be in decline, the marketing concept itself appears to be

gaining wider acceptance in firms (Doyle, 1995). Marketing is becoming an enterprise-wide activity rather than the exclusive domain of a specific department. Firms see MKIS as a way to use marketing information to make everyone in the firm realize that they must be more responsive to customer needs and wants and to the competitive environment.

Historically, a major function of information systems has been to provide timely access to information. MKIS can now integrate end-user decision models with traditional information systems to enhance the firm's ability to use marketing engineering. Seven current trends favor this integration of information. Firms are

1. investing in the infrastructure they need to develop and maintain extensive corporate databases (also called data warehouses);
2. using online analytical processing (OLAP) to integrate data retrieval and modeling capabilities with databases;
3. exploring the application service provider (ASP) model to increase the value and flexibility of their data and models by making them more widely accessible (on an as-needed basis) among employees, as well as among vendors and strategic partners;
4. deploying intelligent systems to automate some modeling tasks;
5. developing computer simulations for decision training and for exploring multiple decision options;
6. installing groupware systems, such as Lotus Notes, to support group decision making; and
7. enhancing user interfaces to make it easier to deploy even complex models more widely.

We focus on Development 3 below; for detailed discussion of the others, see Lilien and Rangaswamy (2004).

Application Service Providers for Analytics

An exciting new development that will greatly expand OLAP capabilities is the emergence of ASPs (Application Service Providers) that offer online access to various types of

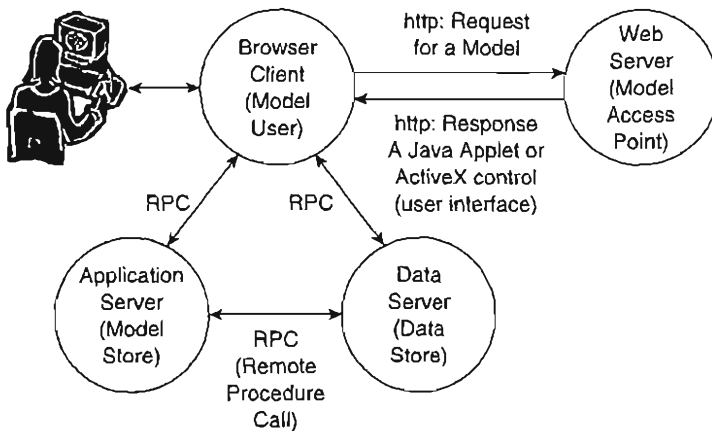


Figure 12.8 Implementing the ASP Approach for Market Engineering

Note: The figure outlines one way to implement the Application Service Provider (ASP) approach for marketing engineering. Models, data, and user interfaces, which are combined together in traditional marketing models, are decoupled in a Web environment. This enables any Internet user to have more flexibility in conducting marketing analyses and interpretations anywhere, anytime.

knowledge resources (software, data, content, and models). ASPs convert knowledge resources into services (e.g., analytics, process control) accessible over the Web, instead of being packaged as products and systems. For example, salesforce.com is attempting to create a viable ASP model for sales force automation by offering such online services as contact management, forecasting, e-mail communications, customizable reports, and synchronization with wireless devices. These services are made possible by dynamically linking data retrieval and analysis software to various databases. Figure 12.8 shows one way to implement an ASP for analytical support. With these developments, there is an emerging capability for offering marketing analytics to anyone, anytime, anywhere. Lilien and Rangaswamy (2000) discuss in more detail the value and implications of these developments for marketing modeling.

Figure 12.9 summarizes our beliefs about how the Internet and ASPs will influence marketing modeling in the years ahead. We classify marketing models along two dimensions: On the horizontal axis (degree of integration), we distinguish between stand-alone models (e.g., supporting a single user for a single task) on one extreme and those that are integrated with organizational processes, databases, and other aspects of the decision environment at the other extreme (e.g., single user, multiple tasks; multiple users, single

task). On the vertical axis (degree of visibility), we distinguish between models that are embedded inside systems (i.e., a “black-box model” that works in the background) requiring few inputs or interactions with the user and those that are highly interactive and whose structures are visible. We discuss below four categories of models that fall at the extremes of these two dimensions and indicate how the emerging networked economy will encourage their use:

1. Visible stand-alone models can be put on application servers (several ASPs already do this—e.g., www.marketswitch.com) and accessed by client browsers. In such an environment, software renditions of marketing models can be maintained in central locations, minimizing costs of updates and distribution. Model users also benefit because they will always have access to the latest versions of the software. Visible models with user interactions can also become more valuable online. For example, applications ranging from simple computational devices, such as mortgage calculators (www.jeacle.ie/mortgage), to sophisticated programs, such as conjoint analysis (www.marketingIQ.com), are available on a 24/7 basis. These applications are supported with online technical help (as well as live support), improved content (help files, tutorials, etc.), and linked to related applications that are available

Degree of Visibility	Visible Models (Interactive)	(1) STAND-ALONE MODELS Example: Conjoint Analysis Tools (www.sawtooth.com) Example: Marketing Engineering Tools (www.marketing.com)	(4) INTEGRATED SYSTEMS OF MODELS Example: Group Decision Systems (Group Analytic Hierarchy Process)
	Embedded Models ("Models Inside")	(2) COMPONENT OBJECTS Example: Automated Software Agents (Price Companson Agent)	(3) INTEGRATED COMPONENT OBJECTS Example: Yield Management Systems Example: Marketing Optimization System (www.marketswitch.com)
		Stand-Alone	Integrated
Degree of Integration			

Figure 12.9 Marketing Models Classified by Degree of Integration and Degree of Visibility That Can Be Deployed on the World Wide Web and Accessed Over the Internet

elsewhere on the Internet. Many traditional marketing models would benefit from being redesigned or reimplemented in newer software packages for deployment over the Internet.

2. Component objects can be deployed more widely on the Internet because they can be structured to continuously monitor and optimize various aspects of how an organization functions. Procter & Gamble's access to purchase data for their products at Wal-Mart allows it to deploy automated models to forecast demand, schedule production and delivery, optimize inventory holdings, and even assess the effectiveness of its promotions.

3. Integrated component objects exploit the blurring lines between software, content, services, and applications to deliver more complete decision solutions to managers. For example, an integrated segmentation system could run not only standard clustering algorithms but could also access data from elsewhere on the Web before model execution and then distribute customized communications to customers in different segments. Revenue management systems at the world's major airlines dynamically optimize schedules, prices, and seat inventories and send messages to targeted customers about new travel opportunities that they might find attractive. Although such models may be fully automated or

used by unsophisticated users, the models themselves are likely to be quite sophisticated (akin to an autopilot for an aircraft) and require frequent updating and validation by highly skilled modelers.

4. Integrated systems of models puts a logically linked set of models in the hands of decision makers (possibly geographically separated) who need to share their different knowledge bases for important common decisions (e.g., negotiation support, bid planning, marketing planning models). For example, Lodish et al. (1988) describe a subjectively calibrated market response model that required collocation of the decision makers. In the Internet world, such subjective data inputs can be obtained online from managers in different locations, consensus facilitated by using models running on a server, and the resource and planning implications made available to all through a group decision support system.

The Internet could drive the prices of digital products (i.e., products, such as marketing models, that can be distributed on the Net) down to their marginal production costs, which are near zero (Evans & Wurster, 2000). As a result, many Internet-based models will be available almost free, at least for limited use (or offered in exchange for viewing commercials),

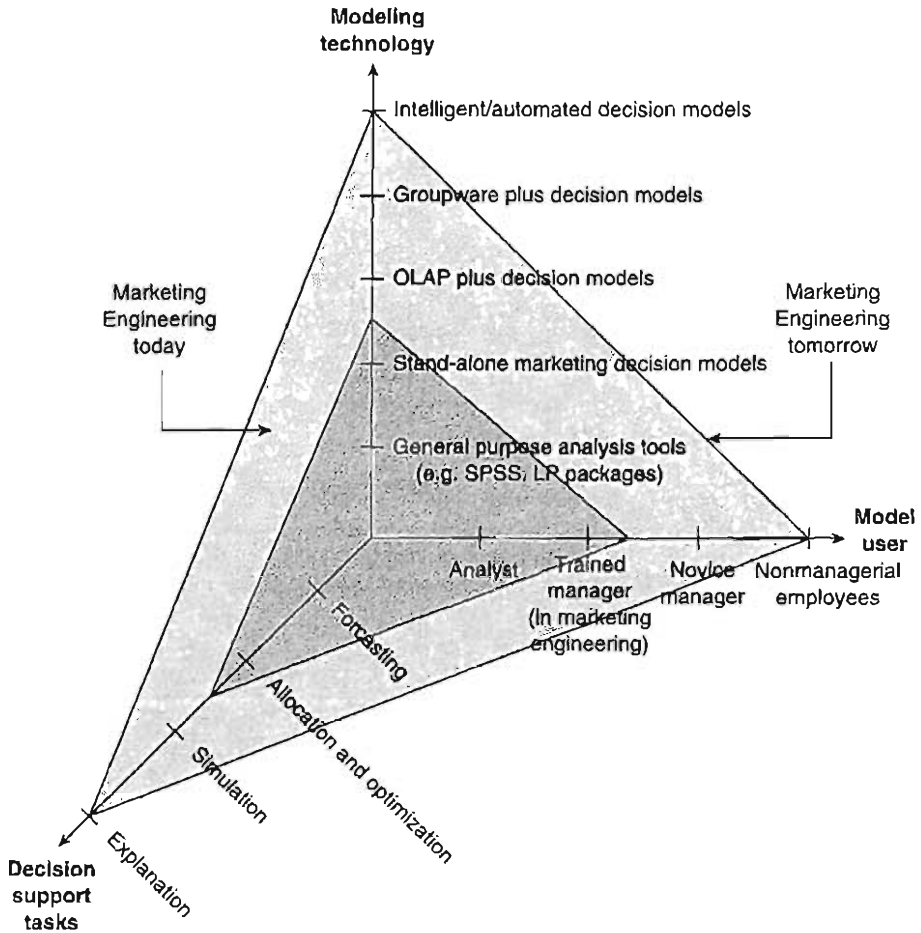


Figure 12.10 An Overview of the Evolution of Marketing Engineering to Support a Wider Range of Users and Decision Tasks Using Emerging Technologies

making them even more attractive for analysts and managerial users alike. Thus, over the next decade, we expect an explosion in the availability of customizable, scalable, and (possibly) embedded decision models on the Internet, available anytime, anywhere, for anyone.

To conclude, Figure 12.10 summarizes our vision of the evolution of marketing engineering along three dimensions: (1) the type of user who uses models, (2) the type of decision tasks supported, and (3) the modeling technologies that enhance marketing engineering. Until the mid-1980s, marketing engineering was carried out primarily by analysts who submitted reports to managers. Those analysts used general-purpose analysis programs running on mainframe

computers (e.g., statistical packages such as SPSS and linear programming packages) to generate forecasts and develop plans for optimally deploying organizational resources. The growth of personal computers has put managers in direct control (e.g., through spreadsheet models focused on specific decision areas), permitting richer manager-model interactions (e.g., simulations based on what-if analyses). In the future, marketing engineering will support a broadening range of users (e.g., customer service representatives) using a wider range of technologies (e.g., OLAP, intelligent systems, groupware systems) to enhance decision making by richer means (e.g., using simulation to explain market events).

While the marketing function in companies may decline in importance in the years to come, marketing as a discipline can only increase in importance. Years ago, Peter Drucker pointed out that marketing is too important to be left to marketers; that statement is even more true today. Marketing engineering, a bridge between conceptual marketing and disciplined, systematic marketing, is poised to take its place among the critical management tools for the successful 21st-century firm.

Postscript

To keep up to date about the concepts, tools, and models discussed in this chapter, visit www.mktgeng.com and www.marketingiq.com. More detail on the concepts and access to a full suite of marketing engineering software is available in Lilien and Rangaswamy (2004).

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