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Using Assumptions-Based Models to Forecast New Product Introduction

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Satellite radio was supposed to be big. One forecast produced in the year 2000 was suggesting 36 million satellite radio subscribers by 2007 (McBride 2006). Within just 12 months, forecasts were becoming less optimistic. A revised forecast in 2001 suggested 16 million subscribers by the end of 2006. Five years later actual figures indicated a subscriber base of 11 million subscribers across the two companies of XM Satellite and Sirius Radio. These significantly lower subscriber numbers resulted in much lower than expected revenue. In turn, the lower-than-expected revenue caused substantial financial losses for XM Satellite and Sirius Radio due to the inability to offset large investments made to secure market channel access, sign radio show personalities, and execute marketing promotions (McBride 2006).

Some say that "numbers don't lie." However, this example shows that numbers can be wrong, if not very wrong. Moreover, the numeric forecasts do not explain why they are wrong. What were the assumptions underlying these numbers? Unfortunately, the sources for these numbers do not present details for any underlying assumptions. The fact that assumptions are not given exemplifies that many managers tend to focus just on the numbers and not the assumptions underlying their numeric new product forecasts. In other words, there is an inherent preoccupation with knowing just the numeric new product forecast and overlooking the assumptions that underlie the given number. Knowing the latter is crucial because new product forecasts are characteristically overladen with emotional hype and optimism (Tyebjee 1987). By knowing what the assumptions are, along with the numbers, we can get a sense of transparency to where hype and optimism may be occurring.

This chapter promotes the theme that companies should focus on the assumptions that underlie forecasts of new product introductions. Doing so provides the necessary understanding to thoughtfully, logically, and systematically evaluate, or even challenge, the numeric forecast. Simply saying that a forecast is too high or low cannot be substantiated, nor acted on meaningfully, if the triggers driving the number are not established. Identifying and understanding assumptions are just as, if not more, important to forecasting new product sales as are the numbers themselves.

One rather straightforward class of forecasting techniques designed to identify and systematically lay out assumptions is assumptions-based models. Judgmental in nature, assumptions-based models are flexible techniques that can be employed at different points during the product development process. Assumptions-based models are especially valuable for discerning critical assumptions during launch planning and identifying necessary strategies that will ensure a successful introduction, given these assumptions. This chapter discusses and illustrates how a manager tasked with constructing a new product forecast can develop and use assumptions-based models for effective new product introduction.

Accordingly, the first section of this chapter discusses what assumptions-based models are and applies a generic assumptions-based model framework to the satellite radio context to illustrate the straightforwardness of these models. Next, discussion shows how the assumptions-based model framework can be adapted to more complex business situations and can incorporate more sophisticated analyses such as risk analysis. Launch planning and assumptions management topics are then discussed relative to using assumptions-based models. The chapter closes with a discussion of pitfalls to avoid and guidelines for proper use of assumptions-based models.

ASSUMPTIONS-BASED MODELS

Assumptions-based models attempt to describe the behavior of the relevant market environment by breaking the market down into components (also called *market drivers*). Values for these components are established and forecasts are generated. These values represent assumptions stemming from judgment because events have not yet occurred to prove the established values. Assumptions-based models are characteristically a class of judgmental forecasting techniques, though numeric in outcome. Other names for assumptions-based models include chain models and market models (cf. Latta 1998).

A generic framework of an assumptions-based model begins with an overall potential target market size and uses various market factors to break down the potential target market proportionally. This emphasizes how important it is to carefully articulate, identify, and detail the intended potential target market before beginning the new product forecasting endeavor and prior to specifying other key market drivers. As suggested in Figure 9-1, the potential

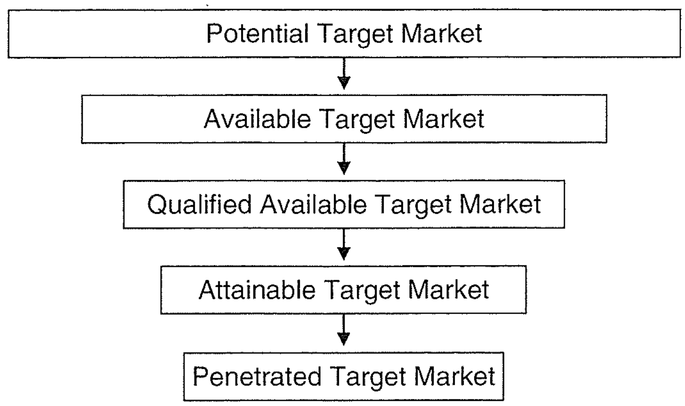

FIGURE 9-1. General framework of an assumptions-based model.

target market is proportioned down to the available target market, then to the qualified target market, then to the attainable target market, and finally, to the penetrated target market. In this chapter, we will look at developing a forecast for satellite radio to illustrate this generic framework and to show how this framework could have been employed in early 2000 to calculate a forecast for the satellite radio industry.

Sizing the Potential Target Market

The starting point in applying the generic framework is establishing the overall potential target market size. By definition, the potential target market size would represent the maximum amount of sales possible for a particular product aimed at a given set of buyers within a given period of time. As will be the case for sizing any market factor in the assumptions-based model, a variety of approaches and thinking may be employed to generate a value for the respective market factor. Time, expertise, and other resources will naturally influence which approach(es) can be employed. There is certainly no one definitive approach.

In the case of satellite radio, a less sophisticated approach is employed, where census data on the number of cars in the United States market serve as the potential target market size. Although apparently straightforward, careful thinking is needed regarding which cars and/or car owners should be considered likely candidates for satellite radio. Is satellite radio being aimed at older or newer drivers, old or new vehicles, and so on? U.S. Census figures in early 2000 indicated that there were approximately 212,706,399 passenger cars, vans, pickup trucks, and sport utility vehicles in the United States, and among these, approximately 17,349,933 were new vehicles. For the sake of simplification, all vehicles are deemed likely candidates, because all cars come equipped with at least some standard radio. Thus, the total potential market for satellite radios is 212,706,399 cars.

Sizing the Available Target Market

The next step in developing the satellite radio forecast is to determine what part of the potential target market is the available market. Available market is defined as the set of buyers who are able to gain access to purchase the product. For the present case of satellite radio, the available market is estimated by distribution capability in terms of how much of the market will be able to purchase from each respective company. Other delimiters for moving from potential target market to available target market are possible as well.

It is presumed that XM and Sirius will be aggressive in garnering channel partners, which would include retailers specializing in electronic products and large mass merchandiser retail chains. A 95 percent estimate of U.S. market availability is suggested due to the large market presence of mass merchandisers in the car radio market and the presumption that almost all retailers that sell car radios will offer satellite radio, too. The 95 percent estimate specifically means that satellite radio will be made available for purchase at 95 percent of all locations where car radios are sold. While this number may seem high, higher percentages are possible, such as in the case of grocery products based on point-of-sale data provided by AC Nielsen (*www.acnielsen.com*) and Information Resources, Inc. (*www.infores.com*), where even a 100 percent figure may be possible (100 percent meaning that the product is sold in all possible locations where that product category can be sold). The 95 percent estimate is applied, leaving 202,071,079 vehicles as the available market for satellite radios.

Sizing the Qualified Market

The qualified market represents the proportion of the marketplace able to actually purchase the particular product of interest. Again, various approaches are possible to determine an appropriate figure to input into the assumptions-based model. One approach could be to use benchmark data from analogous market situations: for example, the percent of migration from free television to cable television (pay-for television) during cable television's first years may be applicable. For the sake of simplification, income is presumed to be an important determinant of whether someone will subscribe to satellite radio. It is further presumed that only half of those individuals owning a vehicle will be able to afford / likely pursue satellite radio. 50 percent of vehicles are therefore labeled as part of the qualified market resulting in 101,035,540 vehicles remaining. Market research via surveys and focus groups would be especially useful, and would be a preferable approach to determining and validating the correct percentage constituting that portion of the available market with the qualifications to buy the respective product.

Sizing the Attainable Market

The *attainable market* represents the reasonable share likely to be obtained by a particular company. One approach may be to consider those buyers who are heavy users of their car radios, such as individuals with a 45-minute or longer commute. These people would be more aware of the value that satellite radio may offer. Awareness also can be a function of marketing communications initiated by the satellite radio companies themselves coupled with publicity through various media sources. For the present illustrative case, attainable market is viewed as the proportion of the market who are aware of satellite radio as a consequence of advertising and publicity. Awareness is an important consideration for gauging the attainable market, because those who are aware might have the propensity to purchase satellite radio, while those who are unaware could not make an effort to purchase satellite radio.

One way to gauge attainability could be the level of marketing communications and corresponding percent of awareness generated by such efforts. Some companies have historical evidence suggesting what the level of awareness will derive from a proposed marketing budget and planned set of marketing communications. Based on the heavy marketing communications employed by satellite radio companies, a 30 percent awareness rate is offered; that is, 3 out of 10 people will have seen advertising and publicity about satellite radio and become aware that satellite radio is available for purchase. Applying this proportion, the forecast is now 30,310,662 vehicles.

Sizing the Penetrated Target Market

The last model component represents the penetration rate, which can be interpreted as that proportion of the marketplace intending to buy the new product. One approach could be to look at the historical penetration rate for similar or analogous products and technologies. Another approach could be to apply an estimate of company market share among competitors. Still a third approach is to rely on diffusion theory, which suggests that customers for new product technologies fall into one of five groups: approximately 2.5 percent are innovators (first users), 13.5 percent are early adopters, 34 percent are early majority, another 34 percent are late majority, and the remaining 16 percent of customers are laggards (last users). Applying the third approach, an estimate of 16 percent is offered to suggest that innovators and early adopters will make up immediate sales—these are the individuals who are most apt to purchase the latest technology in a marketplace (cf. Rogers 1995; Moore 1995).

Taking this approach, 16 percent of the attainable market is presumed to be likely candidates for purchasing the emerging satellite radio technology. 16 percent of the attainable market results in a market size of 4,849,706 vehicles. A further assumption is made that there will be only one satellite radio per vehicle so this value represents an annual estimate of the number of satellite radio subscribers.

Other Market Factor Considerations

One might conclude that if this is an annualized estimate, a five year estimate could be determined by multiplying this number by five. Had this product been a grocery product or similar consumable good, then such logic might be appropriate. In the case of satellite radio subscribers, there are three consumer outcomes per year: a consumer keeps the satellite radio subscription for another year (maintain outcome), the consumer cancels the satellite radio subscription (loss outcome), or a new consumer signs up for satellite radio (gain outcome). Discussion on these values would be undertaken and actual figures from each year could be applied to subsequent years. For purposes of illustration, a subscriber growth rate of 15 percent is used coupled with a customer defection rate of 5 percent, resulting in an incremental gain of 10 percent per year over five years. This value is applied and suggests a market forecast of 7,810,500. As one can tell, this figure is far below the 36 million subscriber estimate but is also below the achieved 11 million subscribers. Determining why this number is wrong would focus on the assumptions. Because of the assumptions-based model framework, such focus is possible due to the transparency of assumptions underlying the forecast.

ADAPTING THE ASSUMPTIONS-BASED MODEL FRAMEWORK

The assumptions-based model framework is flexible and can be adapted to multiple market forecasting situations with any number of assumption combinations. Consider the following example illustrating the generation of a meaningful new product forecast for first-year sales of a new computer network security product. The product to be forecast was a newly developed computer host and network-based architecture and software application. The application was specifically designed to meet security requirements, provide comprehensive protection of any networked environment, detect anomalous activity, and dynamically respond to security events. A distinction of the application was enhanced operational efficiency through customizable, centrally administered configuration tools and automated solutions that isolated and mitigated threats. In light of the information technology nature of the product, the designated target market was information technology personnel, including chief technology officers, wishing to better secure their companies' existing computer server networks. Product management was the function charged with developing the forecast.

A half-day cross-functional team meeting was held to discuss the forthcoming product. It included the product manager overseeing the application's development and launch, the director of product management, lead product managers for other major product lines, director of sales, director of sales support, and director of the sales and operations planning process. Note that in the case of this company, all new products and product launches were managed through the product management department, with launch closely coordinated with sales and operations planning.

One specific task assigned to this team by senior management was the development of a forecast on which to plan and gauge launch decisions for the new application. In the course of meeting discussions, important factors for successfully marketing the product were identified, the nature of relationships among these factors were determined within the structure of an assumptions-based model framework and deemed key model components, and assumptions for each model component were specified. The team decided to put forth to management the following assumptions-based model framework: total market size, the intended/marketed use, company market share, buying intent, and company market coverage. Although other model components could have been included, these five model components were viewed as most relevant, and more importantly, each of these specified components could be quantified based on existing data sources.

Market size was predicated on a recent Gartner Group study (*www.gartner.com*) and was supplemented by customer data collected by the product management group. Gartner estimated the value for total market size for new computer security technology at $3 billion. Note that because this figure is in dollars, the basis of measurement becomes dollars; had this value been in units, units sold would have served as the basis.

Intended/marketed use was defined as the percent of the marketplace using the new product technology as core technology. That is, the product technology could be used as the primary security system or as a peripheral or back-up system. The value of 65 percent was determined through interviews with sales management and product management groups in the company, suggesting that two-thirds of prospective customers would be looking for a primary security system.

Company market share in the core technology use segment was estimated from published industry reports noting competitor market shares, supplemented by sales management and product management personnel intuition. Market share was estimated to be 20 percent.

Buying intent was defined as the percent of the market interested and likely ready to migrate to a new core technology. Sales management was the predominant source for this value and indicated that a follow-up using its sales pipeline tool would be used to validate the number. Buying intent was estimated to be 25 percent.

Company market coverage was based on current worldwide sales networks. This value represented the extent of distribution that the company had worldwide. An 80 percent market coverage rate was given, indicating that the company could serve 80 percent of world markets through its existing distribution system.

The assumptions-based models framework is applied by multiplying the values for the five model components. The forecast for the new computer product is thus $78 million, which is calculated by multiplying $3,000,000,000 × 65 percent × 20 percent × 25 percent × 80 percent to equal $78 million. Presuming that the data are valid, the figure of $78 million stands as the forecast for first year sales of the new computer technology application. This figure can be broken down into quarterly estimates by simply dividing by four quarters, or $19,500,000 per quarter, although it is more likely that some degree of seasonality would exist because sales are very seldom uniform throughout the year. First-year sales fluctuations due to channel pipeline fill, ramping-up, and market diffusion effects are also important considerations. Breaking the annual figure into monthly estimates would require similar thinking. Note that the nature for how the annual forecast should be broken down into quarterly and/or monthly estimates would be predicated on further assumptions.

CONSTRUCTING AN ASSUMPTIONS-BASED MODEL

As these examples show, applying the assumptions-based models framework is straightforward. What is not straightforward is data collection and getting consensus on the assumptions and corresponding numbers to input into the framework. Numerous variations for the types of data to be collected and the specific assumptions to be made are possible, all depending on the company and the business. The best way to start is to hold at least one meeting to lay out assumptions and to identify where data can be found and what numbers and assumptions are most relevant. More likely, a series of meetings that include representatives from different parts of the company such as marketing, operations, sales, product management, and research and development will be necessary. Specifically, when dealing with a new product introduction, a meeting of the sales and operations planning team (cf. Wallace 1999) is the logical starting point to determine which assumptions to include in a tailored assumptions-based model.

When constructing an assumptions-based model, one should be particularly cognizant of issues pertaining to validity, precision, and data availability. Validity of assumptions is paramount to successfully developing a reasonable and meaningful new product forecast. An uneducated, wild guess on any particular assumption will almost always result in an erroneous new product forecast because each individual assumption impacts the forecast outcome. If a number of assumptions are not valid, the new product forecast will only be more erroneous.

Precision is another consideration. Slight deviations in any assumption have the potential to significantly change the resulting new product forecast. This is particularly evident when an assumptions-based model is predicated on only a select few assumptions. Such sensitivity to assumption precision highlights the use of range forecasting versus point forecasting. That is, a range around each assumption is determined, versus reliance on one specific number for each assumption. A what-if analysis can then be employed to determine the range of forecast outcomes, depending on the low and high values for each assumption. This exemplifies how assumptions-based models can be used as tools for what-if scenario analysis and sensitivity analyses can establish critical assumptions and examine risk.

Data availability is a third consideration. While determining the assumptions to include in the model is important, determining how to quantify and collect a value for that assumption is just as important. An assumption that cannot be quantified to serve as an input in the assumptions-based model is not useful, nor meaningful. This does not mean that the assumption must be solely objective; managerial intuition may be a necessary element in deriving a value for a given assumption. The latter, though, will require careful thinking about how to systematically collect and quantify the subjective data.

CONDUCTING RISK ANALYSES

Assumptions-based models lend themselves very easily to conducting risk analyses. Risk analyses are conducted by establishing high and low points around each of the given model assumptions, which corresponds to best case (optimistic) and worst case (pessimistic) scenarios on each assumption, respectively.

Risk analyses were applied to the computer network security product previously discussed, where the base case (also referred to as the likely case) was the original $78,000,000 calculation. Product management personnel held discussions with sales management personnel to lay out potential best-case and worst-case scenarios. As shown in Table 9-1, it was determined that Core Use had the potential to run as high as 80 percent, but could be as low as 40 percent. History had indicated that market share regularly fluctuated between 30 percent in good months and 10 percent in difficult months. Buying intent was seen as a variable, falling between 20 percent and 30 percent. And market coverage, which was viewed as the most certain of the given assumptions, had the potential to increase to 95 percent based on distributor growth. Note that best-case and worst-case scenarios were envisioned for four assumptions, excluding target market size. Managers in sales management and product management determined that target market size could be considered a constant. Table 9-1 presents all best-case and worst-case scenarios.

Using these values, a sensitivity analysis was conducted within the assumptions-based model framework. This is done by holding all values constant to the base case, and changing the assumption under consideration to its best-case and worst-case values. The resulting forecasts when the best-case value is used and when the worst-case value is used are recorded and compared to the initial (base case) forecast. For example, the *core use* assumption is scrutinized on its best-case and worst-case scenarios. Holding all assumptions

TABLE 9-1.
An Example of Pessimistic, Likely, and Optimistic Values for Input Assumptions

Assumption	Base Case	Best Case	Worst Case
Core Use	65%	80%	40%
Market Share	20%	30%	10%
Buying Intent	25%	30%	20%
Coverage	80%	95%	80%

constant but allowing for a *core use* best case of 80 percent results in a new product forecast of $96 million ($3,000,000,000 × 80 percent × 20 percent × 25 percent × 80 percent). Holding all assumptions constant but allowing for a *core use* worst case of 40 percent results in a new product forecast of $48 million ($3,000,000,000 × 40 percent × 20 percent × 25 percent × 80 percent). These values indicate that if *core use* is really as high as 80 percent, then the market is $18 million larger than the base case ($96,000,000 – $78,000,000 = $18,000,000). If the *core use* is really as low as 40 percent, then the market is $30 million smaller than the base case ($48,000,000 – $78,000,000). These differences portray the sensitivity and risk surrounding the *core use* assumption. The same line of thinking and analyses would be applied to the remaining assumptions to assess model sensitivity and risk surrounding these assumptions. Such sensitivity analyses help identify which assumptions should be deemed too uncertain. Refer to Tables 9-2 and 9-3.

The range between the best case and worst case is another metric for evaluation of risk and sensitivity. For example, *core use* with a best-case scenario of $96 million and worst-case scenario of $48 million, indicates a

TABLE 9-2.
An Example of Model Sensitivity with Regards to Financial Outcome

Assumption	Base Case	Best Case	Worst Case
Core Use	$78,000,000	$96,000,000	$48,000,000
Market Share	$78,000,000	$117,000,000	$39,000,000
Buying Intent	$78,000,000	$93,600,000	$62,400,000
Coverage	$78,000,000	$92,625,000	$78,000,000

TABLE 9-3.
An Example of Evaluating Potential Shortfall, Upside, and Total Risk

Assumption	Best Case: $ Above Base Case	Worst Case: $ Below Base Case	$ Range Between Best Case and Worst Case
Core Use	$18,000,000	–$30,000,000	$48,000,000
Market Share	$39,000,000	–$39,000,000	$78,000,000
Buying Intent	$15,600,000	–$15,600,000	$31,200,000
Coverage	$14,625,000	$0	$14,625,000

possible swing of $48 million. As shown in Table 9-3, the assumption of *market share* has the greatest range compared to the other assumptions. This suggests that *market share* has the greatest level of uncertainty. Interestingly, the lowest worst-case value and highest best-case value also correspond to *market share*, highlighting that market share assumptions are crucial components of the new product forecast (refer to Table 9-2).

One tool for visualizing this sensitivity analysis is a *Tornado chart*. A Tornado chart shows the financial values associated with each assumption. Proper use of the Tornado chart would involve first sorting the assumptions from high range to low range, and plotting accordingly to draw a tornado-like picture (cf. Clemen 1996). The Tornado chart simplifies the effort in determining where risk exists; those assumptions with the longest bars in the negative side of the chart would be assumptions deserving close scrutiny. Those assumptions with the greatest range also would be deserving of discussion by the management team. Figure 9-2 portrays the Tornado chart of the data found in Tables 9-2 and 9-3.

A further analysis that can be conducted using the assumptions-based model framework is a business simulation. Specifically, a Monte Carlo simulation can be applied to those assumptions where there are best-case and worst-case values. The simulation would randomly generate a value falling between the best case and worst case on each assumption and would calculate the resultant new product forecast. Running a number of iterations of the simulation would then provide a distribution of outcomes for determining the probability of attaining a given new product forecast.

There are a variety of ways to generate random numbers and conduct a Monte Carlo simulation. One approach is to use the RAND function in Microsoft Excel, which randomly selects values between the pessimistic and optimistic cases based on a uniform distribution between 0 and 1. The formula for using the RAND function to generate an outcome for each assumption

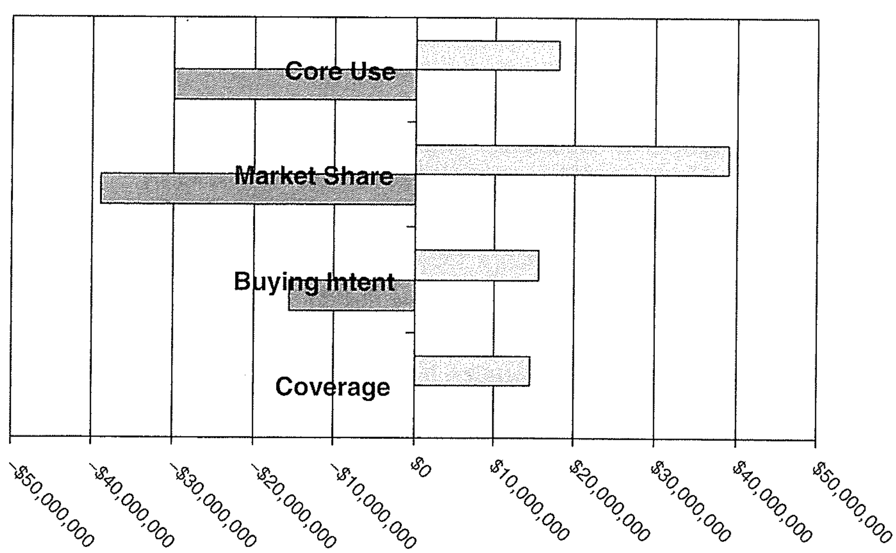

FIGURE 9-2. A Tornado chart showing risk around assumptions.

would be as follows:

Assumption Outcome = [RAND() × (Bestcase − Worstcase)] + Worstcase

For illustrative purposes, presume that the RAND() function generates the random value of .3324 in one iteration of the simulation. This value is used to calculate a core use estimate of 53.296 percent as follows: [.3324 × (80 percent − 40 percent)] + 40 percent. The values of the other assumptions and subsequent simulations runs would be calculated similarly, though with different random numbers generated by the computer program.

Note that use of the Random Number Generator found in Microsoft Excel's Analysis ToolPack is an even simpler approach for generating random numbers and allows for other distributions to be modeled, in addition to the uniform distribution (other computer programs are available to do this as well) (cf. Weida et al. 2001).

As shown in Table 9-4, 1,000 iterations of a Monte Carlo simulation were run using the best-case and worst-case data for each assumption as simulation parameters. Tabulation of the results from the simulation form a distribution around the new product forecast and provide a probabilistic view of the new product forecast. As shown in Figure 9-3, 27 percent of the simulations resulted in a financial value falling between $60 million and $80 million. The cumulative percentages of these results further indicate that 58 percent of the simulations had a financial value of less than $80 million. Referring back to the base-case estimate of $78 million, these results roughly suggest that there is approximately a 42 percent chance (100 percent − 58 percent) of reaching or exceeding this base-case estimate. This therefore forces the issue of whether management is comfortable with the probability in attaining this number. In short, is management comfortable with a 42 percent chance of success? If no, discussions would focus on the level of risk that management is comfortable

TABLE 9-4.
Sample of Monte Carlo Simulation Data

Simulation Run	Core Use	Market Share	Buying Intent	Coverage	Financial Outcome
1	68%	21%	22%	85%	$79,658,870
2	57%	25%	26%	94%	$104,365,372
3	66%	24%	21%	84%	$83,327,863
4	69%	29%	28%	83%	$138,039,675
5	74%	17%	27%	88%	$88,769,425
6	60%	18%	29%	92%	$87,420,466
7	53%	26%	29%	90%	$109,708,715
8	53%	22%	24%	85%	$72,116,748
9	47%	16%	30%	81%	$53,424,659
10	59%	23%	23%	86%	$81,347,268
...	...	...	...	...	...
1000	71%	30%	20%	89%	$115,924,185

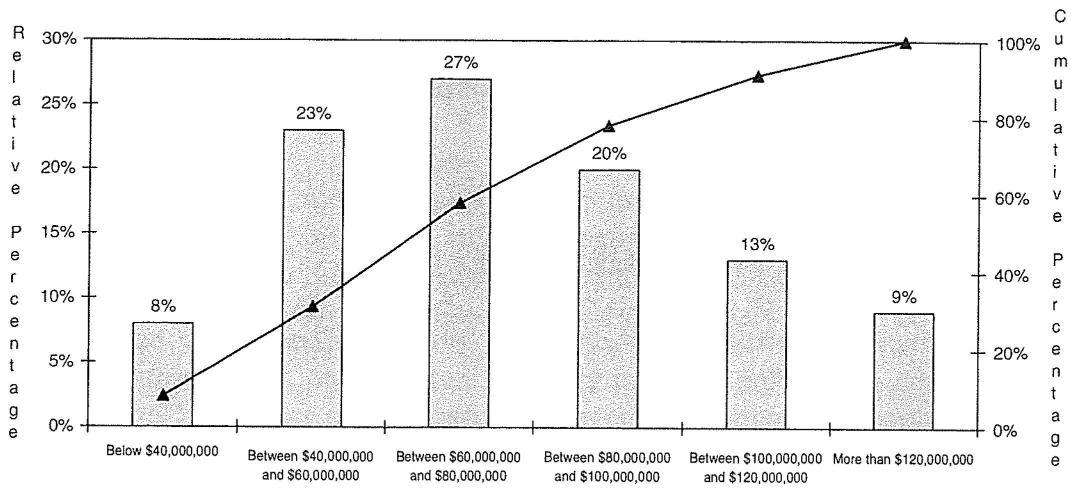

FIGURE 9-3. Distribution of financial outcomes from a Monte Carlo simulation.

with and/or what assumptions need to change and what the values need to be in order to make this initiative have a higher chance of attainment.

LAUNCH PLANNING

Assumptions-based models can be quite useful in the course of launch planning. For instance, following a risk analysis, a list of assumptions deemed critical can be constructed and further evaluated in preparation for the new product introduction. Subsequent discussion would then focus on the likely values for these critical assumptions and the nature of their effect on the new product introduction. This keenly focuses discussion on assumptions versus solely a numeric forecast. This is a particularly important matter during launch planning. In many cases, managers unfortunately become preoccupied with the forecast value and not how the value was calculated. It is just as important to know how a forecast was derived.

Leading companies also have found that establishing a set of common, consistent assumptions that would apply across all products within a strategic business unit (SBU) helps focus discussion and evaluation of forthcoming introductions. Similar questions can then be asked across projects, allowing for an equivalent evaluation of each project's forecast. In other words, managers can compare forecasts and their assumptions on an apples-to-apples basis. Failure to use common assumptions across projects makes comparisons of forecasts more difficult due to different assumptions. For example, a shipments forecast cannot be equated to a consumer demand forecast; leading companies predetermine which forecast is the focus. Use of common assumptions also can allow for the development of a standardized launch scorecard for evaluating the progress of each new product introduction. Tracking sales along with data for each assumption will provide insight into the nature of market behavior and will answer the question of why the market is behaving the way it is.

Should the new product not reach its target value for sales, then an analysis of the tracking data that corresponds to the forecasting assumptions will likely provide an answer for why the product is not performing well. Sales data alone cannot answer this question.

ASSUMPTIONS MANAGEMENT

New product forecasting is inherently a process of *assumptions management*. When employing an assumptions-based model, the assumptions are clearly defined and made transparent during decision making. New product forecasting occurs throughout the new product development process (Kahn 2006), but it is crucial to establish a final set of assumptions so that a forecast can drive launch decisions such as marketing budgets and supply chain commitments.

Thinking of new product forecasting as assumptions management leads a company to begin tracking assumptions from the point when the first forecast is generated through the point when the new product is introduced. At each review gate between these points, the new product forecast and corresponding assumptions are revisited, verified, and reissued to underlie an updated new product forecast. Risk relative to base, pessimistic, and optimistic cases are noted at each gate, and actions are pursued (such as conducting a market research study) to reduce high-risk assumptions and increase confidence in the proximate accuracy and meaningfulness of the new product forecast. Over time, the tracking of assumptions across multiple projects will create a sizable database of assumptions data on which analysis may be performed to assess the relationship of various assumptions to new product success and failure. This will further validate whether assumptions can be characterized as critical. Internal company benchmarks and guidelines for model assumptions can be established for future projects and new product introductions.

PITFALLS TO AVOID WHEN USING AN ASSUMPTIONS-BASED MODEL

Assumptions-based models are certainly not a panacea for forecasting new-product introduction. It is presumptuous to say that use of an assumptions-based model will immediately result in accurate new product forecast. There are many other forecasting techniques that could be used to forecast a new product introduction, and these might be better suited for the new product forecasting task at hand (see Kahn 2005, 2006). Unlike other techniques, however, an assumptions-based model forces robust discussion over the assumptions and the issues that underlie the new product, resulting in a more thoughtful determination of the new product forecast. Assumptions-based models thus offer transparency to forecast assumptions so that reappraisal and verification of forecasting assumptions can occur across functional departments, where each department can bring incremental data and knowledge about the marketplace and technology capabilities.

Another pitfall is the failure to undertake due diligence to clarify an assumption. If there are data, then some degree of validation and verification of subjective inputs should be undertaken to solidify an input assumption. Such analysis can include past data, surrogate products, and consumer data. Available data and information should be readily analyzed and referenced in the course of building an assumptions-based model. A tendency to rely solely on judgment, anecdotal evidence, and gut feel, in lieu of analysis, can lead management decisions astray. In short, use of an assumptions-based model should not excuse thoughtful data analysis.

Third, employing an assumptions-based model without a mindset of new product forecasting as assumptions management may not result in a meaningful forecast. Such a mindset emphasizes systematic thinking around assumptions, data collection, and forecast calculation. Without an assumptions management mindset, assumptions in the model are not regularly verified, nor are they tracked to gauge consistency. Assumptions not documented or tracked have the greater tendency to meander, be manipulated without notice, and fall suspect to internal company politics.

KEYS TO SUCCESS IN APPLYING ASSUMPTIONS BASED MODELS

It is important to mitigate these pitfalls when developing an assumptions-based model. Thus, several questions are posed to stimulate thinking around the ability to establish a model and manage assumptions. These questions are offered to frame your evaluation of your company's new product forecasting endeavor and readiness to use an assumptions-based model. Although there are no right or wrong answers, the ability to readily generate an answer to each question is an indicator that at least an effort toward developing and establishing an assumption-based model may be possible and worthwhile:

- What factors can be used to forecast a new product introduction?
- What assumptions should be associated with each relevant factor?
- How can/should these assumptions be operationalized?
- What assumptions appear to be common across new product forecasts?
- What prelaunch data sources are available?
- What assumptions/variables can and should be tracked?
- How can these variables be tracked, both prelaunch and postlaunch?
- How can the endeavor for developing a new product forecast be effectively linked to the processes of new product development and sales and operations planning?

SUMMARY

The task of new product forecasting is certainly laudable, but a systematic approach and delineation of assumptions for the purpose of understanding, versus target setting, will result in a meaningful forecast at the point of new product introduction. Through use of assumptions-based models and the practice of assumptions management, the new product forecasting process can be managed and repeated in a valid and reliable fashion. As defined, forecasting is the process of deriving an estimate of attainable demand under a given set of conditions (Kahn 2005). new product forecasting via assumptions-based models clarifies what the conditions should be along with a numeric output. So, rather than a numbers exercise or a computer-generated statistic, new product forecasting is truly analysis aimed at gaining underlying insight.

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