

USING QUANTITATIVE RISK ANALYSIS TO SUPPORT STRATEGIC DECISIONS¹

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ABSTRACT

Many see statistical simulation techniques as low-level technical tools relevant only to detailed risk analysis. The approach offers much more however, when the results are used at the strategic level to support better decision-making. This briefing makes the case for using the results of quantitative risk analysis at this level, highlighting the benefits and outlining potential shortfalls. It also describes what senior management should expect, or demand, of the practitioners of risk analysis and what, in turn, senior management must do to establish an environment conducive to successful risk analysis.

INTRODUCTION – STRATEGIC AND BUSINESS RISK

Planning for organisational success involves dealing with many kinds of risk. Without risk there would be no challenge in business. Threats, if they materialise, can make a seemingly-successful strategy fail and opportunities, if captured, can enhance the results from an otherwise marginal strategy.

Strategic planning involves balancing many factors that are risky. Yet businesses often do not understand the way risk contributes to results from competing strategies or how to identify and analyse strategic risk. Risk analysis of strategy may lead an organisation to choose an alternative that has lower return if it has less risk than an alternative with higher nominal returns but more risk.

Whether an organisation is risk-averse, risk-seeking or risk-neutral, it should evaluate the risk associated with its prospective strategies before making important decisions. This briefing discusses how quantitative risk analysis can contribute to understanding risk exposure and making better strategic decisions.

THE ROLE OF MONTE CARLO SIMULATION IN ANALYZING THE STRATEGIC PLAN

We will define business risk as including *uncertain events and conditions that, if they occur, have a positive or negative effect on the organisation's objectives*. Factors both external and internal to the organisation are involved in making good strategy decisions, and uncertainty attaches to each of these factors.

Strategy development requires looking forward in the business. Since there are no facts about the future, the future is best described in statistical terms such as:

1. "Sales may be as low as X or as high as Y but are most likely to be in the neighbourhood of Z."

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2. “Competitors may respond to our price reduction by keeping their prices even or by lowering theirs to A, or in the extreme to B.”

These parameters translate easily into *probability distributions* of uncertain sales or competitor prices respectively. It is clear that these uncertain variables will have a major influence over whether the strategy is successful or not.

Often the strategic plan will be expressed in a spreadsheet model that represents objectives such as sales, internal rate of return, net present value or return on assets employed. Organisations usually build the models with the assumption that they know the models’ components, structures and parameters with certainty. This assumption is dangerous. It can lead to less-than-optimal or even quite wrong decisions. Understanding the uncertainty in the factors that contribute to the strategy’s success or failure is crucial to making good decisions. We sometimes call these “risk-adjusted decisions”.

Including that uncertainty in the model of the strategic plan of the organisation can provide concrete and calibrated information that executives need to make decisions. Monte Carlo simulation offers one powerful and well-understood way to evaluate the impact of uncertainties on the key measures of success that attach to a strategic plan. Using Monte Carlo simulation, we can quantify several issues that are important in making the decision, for example:

1. *How likely are we to achieve the desired target*, e.g., a return on investment or net present value of the plan? This might tell us whether to pursue the strategy at all.
2. *How different are the results of two (or more) competing strategic options* that are available to us, when we take into account the uncertainty inherent in them? This comparison will help to choose between competing strategies when resources are limited.
3. *Which risk drivers or other environmental factors should be targeted* to enhance the strategic plan’s chance of success? The answer to this question may make it possible for us to improve the strategy’s projected risk-adjusted results, by mitigating threats and enhancing opportunities.

These are questions that cannot be answered by simple deterministic models, which assume the inputs are known with certainty. Once we admit uncertainty in our assumptions or input calculations we venture into the world of realism and can start to make risk-based decisions.

QUANTITATIVE RISK ANALYSIS USING MONTE CARLO

When the future is uncertain and several uncertainties may be important in the outcome, a method of analysis is needed that can:

1. Encompass all risks simultaneously, and
2. Provide a picture of the effect of risk on strategic outcomes.

Application of Monte Carlo simulation to a strategic planning model will meet both of these requirements. Monte Carlo simulation is a method of examining the impact on a strategy of the main risks, including technical, external, competitive and regulatory factors, as they may act simultaneously to modify the result found in the nominal or deterministic strategy model.

Effective risk management of business strategies requires several processes, each of which can be performed at a summary or detailed level:

1. *Specify the objectives of the business.* The business objective may be expressed as internal rate of return (IRR), net present value (NPV), market share or some other quantifiable measure of success.
2. *Develop a model relating objective(s) to influencing factors.* For instance, market penetration may be a factor of prices, competitor response, market forces, regulation and like factors. The model, often built in a spreadsheet, must be quantitative and may use assumed or estimated parameters linking causes and effects. There are two examples of these models later in this briefing.
3. *Determine the various risks that contribute to or may deflect from strategic success.* This is usually done in a brainstorming session that looks explicitly at risks. Technical, organisational, external and other risks should be considered and placed in the model. A technique that may assist is the Risk Breakdown Structure (RBS) that catalogues the sources of risks in major categories and detailed sub-categories.
4. *Express the risky factors in the model using probability concepts* such as a probability distribution, which reflects not only the alternative values possible but their relative probability of occurring. Other statistical concepts may be employed, such as the correlation of various uncertain factors, or the use of stochastic branches.
5. *Perform a Monte Carlo simulation of the model,* varying all the uncertain inputs simultaneously. The result is a probability distribution of the result variable, e.g., market penetration or internal rate of return (IRR). Since some of the inputs are uncertain, the output is a probability distribution reflecting the uncertainty in the business environment. This presents the range of possible outcomes (best to worst case), and the expected value within that range.
6. *Compare the probability distribution of the objective to the target level.* For instance, an analysis may indicate that the expected IRR is 28%. The minimum acceptable IRR (often called a “hurdle rate”) may be 20%, and the output distribution may show that there is a one-in-three chance that the actual IRR will be below that level. The organisation then needs to balance that information with other factors, such as strategic direction, to see if one-in-three is too much of a chance of failure.
7. *Focus on the main drivers of the uncertain result to identify options to enhance opportunities or mitigate threats.* The simulation will provide indications of which uncertain factors are important in driving the uncertainty in the objective, in this example the IRR. A sensitivity graph or “tornado chart” will highlight those elements that are closely related to the result.

COLLECTING REALISTIC DATA ABOUT STRATEGIC RISKS

An essential underpinning of understanding the risk in business strategy is an honest and searching inquiry into the risks that may affect the strategy. This would seem to be what businesses do all the time. Yet many businesses (and governmental organisations) do not consider risk in their strategic decisions. This lack of

appreciation of the role of risk in making organisational strategy may be based on several factors:

1. *Organisations typically are “success oriented”* in their planning and execution. Planning for alternative outcomes is not always practiced, tolerated or often rewarded. Most plans assume success of the activities and certainty of the assumptions underlying that success. One way to address this issue is to require staff to be honest about “the good, the bad and the ugly” in the business situation. Emphasising that “we cannot get where we want to go unless we know honestly where we are today” underlies the seriousness of this approach.
2. *Risk is viewed as a bad thing*, causing the organisation to miss its objectives. For this reason, many organisations’ cultures do not allow them to deal with risk clearly and in a straightforward manner. Put succinctly, “risk” is often associated with failure and unpleasant outcomes, and discussions about risk are often discouraged within the business environment and culture. One way to combat this perception is to include opportunities for improvement, if they are uncertain, in the definition of risk.
3. *Some risks may be unspeakable* – for example, a software company may fear that it is squandering hundreds of programmer-years on failed software, or telling the public that an announced product will not be on time or have the features promised. Many organisations are just postponing the inevitable and have to become more mature in their practices.
4. *Organisations do not understand quantitative risk analysis*, with techniques such as Monte Carlo simulation or other analytical tools that can help them analyse the risk, to put risk in the strategic picture. University courses may not put much emphasis on risk in dealing with strategy. People in leadership have learned leadership from others who do not understand risk, so they may not have a background in the subject.

Unquestionably, the factors included in any strategic model are not known with certainty. There are three different types of risk to consider:

1. *Estimating uncertainty*. As the strategy becomes better-known, the accuracy of the estimates of the inputs and their underlying assumptions should become greater. Estimating uncertainty may be viewed as symmetrical around the value, often reported as “plus or minus 10%.”
2. *Biases of individual or organisational nature in making the estimate*. These biases often have the effect of making the strategy look better than it should realistically be – seldom does an organisation want to make a strategy look bad for fear of angering someone in power or losing a bid to another company. It has long been observed that strategies’ results look like a hockey stick, with cash flow starting off negative and then expanding exponentially for the foreseeable future – though this is clearly unrealistic.
3. *Uncertainty in the assumptions underlying the plan*. A much more variable and potentially disruptive problem is that the assumptions made, either implicitly or explicitly, either do not actually lead to the estimates of the factors underlying the strategy or are not solid and may themselves change, calling into question the entire basis of the strategy. These assumptions may be about internal (e.g.,

organisational) or external (e.g., the economic or political environment) factors. Whatever the cause, there seem to be more ways that the assumptions can cause strategies to fall short of, than to exceed, expectations. Strategic plans seem to adopt optimistic assumptions, making the plan appear to be more successful than it is likely to be. This phenomenon probably stems from the fact that the planners are advocates for their plans and see mostly success.

Interviewing individuals knowledgeable about this strategy and with experience in past similar strategy development exercises can help us understand the uncertainty in the estimates.

EXAMPLE: MONTE CARLO ANALYSIS OF A SALES STRATEGY

One common example of uncertainty is the reaction of competitors. If we try to capture market share by reducing prices, they may change their prices in response. What are the prices they may choose?

The Model: A simple corporate strategy can be illustrated with a sales model. Suppose that a business wants to increase its sales. The factors that contribute to the success of an overall sales strategy may be simple or complex. For illustration of the role of risk analysis using Monte Carlo simulation, let us make a simple model of product sales as a function of a strategic decision including price and marketing budget.

The factors that influence sales may be as simple as marketing budget, price and competitor response. If the business can develop a model that combines these factors, leading to a sales calculation, then it might have the following model:

$$\text{Sales} = a * (\text{marketing budget}) - b * (\text{our price}) + c * (\text{competitor's price})$$

This simplified model can be estimated using econometric techniques with market data. If that estimate is shown to be somewhat able to explain the past, it could be predictive of the future. There are, however, several uncertainties in this model:

1. The competitor's response, represented by competitor's price, is uncertain. Will they lower price to try to offset an increase in our marketing or lowering of our price?
2. How well does the model explain reality, as represented in the confidence we have in the overall equation and the parameters a, b and c?

The original situation *vis a vis* the competitor might look like this:

Sales Model			
Model Component	Value	Parameter	Contribution
Marketing Budget	500	a = 90	45,000
Our Price	1,000	b = -100	-100,000
Competitor's Price	1,000	c = 100	100,000
Sales			45,000

The Strategy: The business wants to develop a strategy that will increase sales. If the business wants to increase sales beyond \$45,000, say to \$50,000, it can either increase the marketing budget, reduce the price or both. Suppose the plan is to reduce our price by \$50, which will increase sales *if the competitor does not respond*. Assuming

the competitor does nothing, this action could lead to an increase in sales that might look like the following, with the company's strategy variable shown in **bold**:

Sales Model			
Model Component	Value	Parameter	Contribution
Marketing Budget	500	a = 90	45,000
Our Price	950	b = -100	-95,000
Competitor's Price	1,000	c = 100	100,000
Sales			50,000

The Competitor's Reaction to Our Strategy: This action increases our sales if everything goes according to plan. Is this a good strategy? Can we confidently predict an increase from \$45,000 to \$50,000 in sales resulting from our strategy? Maybe, but before drawing that conclusion we need to consider the risks that are inherent in the plan.

1. The competitor may not respond with lower prices. This is what the initial, partial analysis, model shows.
2. The competitor's reaction may be different, however. The competitor may see our price reduction and may react with lower prices on its brand. We can predict something about that reaction but it is uncertain.
3. Also, the parameters of the equation are uncertain. They may be based on a small sample of data. The relationship may be uncertain as well because of variables (e.g., demographics, overall economic factors, imports, government policies or regulations) that were not included.

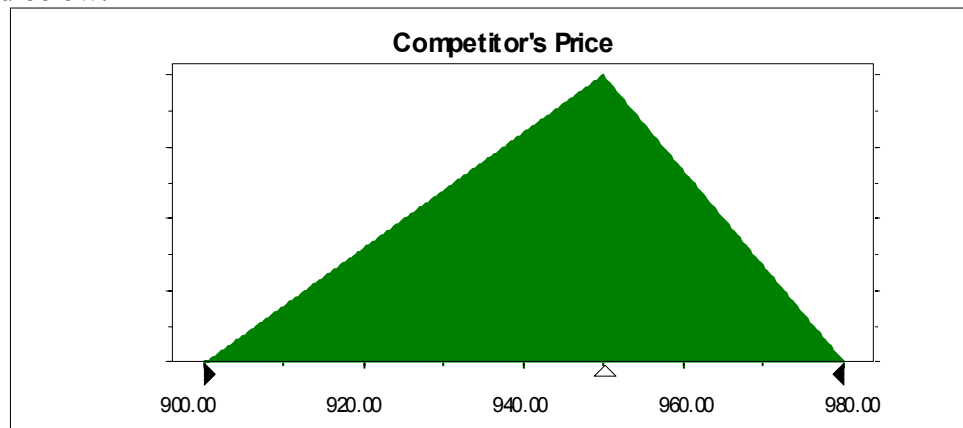
Let us elaborate the model a little to take account of the competitor's response. Suppose our best estimate of the competitor's response is to lower his prices to \$960, a little above our price. That would wipe out most but not all of our anticipated gain.

There is uncertainty in our assessment of the competitor's pricing decision, however. Suppose we believe the competitor may not respond at all, in the best case, or may drop prices down below our new level? How do we analyse our strategy now?

Representation of Competitor Uncertainty: We can use a probability distribution to describe uncertain events when we cannot predict them with certainty. One simple way to do this is to employ a "3-point estimate" that represents the lowest, highest and most likely value of the variable, in this case the competitor's price.

1. It is unlikely that the competitor will raise prices, but there is a chance that the competitor will reduce prices only a little, say by \$20 to \$980. This is viewed as the "best case" for us and results in the greatest increase in sales.
2. There is a chance that the competitor will reduce its prices the full \$50 to match our price reduction. This is viewed as the most likely scenario.
3. There is some chance that this competitor will declare an all-out "price war" and reduce their price by \$100 to \$900. This is the worst case for our sales results, and it might require a backup plan that involves further price cuts or more marketing revenue.

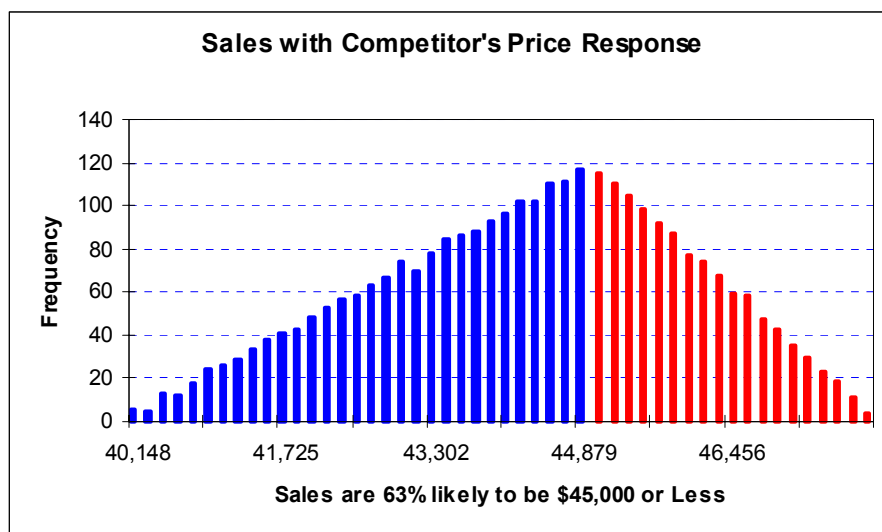
The 900/950/980 distribution chosen has a simple triangular shape. This is represented below:



Monte Carlo Simulation of the Uncertainty: Since we do not know what the competitor will do, one way to evaluate our prospects with this strategy is to try all possible combinations of the competitor's reaction and see what that may do to our sales results. This is done using Monte Carlo simulation. The steps are simple:

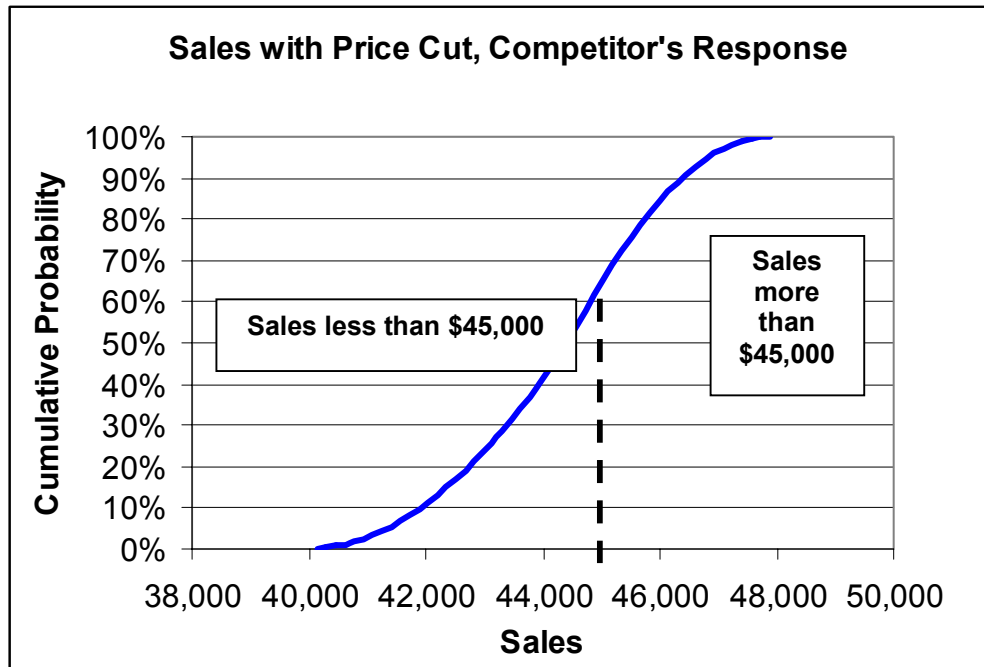
1. Estimate the parameters (3-point estimates are often used) of the uncertain value. In this case it is the competitor's prices and the three points are \$980, \$950 and \$900.
2. Define the shape of the distribution of the uncertain value. In many cases a simple triangular distribution is sufficient, although other distributions such as normal, Beta, lognormal and uniform are sometimes used.
3. Simulate the model by computing the target value (in our case, total sales) many times where each time ("iteration") is based on a value of the uncertain competitor price chosen from the distribution at random.
4. Show the result with probability distribution and cumulative distribution.

Monte Carlo Simulation of the Strategy – Results Histogram:



Monte Carlo Simulation of the Strategy – Results Cumulative Distribution (S-Curve):

The simulation of results shows the triangular characteristic of the one uncertain assumption. The cumulative distribution or S-curve shows the results of interest in a clearer way.



Going along with the cumulative distribution is a table of values for sales, along with the probability that the actual sales will be of that value or less.

Sales Cumulative Distribution	
Percentile	Value
0%	40,069
10%	41,997
20%	42,828
30%	43,464
40%	43,999
50%	44,470
60%	44,897
70%	45,316
80%	45,809
90%	46,450
100%	47,954

The first thing we can see is that there is virtually no chance of meeting our sales goal of \$50,000, since the competitor is expected to react with price cuts. Most (over 60%) of the results show a sales value below \$45,000. This implies that there is only about 40% likelihood that sales will be \$45,000 or more, given the competitor's likely price

response. Our strategic aim is to raise sales above \$45,000, and we want at least a 75% chance of success. Lowering prices seems not to be sufficient. Could we do better?

Adding Marketing to the Strategy: There is some chance that we can increase our marketing budget to increase sales without the competitor’s noticing it. How much do we need to increase marketing expenditures to give the inclusive strategy (price reduction and marketing increases) a fighting chance, defined as a 75 – 25 chance of improving sales?

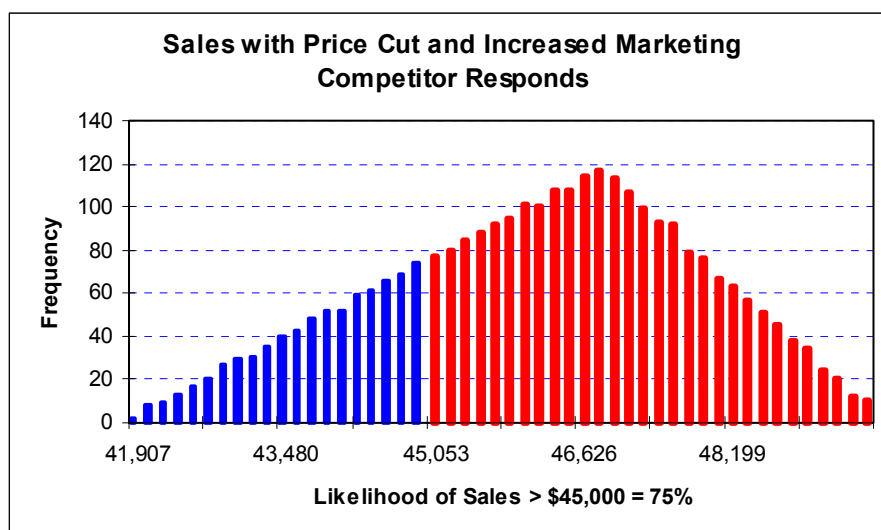
First, notice that we are talking a different language now from before we started analyzing risk. We are asking: “What is the likelihood that our strategy will succeed?” We cannot answer whether our strategy will be successful, since that assumes we know what the competitor *will* do, as opposed to what they *might* do.

With the tool of statistical simulation and a model of the market responses to the strategy, we can answer the real question, what might happen and with what probability?

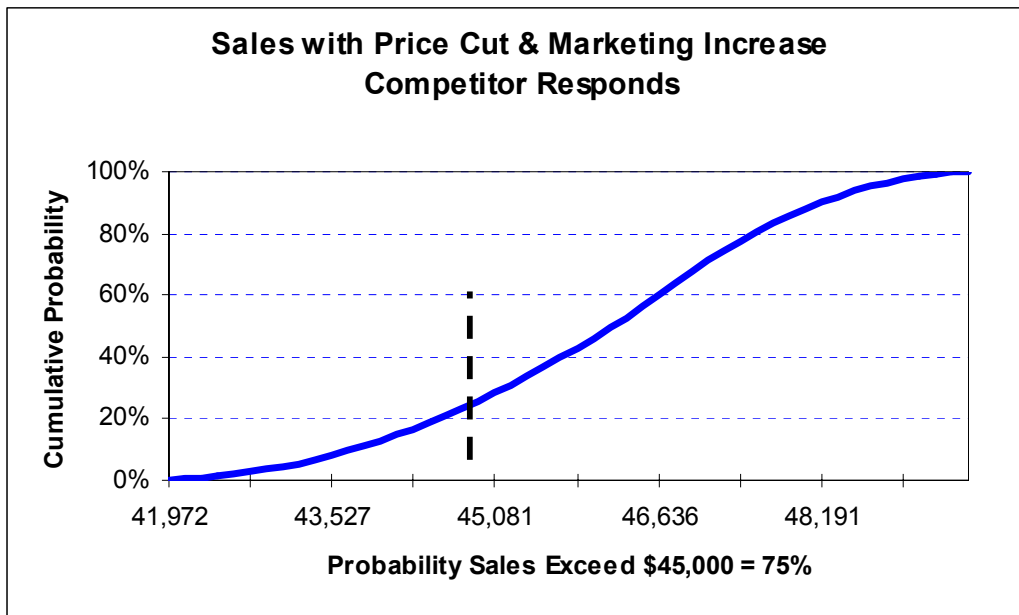
It turns out that we do not have to increase the marketing budget very much to achieve the desired results. Increasing marketing expenditures to \$520 will overcome the market’s reaction to the possible competitor price reaction. The following model was simulated with the strategy in **bold** and the competitor uncertainty is in ***bold italics***:

Sales Model			
Model Component	Value	Parameter	Contribution
Marketing Budget	520	a = 90	46,800
Our Price	950	b = -100	-95,000
Competitor's Price	<i>1000</i>	c = 100	100,000
Sales			51,800

Now the results show that expected sales increase above \$45,000 in 75% of cases, giving the required confidence level.



The same information is presented more clearly in a cumulative distribution, shown below:



Accuracy of the Model: There is, of course, uncertainty in the model itself. No model can completely represent the way the market, which is made up of many thousand individual decision-making entities, will react to relative prices and to marketing expenditures. There are several reasons for this, but principal among them are:

1. The model may not include all the factors that influence sales. For instance, we have not included overall economic measures such as income or wealth, nor have we included any demographic factors.
2. The phenomena being modelled may be inherently variable, and even with the complete set of influential variables the explanatory power may be weak.

These items can be summarised, crudely, by a variation around the overall estimate of sales. That variation is usually viewed as normally distributed with a zero mean and a standard deviation that can be estimated. Often this variation is represented by the coefficient of variation (so-called R^2 in statistics). The variation in predictive power of the model can also be represented by the accuracy in the specific coefficients that apply to the price and marketing budget forces.

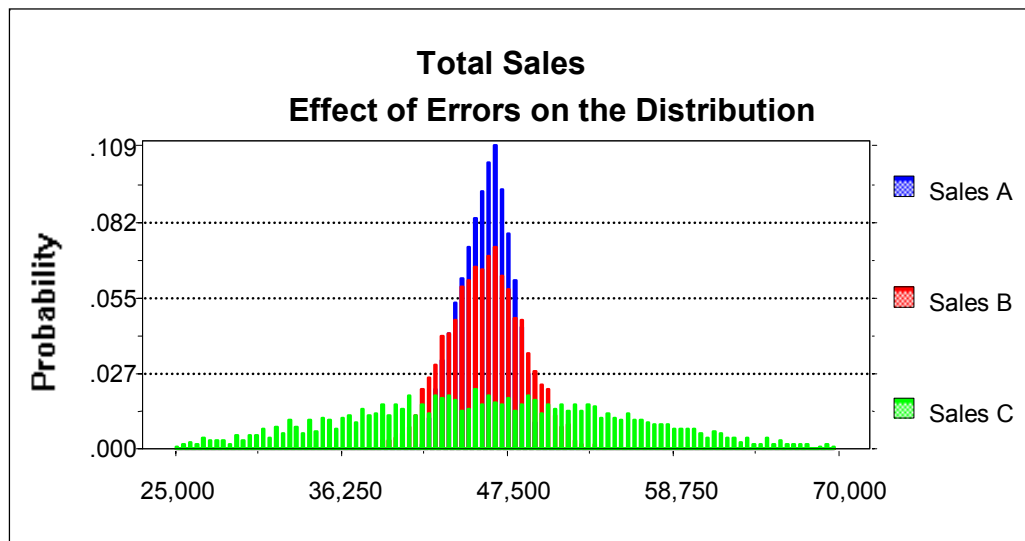
Suppose one measure of success of the strategy is minimising the likelihood that sales will decline below the baseline of \$45,000, minimising the losses so to speak. The accuracy of the model may be a serious determinant of this strategy. Let us include an additive uncertain value to the model, shown below as the Error Term.

Sales Model			
Model Component	Value	Parameter	Contribution
Marketing Budget	520	a = 90	46,800
Our Price	950	b = -100	-95,000
Competitor's Price	1000	c = 100	100,000
Error Term			0
Sales A			51,800

Notice that the error term does not affect the results if we do not consider uncertainty, but it surely does affect the result when uncertainty is considered. The likelihood of sales declining is larger with greater inaccuracy than with less inaccuracy of the model, as shown below:

Impact of Model Accuracy on Results	
Scenario Assumptions	Likelihood of Sales Declining
Sales A: No Error term	25%
Sales B: Error term Normal (0, 2,000)	33%
Sales C: Error term Normal (0,10,000)	45%
Notes for this Analysis:	
Our price = \$950	
Marketing Budget = \$520	
Competitor price = (\$900, \$950, \$980)	

The overlay chart below illustrates the simulation results for the three error scenarios and highlights the importance of accuracy in this model.



SIMULATING THE INTERNAL RATE OF RETURN TO EVALUATE THE STRATEGY

Monte Carlo simulation can be applied to more sophisticated models of business strategy than the one shown in the example above. Usually strategy is evaluated using a measure of value such as the net present value (NPV) or internal rate of return (IRR). Such a model is presented below to show that simulation can be applied to more complex and realistic spreadsheet models.

Let us analyse an investment in a strategy to develop a new product. This plan is to be evaluated on the basis of its IRR. Because the company has more investments than it can fund, it has a “hurdle rate” of 30% – it will invest in a strategy only if that strategy promises an IRR of 30% or more. The assumptions of the model below include:

1. Investment is assumed to be \$90,000.
2. After the product is developed it is estimated that the product can be sold for \$100,000 at a cost of goods sold (CGS) of \$75,000 in the first year.
3. Revenue and operating costs are expected to grow at 10%.
4. The forecasts of revenue and cost of goods sold will be made for a 5 year period, and then be assumed to remain constant at the levels of cash flow established in year 5 of production. The net present value of years after year 5 is represented by a “going concern residual value” which is the value of an annuity that throws off that cash flow at a rate of 15%, their cost of capital.

The model shown below illustrates those assumptions and shows that the IRR of this strategy exceeds the company’s hurdle rate at 45.7% - if the assumptions are accurate and true.

New Strategy Value Calculation							
	Assumptions (\$ in thousands)						
	Starting Revenue	100					
	Revenue Growth	10%					
	Starting CGS	75					
	CGS Growth	10%					
	Investment	90					
		Year 0	Year 1	Year 2	Year 3	Year 4	Year 5
Revenues		100	110	121	133	146	
Cost of Goods Sold (CGS)		75	83	91	100	110	
Cash Flow		25	28	30	33	37	
			<i>Going concern Residual Value</i>			244	
Project Cash Flow	-90	25	28	30	33	281	
Internal Rate of Return	45.7%						

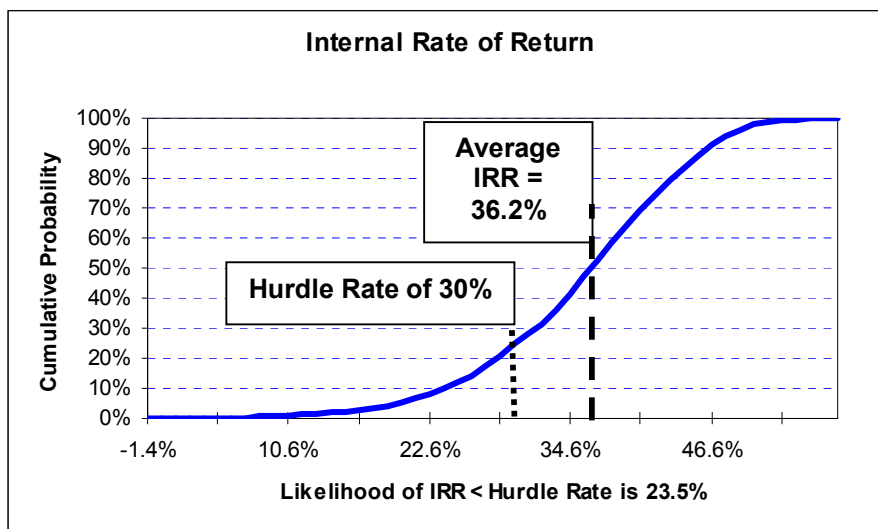
The model shown above includes some complex calculations. The revenue and cost lines experience exponential growth, and the IRR is calculated from the cash flow line. When uncertainty is included, will we be able to simulate the model using Monte Carlo techniques? Of course we can.

Let us add some assumptions about the uncertainties of revenue, CGS, and project investment, and see if we can tell whether this strategy should be followed:

New Strategy Value Calculation With Risk				
	Assumptions (\$ in thousands)		Low	High
	Starting Revenue	100	90	105
Revenue Growth	10%	9.0%	10.5%	
Starting CGS	75	70	85	
CGS Growth	10%	9.5%	11.0%	
Investment	90	85	110	

Notice that revenue and CGS are now likely to grow less favourably (cost may grow as much as 11% while revenue may grow as little as 9%) and go against the success of the strategy. The amount of investment is viewed as uncertain but likely to be higher than \$90,000 at the end of the day.

What about the IRR for this strategy? Does it still look good and how likely is it to exceed the hurdle rate? A Monte Carlo simulation evaluates this risky strategy for us:



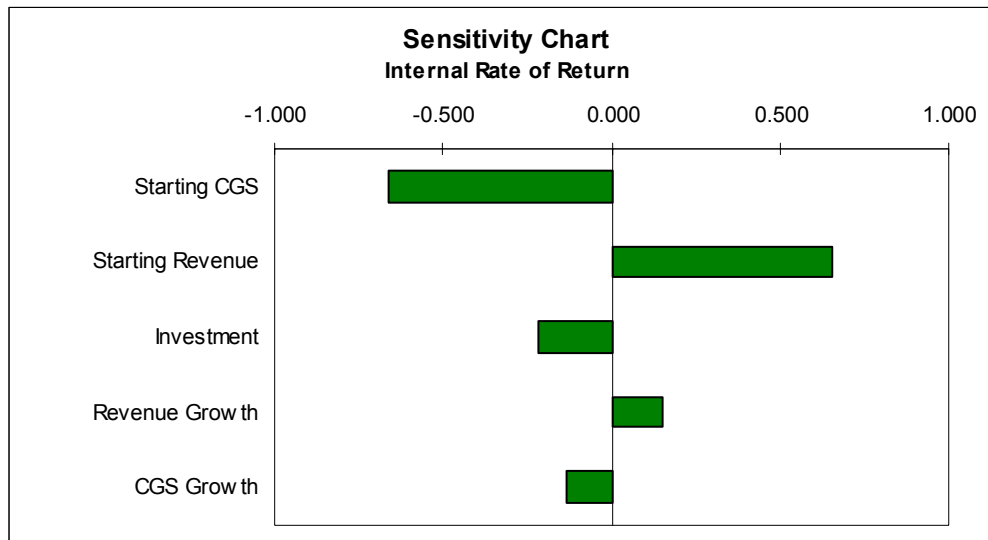
Some conclusions can be drawn from this Monte Carlo simulation.

1. The expected IRR is 36.2% when the effect of risk is included, not 45.7% as the base forecast put forward by the strategy team.
2. It is 23.5% likely that this strategy will not exceed the hurdle rate.

This strategy should be compared with the other strategies under consideration similarly risk-adjusted. It may be that this strategy should be adopted, even though it does not appear to offer quite the benefits to the company that had been advertised. All strategies competing for limited capital funding need to be evaluated on the same basis, risk-adjusted using Monte Carlo simulation techniques.

One benefit of using the Monte Carlo simulation approach with a complex model is that it can sort out and order the relationships between the inputs and the outputs. It puts the inputs in an ordered list by their association with the objective. The method

provides some guidance about the ways to respond to the risks for a higher likelihood of success. A ranking of the inputs by their rank correlation with the IRR, shown in the “tornado diagram” below, helps to sort through the combination of relative risk and role in the strategy model.



This table shows that the uncertainty in the starting (first year) cost of goods sold and in the starting revenue are the two most important risks. This information may help the company to act to improve the strategy’s likelihood of success.

CHALLENGES TO USING MONTE CARLO FOR RISK IN STRATEGIC PLANNING

The following challenges for organisations evaluating risk at the strategic level can be identified, and must be addressed:

1. What does the high-level decision-making committee think about strategic risk?
2. Organisations often do not discuss risk at all. The corporate culture may keep them from recognising risk since it is not discussed. “I don’t want to hear that” is a common way to react to risk in the business setting.
3. Data about risk are often unavailable or ambiguous. Data collection is the most difficult and time-consuming part of a risk analysis.
4. The statistical nature of the Monte Carlo simulation approach may put off the organisation, which thinks of this technique as mysterious and a little out of their league.

Each of these four challenges is discussed in the following paragraphs.

1. Risk at the strategic decision-making level: High-level committees make corporate decisions that are supposed to be cognisant of the risk facing them. These committees talk about risks to the strategy, but those discussions are often not focused or disciplined, nor are the committees provided the right data. While the participants are

experienced in many areas of business planning and management, they may not be steeped in the discipline of risk analysis or Monte Carlo simulation.

It is fair to say that not all of these committees have a systematic grasp of strategic risk identification and analysis. They all talk about risk but it is not clear that they implement a standard operating procedure that deals with risk using the discipline or rigor available from the profession. Often, where risk plays a part, decisions are made in an *ad hoc* fashion after some discussion.

The committee members may not understand about risk analysis or the use of Monte Carlo simulation of the strategic models. They do not know what to ask their staffs to get a clearer picture of the strategy's risk. The committee staffs may not be aware of the availability of the technique either.

Some people at the decision-making level are known to be hostile to new ways of analyzing decisions. They may prefer the intuitive and *ad hoc* approach that has served them well in the past. They are generally sceptical about new methods, especially those that seem to be precise and scientific such as risk analysis using Monte Carlo simulations. Who will point out the fact that some bad decisions could have been avoided if only the options had been analysed more thoroughly and systematically?

A useful way to approach the decision makers to overcome their reluctance or antagonism concerning the statistical approach to risk analysis is to illustrate the benefits of the methods on a simple strategy. Briefing the decision makers individually and informally first on what to expect before presenting it to the committee would be a good idea. Individually the decision makers may have questions and concerns, and these can be addressed in advance, outside of the view of their colleagues. It is difficult for most people to admit they do not know something in the committee room, but rather more easily done in the office.

If the impetus for using Monte Carlo simulation of strategic risk is coming from the staff, another consideration about introducing this approach is to identify a person on the decision-making committee who might be a champion of the new method of analysis. That person could be enlisted to use the method on one strategy and illustrate its usefulness.

If the impetus is coming from the executives, it is important to get some expertise in the use of the technique and have a successful implementation the first time out. A strategy could be chosen for the first implementation that is not the most important or risky strategy under consideration.

2. The corporate culture may not be friendly to risk analysis: Corporate organisations and their leaders are often not friendly to considering business risk in a careful, explicit and objective way. There are many leaders who “do not want to hear” about risk of their plans and strategies. This factor may be caused by the need to consider strategic elements that are not pleasant to discuss. They may also be angry that someone who talks about strategic risk is challenging their good ideas.

The topic of risk is not very popular with corporate leaders when they are trying to make a decision. Risk clouds up decisions, making decision making more difficult. Managing a business is easier when decisions are simple and straightforward. Risk is just the opposite, being ambiguous and even contentious. Decisions made will not be

clear-cut when risk is considered. Characterisation of risk is made based mostly on the judgement of subject matter experts. Because risk is in the future, if the experts disagree there is no absolute metric against which to judge the competing views of risk. All of this means that strategic risk is not always a welcome subject in the organisation.

Corporate leaders might balance this fear with the commitment to evaluate the business decision from all perspectives. Risk is a common fact in most businesses, and it should be addressed in a healthy way. Risk health includes being open to discussions that may be difficult but are essential. Even if risk is a difficult subject to discuss in advance of the risk's occurring, it is more painful yet to ignore the risk and try to clean up the mess after it has occurred. Leaders of businesses and other organisations are aware of strategic risk. A full, open and frequent discussion of it is a key to being able to address risk in making high-reliability decisions.

3. Risk data are difficult and expensive to collect and validate: One obstacle to conducting risk analysis, particularly that utilising quantitative methods such as Monte Carlo simulation, is that the data required is difficult to collect. Further to that difficulty is the essential scepticism about its validity when collected. Risk data is usually derived from discussions and interviews with people who are subject matter experts. These people are often asked to use their powers of estimating and judgement to provide data on the 3-point estimates such as those shown in the two examples in this briefing. There are several difficulties involved in risk data collection:

1. Usually there are no available databases of any relevance to the topics covered. This implies that the data about strategic risk will be based on expert judgement of a few knowledgeable individuals. These data will be gathered in risk interviews of individuals or groups.
2. The interviewees are often new to risk analysis and are struggling with the concepts of “optimistic case,” “most likely case,” and “pessimistic case.” Underestimation of risk is common among people providing risk data for the first time.
3. The individuals thought to provide the most relevant data are often biased, usually in favour of making the project look good. Under-estimation of strategic risk is common among the more highly-placed project participants.
4. The people with the best data on risk are usually working hard on the strategy and not very available for interviews.

Executives should become committed to the collection of the best quality data on risk. Because the data are based on expert judgement, the data collection process must be supported and encouraged. Fearing that the data will be of low quality is not the equivalent of certainty, since ignoring strategic risk does not make it a risk-free strategy.

It should be understood that the collection of risk data is the most important idea about project risk. The results of a Monte Carlo simulation will clearly reflect the risk data that are put into the model. Data collection should be about 90% of the effort in developing a risk analysis of a strategy. The executives should be clear that contributing to the risk analysis by providing unbiased data is part of the job of

everyone. An emphasis should be placed on honesty in data gathering and providing. One way to do this is for the executive or decision maker to indicate that we want “the good, the bad and the ugly” risk data so we can make a proper decision.

4. The Monte Carlo simulation methodology may be mysterious to some: Some individuals who are unfamiliar with such methods as Monte Carlo simulation may regard it with suspicion. There may be a culture that says; “If it is sophisticated and not common sense, we do not want to use it.” This idea may be expressed in terms such as; “If I do not understand it, how can I trust it or explain it to others?” Some are concerned that such methods that use specialised concepts and software are suspect and vaguely threatening. Experts in the new techniques are generally lower-level specialists who can be passed off by the decision makers. Some executives celebrate the idea that they cannot stand to listen more than 15 minutes to experts or consultants who have new ideas or approaches.

Making business decisions is serious enough to take help from as many places as possible. Executives should be very interested in exploring ways to look at strategic risk. The fact that the method is explicitly scientific and, at the same time is based on data derived from judgement cannot be an excuse to ignore the benefits. The Monte Carlo simulation method is a 50-year old method that is well known and trusted. The software that implements the method is off-the-shelf and well established. This is not a new technology for decision making. Others are using it to make their decisions. Any company that does not consider simulation of strategic risk could be facing other companies who are availing themselves of this technology.

Practitioners of risk analysis and Monte Carlo simulation are experienced in gathering the data needed to represent the risk. No data about the future will be perfect, and no practitioner will guarantee that all risks have been identified or quantified with great accuracy. Still, as compared to ignoring risk altogether, evaluating some 90% of all the risk in the strategy is a major contribution to good decision making.

OPPORTUNITIES FOR USING MONTE CARLO IN EVALUATING RISK IN STRATEGIC PLANNING

Monte Carlo simulation provides a number of benefits to the evaluation of risky business strategies, including:

1. Risks to strategic decisions are uncertain events in the future, and statistical approaches are specifically designed to handle such problems. Monte Carlo does all the statistics so the individual can concentrate on the model and the input data.
2. Monte Carlo simulation considers all the risks simultaneously in evaluating the risk, just as the real strategy can be affected by many risks at once. This benefit provides an estimate of the overall risk to the strategy coming from different sources.
3. Monte Carlo simulation is a respected method of risk analysis.
4. As a benefit, the gathering of the input data for Monte Carlo provides greater understanding of the strategy and where it may be in jeopardy.
5. Risk responses can be devised when risks are evaluated specifically within a valid model of the strategy.

Each of these is expanded in below.

1. Monte Carlo is specifically about future risks: Uncertainty is best expressed in probability terms. Probability distributions are explicitly suited to represent and calibrate our current estimate of possible events. Monte Carlo simulation uses these concepts and makes them operational. The approach is specifically designed to the problem of risk, and business strategic risk can use simulation.

2. Monte Carlo can provide an assessment of the overall risk to the strategy: Monte Carlo simulates all the risks simultaneously, and computes the overall risk to the strategy. It uses simulation of the model to translate the element-level risks to the overall strategy where the objectives are (e.g., total sales, IRR). Other risk analysis methods consider each risk one at a time and prioritise them, but cannot evaluate the impact of all risks simultaneously. For this reason, Monte Carlo simulation is a powerful way to evaluate the specific strategic objectives.

The only requirement is that the objective can be modelled in a spreadsheet. This requires risks and objectives to be related by mathematical rules. Most strategic analyses resolve around some financial objective and financial models of strategies are common. The risks to success must be represented in the model somewhere or they cannot affect the outcome. To make this happen, some models must be elaborated with additional detail or in additional dimensions. This elaboration is viewed as a benefit of the analysis since it improves the usefulness of the model.

3. Monte Carlo simulation is a respected method of risk analysis. Monte Carlo analysis was used to predict submarine movements during World War II. It continues today to have its scientific and engineering uses.

In the analysis of project risk, as an example of current day use, Monte Carlo simulation is frequently used to evaluate the risk of project costs or completion dates. Specific Monte Carlo programs are built to interface with scheduling tools. General Monte Carlo programs simulate any phenomena that can be modelled in spreadsheet format, such as project costs or, in this case, corporate strategy.

Monte Carlo simulation does use specialised software, and it is not possible to do this analysis by hand. That does not mean that it is a mysterious or sophisticated tool. In fact, this tool is basically a brute force approach to trying all possible combinations of uncertain variables and building up a pattern of the overall project objective distribution. What is sophisticated is that these tools make many computations in a short time, and how they implement some features not shown here. Most risk practitioners should be able to describe how Monte Carlo simulation works to the satisfaction of management.

4. Risk data gathering has its own benefits: Opportunities to understand the strategy better occur through the collection of data on strategic risk. Identification of strategic risk should include risk from all areas of the strategic landscape. Internal and external risks are all important in determining the strategy's success. The net for identifying these risks must be flung widely over the business, the strategy, the competitors, government and international players, technical issues and even tax and accounting issues.

In gathering or providing data, in researching it from others, the participants in a risk analysis will come to understand the strategy more completely than before. The individuals end up being more productive and relevant value added contributors to the

design and execution of the strategy. They also become a more coherent and productive strategic team after the exercise.

5. Risk responses can be evaluated within the context of the risk model: Risks to the strategy will be represented in its model. The main risks are identified with the sensitivity chart as shown in the IRR example. A key benefit of using Monte Carlo simulation with a strategic model is the ability to calibrate each risk and assess its importance within the strategy in comparison with each other risk. This helps decision makers understand where the risk is greatest, but it also indicates fruitful areas of risk response.

Priority risks can be responded to or handled, increasing the likelihood of a successful strategy. Each strategic response will have its own set of risks, like the original strategy. The model, configured with each risk calibrated in a probability distribution, is the perfect vehicle to use in evaluating risk responses. With each response having its own risk, the model that is configured for the analysis of risks is the correct place to make the evaluation of the responses to risk as well as the risks themselves.

SUMMARY

Businesses and other organisations such as government agencies should make their decisions about future strategy with full understanding, calibration and evaluation of the risks that surround the strategy. Quantitative risk analysis techniques such as Monte Carlo simulation help the organisation to focus on risk, to calibrate risk in the context of the strategy model, to assess the overall risk to the strategy and to plan risk responses to improve success likelihoods.

Monte Carlo simulation contributes to the ability to see the risk in the strategies and hence to make more enlightened decisions. It helps to compare strategies which are competing for scarce capital resources. It helps explain the strategic risks. It helps the organisations, which are often reluctant to talk about risk, to embrace risk objectively as a major impact on business.

Monte Carlo simulation is often used in technical and business environments, and it is often taught in schools of business or engineering. Some organisations do not want to talk seriously or in specific about strategic risk, so they use the slightly mysterious and sophisticated nature of this tool as a scapegoat for not talking about risk in any detail. Executives should see how simulation can help calibrate and focus on the risk to any strategy, and that its ultimate aim is to improve the performance of the business, not to point out its weaknesses.