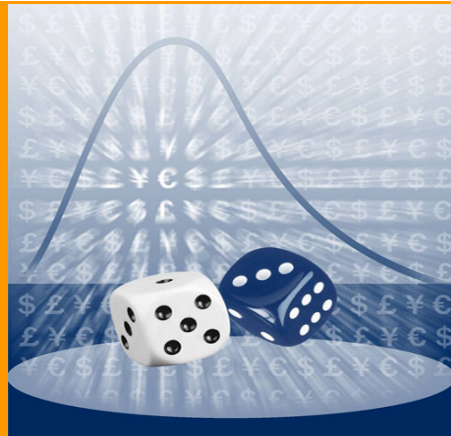


**McKINSEY WORKING
PAPERS ON RISK**



Probabilistic modeling as an exploratory decision-making tool

**Number 6 | Martin Pergler and
September 2008 | Andrew Freeman**

Confidential Working Paper. No part may be circulated, quoted, or reproduced for distribution without prior written approval from McKinsey & Company.



Probabilistic modeling as an exploratory decision-making tool

Contents

Executive summary	2
Introduction	3
Probabilistic modeling and Monte Carlo simulation	3
The case against probabilistic modeling	4
Are you overconfident?	6
Response to the indictment	6
The meaning of probability	7
The benefits of good probabilistic analysis	8
Minimizing biases in groups of experts	12
Learning from risk modeling in financial institutions	13
Putting probabilistic modeling into action	14

McKinsey Working Papers on Risk is a new series presenting McKinsey's best current thinking on risk and risk management. The papers represent a broad range of views, both sector-specific and cross-cutting, and are intended to encourage discussion internally and externally. Working papers may be republished through other internal or external channels. Please address correspondence to the managing editor, Andrew Freeman, andrew_freeman@mckinsey.com

Executive summary

For decades we have used analytical tools such as probabilistic modeling for dealing with uncertainty. However, outside the financial services industry only a few of companies have embraced them. Instead, executives often make big strategic decisions just “from the gut.” Some of the reasons for this include the perceived complexity of modeling techniques, lack of transparency, and the “garbage in, garbage out” syndrome. Indeed, numerous examples, including the current credit crisis, suggest decision makers rely too much on the seemingly sophisticated outputs of probabilistic models, while reality behaves quite differently.

In our opinion, the problem is not with the tools, but rather in a misunderstanding about their purpose and use. Due to the complex dynamics of real strategic business problems, expectations that the likelihood of all possible outcomes can be accurately estimated (or even imagined) are obviously unrealistic. Claims that a strategic decision is safe or optimal to some highly quantified confidence level (e.g., 95 percent) or that it carries a specific 95 or 99 percent value at risk, are usually inappropriate. Such claims might be meaningful where risk arises solely from the aggregate of a long sequence of micro-risks whose behavior can be predicted adequately from extensive historical data (for instance – and with caveats – risks of default in a truly diversified credit portfolio). But they are rarely meaningful when managers face one-of-a-kind business decisions involving strategic, execution, or macroeconomic risks.

Even in these cases, however, and perhaps especially in these cases, probabilistic and similar modeling methods can be tremendously useful as a structuring device to organize and combine all available insights about the relevant uncertainties and their impact. Used as an exploratory decision making tool, they improve decision makers’ understanding of the key business value drivers, the importance and interdependencies of the most relevant uncertainties, and how sensitive a decision is to the assumptions that have gone into making it. Used correctly, the methods offer essential support to the process of making risk-informed decisions. They can also help managers explore the potential value of managerial flexibility.

In this paper, we highlight how probabilistic modeling can fail when used in the wrong way. We explain two different relevant definitions of the term “probability” and discuss some fundamental problems in dealing with uncertainty that arise from human biases. We then give concrete examples of questions that probabilistic modeling can answer well, and suggest frameworks for how it can be used for better strategic decision making.

As recent events have shown, the mere existence of a probabilistic model is a poor reason to feel that your risks are under control and that you can sleep well at night. In situations where there is significant uncertainty, however, the process of building a probabilistic model and interpreting the results can give you the confidence of having understood the key risks in as robust a way as possible. As with financial valuation models, much of the worth in probabilistic modeling derives from its role of structuring a more meaningful management dialogue.

Introduction

Business executives cannot escape the need to make strategic decisions in the face of uncertainty and the study of this process has long been at the forefront of management science. However, there is an intriguing paradox. Key analytical tools, such as probabilistic modeling using Monte Carlo simulation, real options, game theory and others, have been around for decades, and since 1969 eight Nobel Prizes have been awarded for related cutting-edge thinking in economics, finance, risk and uncertainty, and decision theory. Yet these approaches remain underutilized, especially by industrial and service companies. How can this paradox be explained? More importantly, how can these analytical techniques be better used in business settings?

We maintain that these tools do present a huge opportunity for managers in all industry sectors facing significant uncertainty, provided that they are used and interpreted appropriately. They should not be seen as ways for executives to make accurate predictions about the future – that would be a foolhardy view. Rather, these tools should be understood as powerful facilitators, allowing managers and decision makers to make use of all available insights about a complex problem. The focus of this paper is on decision making in corporates, whose issues in this domain are slightly different from financial institutions. However, we highlight some of the similarities and differences in passing in one section below.

Probabilistic modeling and Monte Carlo simulation

Probabilistic modeling is any form of modeling that utilizes presumed probability distributions of certain input assumptions to calculate the implied probability distribution for chosen output metrics. This differs from a standard deterministic model, say a typical Excel spreadsheet, where you can change the values of input assumptions at random and see the impact of those changes on the outputs. You however make only a limited effort to determine just how likely it is that the assumptions and therefore the outputs will change.

Monte Carlo simulation is the most commonly used technique for probabilistic modeling. The name, referring to the casino at Monte Carlo, was first applied in the 1930s, the link being the random sampling element of the method. The approach involves taking an underlying deterministic model and running it several thousand times. In each iteration, different values for the input assumptions are fed into the model. The values for each assumption are sampled from probability distributions chosen as the basis for understanding the behavior of that variable. Specialized, easy-to-use software ensures the random sampling is consistent with all the postulated relationships between assumptions, and keeps track of the value of the outputs in each iteration. The histogram of all the output values aggregated across all the iterations then describes the likely probability distribution of the outputs. In essence, the simulation software acts as a master of ceremonies in re-running the basic model through several thousand alternate future universes that are defined so as to be consistent with the chosen understanding of how different variables will behave.

This sounds like a lot of work, but in truth it requires only proper problem structuring up front, and then – given the advances in computing technology – only a few minutes of computation time for even fairly sophisticated business models.

There are other probabilistic modeling approaches. According to one, a certain number of discrete scenarios – anything from a handful to a hundred or so – encompassing all the input assumptions together can be defined and assigned probabilities. The aggregate outputs of all of these scenarios weighted by the appropriate probabilities can then be analyzed.

Alternatively, where individual probabilistic assumptions are simple standard probability distributions (e.g., normal distribution with specified parameters), what will be the shape of the output probability distribution can sometimes be exactly calculated in closed form using mathematical rules, with no scenarios or iterations. However, as the technology improves, fewer situations arise for which such alternative probabilistic modeling techniques are preferred to Monte Carlo simulation (whether in pure or modified form).

The case against probabilistic modeling

Most business leaders agree that techniques such as probabilistic modeling have their benefits – in theory. Computational technology is easily accessible – plug-ins such as @Risk or Crystal Ball allow Monte Carlo simulation to be performed on any laptop with a spreadsheet, and there are also numerous off-the-shelf computing solutions for real option valuation.

However, as a survey by Deutsche Bank and GARP showed in 2006, only a quarter of corporate strategic planning departments truly use simulation analysis; only a third quantify their risks at all; and less than half even do scenario analysis. We all know decision makers who have had bad experiences with probabilistic models and consequently mistrust them – “garbage in, garbage out” seems to be a favorite complaint.

One executive – an engineer by background – recently described to us how he and his group adopted Monte Carlo simulation approaches a few years ago, enthusiastically at first. Each year since, however, he has been presented with beautiful probability distributions for all projects under consideration, all showing a 0 percent probability of being unprofitable. Several of those projects have subsequently delivered well below break-even. No one, he said, has ever discussed why. Under these conditions it is hardly surprising that his enthusiasm for probabilistic approaches has waned.

Even in situations where these approaches can't be directly charged with failure, they are often perceived as being too difficult, too opaque, and therefore, most damningly, not worth the effort. Another manager reported that he gets “interesting spiky pictures with percentages,” but no guidance as to what to do with them. He feels certain he could learn to understand them, but, given other priorities, has never taken the time to do so. The outputs may be useful, but they are inscrutable, as if locked up in a “black box.”

Recent market events also do not inspire confidence in probabilistic models at first glance. In industry sectors where sophisticated probabilistic models have been used most extensively (hedge funds, bank credit risk portfolios, etc.), reality just hasn't behaved like the models. The most sophisticated risk models have not done a good job of accurately tracking the true risk

exposures after all the slicing, dicing, and collateralizing in the financial risk intermediation markets. They failed to anticipate the overall liquidity effects that the unexpected (but not unforeseeable) sub-prime mortgage mess could create. What is more, the failure was not an exceptional one – model failure was a key element in the Amaranth and the LTCM meltdowns of a few years ago, for instance, and in numerous other risk-related implosions. To put it bluntly, experience is showing that those who place too much faith in sophisticated modeling get overambitious, and eventually get punished by fate.

Nicholas Nassim Taleb has discussed some of these problems convincingly in his books, *Fooled by Randomness* and, more recently, *The Black Swan*. Black swans are “unknown unknowns,” those unexpected events that can cause grievous harm precisely because no prior consideration allowed for the possibility of their existence. After all, before black swans were discovered in Australia, everyone believed that all swans were white. Taleb argues that these black swans are the dominant uncertainties we need to worry about. The world is inherently nonlinear, full of complex systems that are chaotic (in both the vernacular as well as the more technical mathematical sense) and do not behave in a nice, “tame” fashion. We idolize the normal distribution, yet real events often have fatter tails and correlations seem to fail just when you want to depend on them.

These concerns are not new and it is unreasonable to expect probabilistic modeling to capture unknown unknowns. However, we can model far beyond our range of expected outcomes to test the robustness of our thinking and alert us to the consequences of correlation breakdowns, with analytic approaches such as fat-tailed distributions, Poisson processes, copulas, and various model stress-testing techniques, to name a few examples. However, Taleb’s idea of the iconic black swan neatly captures the notion that the predictability of the world has limits beyond which even our best efforts are of no avail. All our approaches to making decisions under uncertainty have inevitable limitations.

On a broader level, work in behavioral economics has highlighted a number of fundamental human biases in dealing with uncertainty. These include a general overconfidence in the face of uncertainty (see sidebar on p. 6, “Are you overconfident?”), anchoring (being disproportionately affected by the first information received), confirmation bias (giving more weight to information confirming one’s existing suspicions), and risk aversion beyond what rational analysis would suggest. Taken all together, these biases raise two general issues: 1) How good can any human-generated uncertainty estimates be, given all the biases the estimator needs to overcome? and 2) How can an inherently irrational decision maker be expected to react appropriately even to the best possible quantitative uncertainty estimates? Human biases make the process of looking into the future rather like viewing a picture taken with a fogged-up camera lens through a pane of frosted glass. Analytical approaches can help us to produce slightly sharper pictures, but we can have no confidence that the result is more trustworthy.

Are you overconfident?

Research has shown that humans are systematically overconfident in their assessments of the unknown, underestimating their own uncertainty. How overconfident are you? Take this “trivia quiz with a twist” to find out. For each of the following questions, write down a range so that you feel 90% confident the actual answers lie within that range. (Your ranges will naturally be wider for topics you know less about.) Then compare your ranges to the actual answers below.

1. What was the world’s population at mid-year 2007?
2. How long is the Nile river?
3. In what year was Johann Sebastian Bach born?
4. How many human babies are born per second worldwide?
5. How many cups of coffee are consumed per second worldwide?
6. What is the height of Toronto’s CN Tower?
7. How many dimples are on a regular golf ball?
8. What was the total revenue of FC Barcelona in 2005-06?
9. How many calories has 12 ounces of Coca-Cola?
10. What was Luxembourg’s estimated GDP per capita in 2007 in USD?

Answers (various sources): **1.** 6.7 billion (May 2007); **2.** 6,825km/4,241mi; **3.** 1,685, **4.** 4.4; **5.** 3,300; **6.** 553m/1,815’; **7.** 336; **8.** € 259 million; **9.** 140, **10.** \$102,284 (IMF estimate).

How did you score? A perfect score would be 9 out of 10 right answers: i.e., 9 of the 10 actual values within your 90% confidence intervals. We have, however, given this quiz in multiple workshop settings, and in our experience most people score between 3 and 5 and very few people score higher than 6 – except for the occasional smart-aleck who carefully answers with nine absurdly wide ranges and one small incorrect one.

We are all overconfident and we can’t do anything about it.

Response to the indictment

Given the foregoing ringing indictment of probabilistic modeling (perhaps set out in a more severe manner than would be adopted by even the strongest skeptics), we could all be pardoned for giving up on probabilistic or other analytic approaches completely. It might therefore seem perverse to argue that such approaches are in fact extremely important and tend to be under-used by most organizations. Yet this is exactly what we are arguing. Used well, these tools become indispensable for managing uncertainty. The problem is that they are typically misused and/or misunderstood.

How can corporate decision makers use probabilistic methods effectively, so that they add value? What conditions have to be satisfied and what modifications to common usage need to be made to avoid the “garbage in, garbage out” problem? For simplicity, we limit ourselves to discussing probabilistic modeling in terms of the Monte Carlo simulation, since it is the most useful and best known method. But the arguments apply more broadly to advanced analytical techniques used in business.

To frame the discussion, let us start with a provocative statement – “**Probabilistic modeling is extraordinarily useful once you stop believing that it should give you a true probabilistic distribution of outcomes**” (see sidebar below, “The meaning of probability,” for a deeper philosophical consideration).

In fact, probabilistic modeling is extremely useful as an exploratory decision making tool. It allows managers to capture and incorporate in a structured way their insights into the businesses they run and the risks and uncertainties they face. It is the best – if not the only – technique for organizing and incorporating all available information on risks and uncertainties so that a good risk-informed decision can be reached. Properly executed, it augments the best possible understanding of the value drivers of a project or enterprise with the best available insight about the potential uncertainties, their probability, impact and interdependencies, allowing the decision maker to have an informed overall view and to weigh the value of options that introduce greater flexibility. This overall view, to be sure, gives a probabilistic distribution of key output variables. However, the true value comes from augmenting that with an understanding of which factors contribute, and to what extent, to the uncertainty of outcomes. The decision maker can then explore what happens when central assumptions are changed. Monte Carlo is also invaluable when the decision maker must analyze multiple and perhaps compounding risks, a challenge for which scenarios are inadequate.

The meaning of probability

Probability is an expression of the likelihood that something will happen. On the surface, this is a simple concept, but on a deeper level the meaning of probability is harder to articulate clearly. There are two main approaches: the objectivist, or frequentist, approach, and the subjectivist approach. It is vital for decision makers to understand how the two approaches differ, and which approach is being used in any specific instance, because otherwise the conclusions drawn can be quite misleading.

The **objectivist-frequentist** approach views probability as the proportion of occasions in an observable sequence of random events in which the event occurs. The probability of a dice rolling a 6, for example, is 1 in 6. This view is tied in most closely with statistical analysis and inference, and needs least explanation. The **subjectivist** interpretation, on the other hand, sees probability as the degree of personal belief that a certain event will happen. This applies even to inherently unrepeatable events – the probability that global warming will drive the human race to extinction, for instance.

In the subjective interpretation probability depends on the perceiver’s experiences and assumptions. Suppose a trusted friend assures us that the new acquaintance we are about to meet is a nice person. In fact, the new acquaintance behaves unkindly at the first meeting. We still generally give this person more leeway than if we had no prior information from our friend or did not trust the friend as much. Nevertheless, if the poor behavior continues, we will increasingly put more trust in our observations and less on the prior information. The mathematics of this process is called Bayesian estimation, where a prior estimate of probability (the assurance from our trusted friend) is adjusted based on observations (poor behavior toward us) to obtain a more refined posterior estimate (our changing opinion of the boor). This type of analysis does not make sense in the context of an objectivist-frequentist view of probability, which would hold that probability is what it is – without ifs, ands, or buts.

In this example, the only way to turn the subjectivist concept of probability into an objectivist one would be to translate the information from the trusted friend into an equivalent number of prior observations: “I’m sure my friend has interacted with this person at least 4 times and I have only once, so he appears to be boorish at most 20% of the time; but if he’s boorish to me the next 3 times as well, then it will be 50/50.” While not absurd, this is just not how we usually think through such an issue. Recent work in behavioral economics has shown that Bayesian estimation actually describes quite well how humans make estimates under uncertainty, with some, but incomplete, prior information. Mathematically, Bayesian estimation has been used productively in such disparate areas as predicting which oil fields might be economical and which e-mails should be blocked by a spam filter.

The distinction between objectivist-frequentist and subjectivist probability first arose in the late 19th century, and was the object of lively philosophical discussion throughout the 20th. Both interpretations allow for a logically and mathematically sound treatment of probability theory, and both are consistent in the context of idealized rational observers reacting to an infinitely repeatable random process. However, the point of view in this article is unabashedly subjectivist – consolidation and analysis of often subjective probabilistic estimates on a subjectively selected list of value drivers. The level of insight depends on the robustness of the subjective elements.

Much of the indictment of probabilistic analysis at the beginning of this article comes from taking a subjectivist definition of the model but an objectivist view of the output. A portfolio manager who feels that his capital is safe based on a 99% VaR (value at risk) calculation is taking an objectivist view. Implicit is an expectation that God or another supernatural force is running a Monte Carlo simulation, according to a model that the portfolio manager has fully understood, and that reality will be one random iteration of this simulation. In 99% of God’s iterations, things should be safe. When a so-called “correlation breakdown” occurs (a loaded term in itself) and performance breaks out of the 99% VaR range for numerous similar portfolio managers, we all wonder how God could have rolled so many snake-eyes at once. It is scant comfort that the subjectivist merely argues that the model assumptions – the priors – were too simplistic, yet that is exactly what happened. The level of personal belief in the assumptions was too high, even though they may well have been the best assumptions available.

Unfortunately, there is no other way to reconcile the incompatibility except to remember when to take the objectivist hat off and put the subjectivist hat on. In particular, that means treating the output of “the model” not with objectivist reverence, but paying as much attention to the embedded subjective assumptions and explicitly considering their limitations. That is the gist of the provocative statement made in the main text, where the wording “true probabilistic distribution of outcomes” carries objectivist connotations.

The benefits of good probabilistic analysis

The single most important benefit of probabilistic analysis is that it offers the opportunity to engage managers in a meaningful conversation about their risks. Put simply, the key output is the conversation, not the spreadsheet. Experience has shown that the **process** of using a probabilistic lens brings four other benefits.

- **Managers gain better information on the possible range of outcomes.** This could almost be viewed as a tautology: more information is always better. However, the investment of time and resources needed to make a deeper analysis demands some justification. Estimates of how good or how bad the outcome could be, and the best possible estimates on how likely that is to happen, constitute useful information for making a good decision. The decision maker gains the ability to frame the range of possible outcomes more meaningfully and to validate this against the organization's tolerance level. Managers often do this implicitly, but the probabilistic process provides the best summary of available information to allow them to do it as correctly and completely as possible. Knowing that the best available insight implies that one possible \$1 billion+ NPV project has a 30 percent chance of losing money, while a second has twice the potential upside but also a 50 percent chance of losing money, is useful information in and of itself.
- **Proper modeling helps remove expected value bias.** Many uncertain outcomes are inherently asymmetric, often (but not always) with longer downside tails than upside. When managers are not thinking probabilistically, they tend to focus primarily on the "most likely" case. They intuitively realize the downside asymmetry when looking at each risk factor individually, but generally do not calculate the true expected value impact of several such asymmetries together – i.e., where the expected value is less than the amalgam of the most likely values of each individual input. In a recent case, a company evaluating potential major investments was systematically off by 8 to 10 percent in overall project value due, to the combined effects of asymmetric downside risk in its build time, capex, and output capacity estimates.
- **Decisions more accurately take into account the value of flexibility.** Everyone is aware of real-options or game-theory approaches to valuing strategic flexibility in decisions – buying the right to build a currently uneconomical plant should market conditions evolve to become advantageous, or to preempt a possible but uncertain competitive entry, for instance. However, companies frequently fail to understand the value of flexibility during regular operations or during project implementation, something which comes out naturally in a good probabilistic uncertainty analysis. Companies do not react passively to changes in externalities, and neglecting that ability understates the value of uncertainty and may lead to suboptimal decisions. For instance, a mining company discovered that the value of a potential new mine was 50 percent higher after accounting for the ability to slow down, accelerate, or even abandon construction and change the geometry of mine exploitation based on mineral price evolution.
- **Modeling can help boost value by encouraging appropriate managerial actions.** By taking the time to do a more sophisticated analysis of the value drivers of their business and their uncertainties, businesses gain the insight needed to focus managerial attention where it matters most. What might drive value erosion and to what extent is it worth it to invest in measures to insure against it? Where can one effectively hedge against a certain risk, or conversely profit from it? The probabilistic approach allows one to ask "what if?"; "what would be the impact?"; and "what can we do about it?" in a fact-based and fully informed way, without a dynamic of "I don't trust you to do what you promised so I'm going to challenge your numbers" that so often gets in the way when less sophisticated approaches are used.

Incorporating the information

To achieve these benefits, probabilistic modeling must be approached in a robust manner, as outlined in the section below, “Putting Probabilistic Modeling into Action.” All the information available needs to be incorporated, which typically includes historical data, expert insights, market-forward information, and fundamentals analysis.

- **Historical data.** Judicious use of existing historical data, including frequencies and impact of previous events, the level of response to previous shocks, and the degree of historical volatility of key externalities, is an important ingredient. Incorporation can be as simple as assuming historical event distributions as probabilistic inputs for the model, or can include statistical distribution fitting, or even more sophisticated stochastic time series modeling calibrated on historical data. The full power of statistical analysis comes into play here.
- **Expert insights.** All human biases in dealing with uncertainty notwithstanding, internal and external expert opinions are key to a company’s ability to “manage through uncertainty.” Indeed, this is just a restatement of the principle that “the people drive the company.” When experts are first consulted, they often naturally resist giving probabilistic estimates, since they may be unfamiliar with the process or have concerns about it. But once it is explained that a probabilistic approach ultimately can be more constructive than the usual reliance on “crystal ball” type predictions, experts often respond with a rich discussion of their areas of expertise. There are an increasing number of tools being perfected that aim to derive insight from groups of experts in order both to minimize the impact of natural human biases and to harness more productively collective wisdom (see sidebar on p. 12, “Minimizing biases in groups of experts”).
- **Market-forward information.** Where there is uncertainty around prices of liquid traded assets, such as currencies and commodities, significant information on overall market belief, including probabilities, can be derived from futures trading in the markets. The classical examples are market-derived volatilities from the options markets. A more recent example consists of CBOT-traded derivatives whose payoff depends directly on whether the Fed changes interest rates at the next policy meeting. From the prices of these derivatives the current market consensus probability of a rate change and the magnitude of the change can be inferred. These are examples of publicly traded markets whose main goal is to let market players transfer their risks or speculate; extracting information on market belief is a side benefit for others. Various companies have also experimented with internal information markets where they provide incentives for trading in carefully set up custom futures. These markets are designed to extract unbiased insight on consensus beliefs about key uncertainties, for instance, likely monthly or quarterly sales in a given geography, or the likelihood of projects being completed on schedule. The incentives to the “traders” become just the cost of obtaining the data.
- **Fundamentals analysis.** Getting true insight on the drivers of the business and the impact of uncertainty often requires building deep understanding of the mechanics of the business and the competitive environment. For instance, many companies are quite inaccurate in their estimates of their currency exposures. They base their estimates on the currency denomination of each item on the balance sheet and each detailed entry in their income and expense books, but miss potentially more significant second-order effects on customers, suppliers and competitors. The importance of basic microeconomics – supply/demand in particular – is great. A U.S. energy utility which had

no natural gas purchases or sales discovered it had an actual exposure to natural gas prices comparable to that of most major oil & gas companies with large gas fields. As it happens, gas plants on the margin of the electricity cost curve drove market-clearing electricity prices and thus the profits of all electricity producers. While oil & gas companies had made conscious decisions on hedging and risk transfer, the utility realized that it was almost completely unprotected, since it had not thought of this indirect risk. A business can have enormous exposures to risks that never touch its operations directly.

Each of these sources of information have their challenges and the trick is to use them in conjunction, iteratively investing more and more effort against those uncertainties which emerge as dominant and where there is cause for concern. Historical analysis is only helpful to the extent that expert insight validates the assumption that the future should be consistent with the historical trend. The wisdom of crowds, as pulled from market forward prices for instance, is limited – but certainly needs to be considered where it might prove to be inconsistent with internal expert or historical estimates. Analysis of fundamentals is crucial, but expert insight must help identify where and how much effort to invest in understanding second-order effects. The underlying theme here is the use of a probabilistic model to capture, compare and consolidate all of this information.

Conclusions, valid and invalid

Finally, let us suppose that all of this information is incorporated and “wired into” the probabilistic model. What can we reasonably conclude from the output? Here are a few examples of conclusions that can – and cannot – be drawn.

■ Valid conclusions

- “If our major assumptions on market behavior are correct, our expansion strategy has a 30 percent chance of being cash-flow positive and meeting targets. We could improve our chances of meeting the full cash needs from internal sources by hedging one key input, even though it will cost us about 1.5 percent of the input cost.”
- “While we have deep expertise in operating new assets and believe we have good market insight, 60 percent of our downside risk comes from our uncertainty around project execution, where we do not have deep experience. We should explore running a small-scale pilot first, even though it delays the overall benefits, or partnering on execution while retaining the operating risks.”
- “We cannot afford the uncertainty of our R&D portfolio without pursuing a JV on at least 2 of our 3 mega bets. But we can’t JV on all 3 because then it’s less than 10 percent likely we would meet our growth targets.”

■ Invalid conclusions

- “We are sufficiently protected against all of our risks at a 98 percent confidence level.” (black swan alert!)
- “We’re 83 percent certain that gas prices will drop below \$6/MMBtu in 2010, and this gives us the confidence to launch our big project.” (What hidden assumptions did you make in your gas model?)

- “Our positions in gold and real estate provide a natural hedge for our exposure to equities to such an extent we are protected from risk.” (Under what conditions? What about correlation failure? Remember LTCM?)

Just like all strategic insights, most of the valid conclusions raise other tantalizing questions for exploration. Are there creative options to reduce the hedging cost to less than 1.5 percent? Is the total level of project execution risk worth the delay from the pilot? Ironically, most of the invalid conclusions can also be turned into meaningful and actionable insights. Since we’re protected from those risks we understand at a 98 percent confidence level (whatever that means – the language needs to be firmed up), how can we improve our resilience to the unexpected? Into which underlying assumptions on gas price should we invest more effort to understand, since they could blindside us?

Minimizing biases in groups of experts

As already discussed, humans bring many biases to their attempts to deal with uncertainty – overconfidence, anchoring, etc. Bringing together experts can help to mitigate some (but not all) of these biases, but groups of experts will also introduce additional biases in the way of “group-think,” or reluctance openly to challenge opinions stated by powerful individuals. There is no shortcut to avoiding these biases completely, but their effects can be offset with a number of approaches.

One approach is the so-called Delphi method, named for the ancient oracle of Delphi. It is an iterative expert polling method designed to maximize information sharing and minimize dysfunctional group dynamics. It consists of defining an explicit question – e.g., what will market growth be over the next 5 years, or what will be the cost of CO₂ credits – and polling all the experts for either their best estimate or a probability distribution of outcomes. In addition, each expert also provides a short written rationale for their answer. The coordinator then aggregates all the estimates and shares them back, usually in anonymous form, with the experts, together with a synthesis of the rationales. The experts are then encouraged to adjust their estimates based on additional insights the shared rationales provided. The process is repeated a few times. The typical result is that a variety of dynamics relevant to the problem come rapidly to the surface, but without the tensions of clashing individual reputations, and the group arrives by consensus at the best synthetic view, capturing the insights all the individuals brought to the table.

With respect to offsetting overconfidence biases, some success has been achieved by training experts to recognize and combat them, and to calibrate their probabilistic estimations and correct for residual bias. In addition, various role-playing exercises that deliberately try to break group-think and anchoring biases have also been successful.

These approaches have already demonstrated their value, though they are still young and will likely be improved upon. However, they usually require a significant investment of time, which often limits their usefulness to a handful of key questions. In some cases, the approaches have usefully attempted to bridge the gap between subjectivist and frequentist approaches to probability. However, while they can minimize the impact of hidden biases, these approaches do not remove biases altogether, and can lose their value if they lead to a false sense of security, or to a masking of the key assumptions being made overall.

To conclude this section, let us be as provocative as we were at its beginning: **“The output of any sophisticated analytic model should raise more questions than it answers. That is a good thing, since the new questions will have advanced the thinking.”**

Learning from risk modeling in financial institutions

Financial institutions have been leaders in the use of probabilistic modeling techniques, as well as leading users of the more sophisticated instruments for chopping up and repackaging risks that these techniques allow. Yet these same institutions have also been the worst hit by the recent credit crisis, which has, in part, highlighted shortcomings in their methodologies. What happened and what can we learn from it about probabilistic modeling? This is of course the topic of much private and public hand-wringing and soul searching. Riccardo Rebonato's recent book, *Plight of the Fortune Tellers*, is a particularly thoughtful and accessible source.

Financial institutions are the world's intermediators and processors of risk *par excellence*. In fact, their business model consists of absorbing, repackaging and passing on risks to others (with different levels of intensity, to be sure). As a result, they have been pioneers in implementing sophisticated analytical techniques to process and combine information on these risks, and quantify the level of diversification in particular. Most of the time, most of these risks are fairly transparent, and a rich set of historical data points exists as a quantitative input for robust statistical analysis. However, basing decisions on these historical data involves powerful, but easy to forget, assumptions that the future will be broadly similar to the past.

In constant pursuit of new profit pools, financial institutions have developed and increasingly use sophisticated structured products to arbitrage every last ounce of risk diversification and leverage potential, in effect, panning the same sand with a smaller and smaller sieve for the tiniest nugget of gold. In that context, they were placing greater and greater trust on their implicit diversification, correlation and liquidity assumptions, while at the same time slicing and dicing the risks in a way that made the assumptions ever less visible.

Before sophisticated risk products became widespread, in the days when managers or institutions cared only about their 80, 90, or even 95 percent value at risk, the fact that Black Swans might mean that probabilistic tails were really a bit fatter was not a burning issue. The bulk of the value at risk at those confidence levels still arose from the aggregate of a long sequence of micro-risks whose behavior could adequately be modeled based on historical data. But once sophisticated risk products started magnifying risk arbitrage opportunities in the tails, and risk managers increasingly began to focus on 99 percent and even 99.9 percent or higher VaRs to pursue them, it was easy to lose sight of the fact that the level of belief in increasingly opaque underlying financial and economic assumptions was nowhere near that level of confidence, and yet it was exactly the risks depending on these opaque assumptions that were magnified.

Indeed, as their analytical approaches and their outputs became more complex, leading financial institutions were losing sight of the biases that make them vulnerable. To be sure, assumptions and analytics do not tell the whole story. At least as important are the aspects of risk management and reporting processes, as well as incentives and agency issues, and risk culture more broadly. In his book, Rebonato nonetheless highlights the lack of reflection and a false sense of quantitative precision as the key elements contributing to the mis-estimation of

risk in financial institutions, which in turn have contributed to some of the spectacular recent market failures. He advocates reducing the blind trust in quantitative models and returning focus to making strategic decisions under uncertainty based on the best possible quantitative – and other – information.

Let us now consider the corporate environment, for instance an energy company, industrial manufacturer, or R&D pharma house. By and large, these companies have gone much less far down the path of quantitative sophistication, probabilistic or otherwise, than leading financial institutions. However, their typical exposures are often much more clearly concentrated in risks where the level of confidence in underlying assumptions is strikingly lower. No one will claim confidence of anywhere near 95 percent, much less 99 percent, in any workable assumption on energy prices several years down the road, or in the chances of success of a pharmaceutical portfolio. It is as if corporates and financial institutions have been walking along a hillside above swampy terrain. The corporates have been slowing down and trailing further behind, while the financial institutions have rushed ahead, but along a low road. They came closer and closer to the swamp, and eventually became mired in it (and sooner than expected). Many are now wishing that they had taken a higher road. The advantage for corporates is that they were on a higher road to begin with (even if lagging behind), yet can see and learn from the financials' experience of the swamp and avoid it.

Putting probabilistic modeling into action

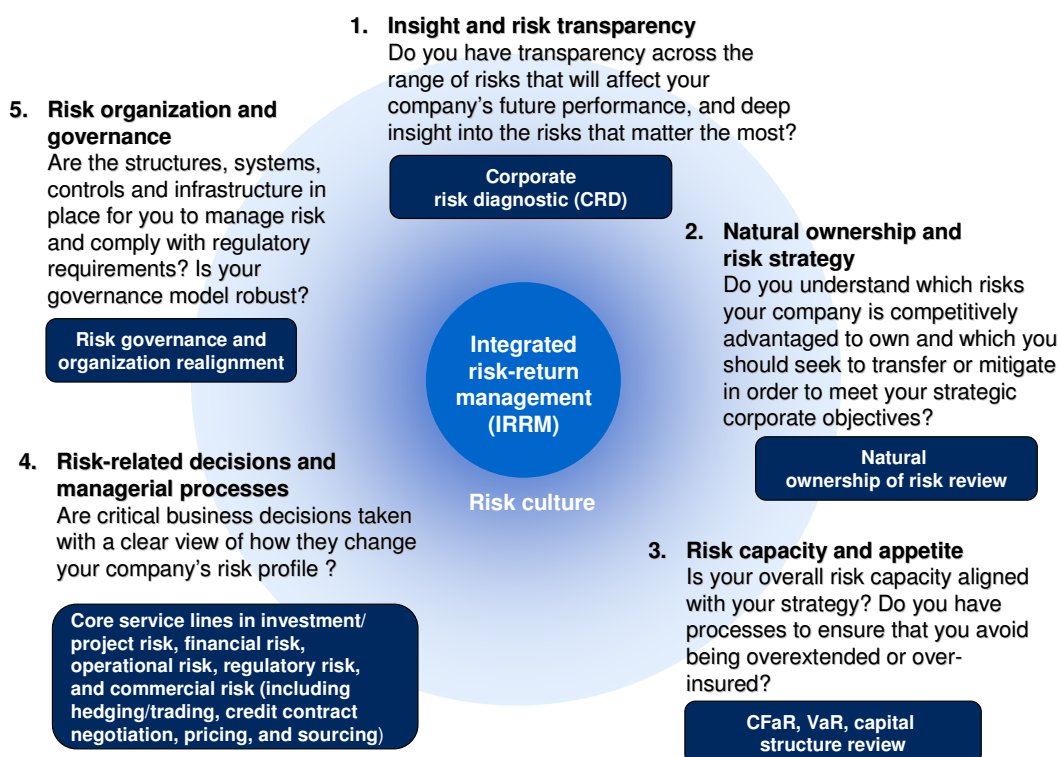
The challenge of putting probabilistic modeling approaches into action does not lie in the technical side of the procedure – though, to be sure, methodological experts are needed to guide, verify and standardize approaches, just as there is a role for lawyers, accountants, and experts of all kinds. Harnessing computing horsepower in a user-friendly way is also not the issue – the final analytic tool can generally run on any decision maker's laptop. The challenge is to design a robust process to identify the key value drivers, the uncertainties around them and their impact, and then to harness all the appropriate sources of information and provoke the right discussions, and so to deliver the benefits discussed.

Integrated risk-return management

As we have stated, probabilistic modeling is a mechanism for harnessing information about uncertainties to enable optimal decision making. Accordingly, it is often a crucial component of whatever approach a company uses to make important decisions in managing risk and return. We have previously outlined the approach we recommend to companies in “The Risk Revolution,” McKinsey Working Papers on Risk, Number 1, by Kevin Buehler, Andrew Freeman, and Ron Hulme.¹ The key elements are shown in this exhibit (more detail is given in “The Risk Revolution”).

¹ This paper has been republished in modified form as two articles in the *Harvard Business Review* of September 2008.

An integrated approach to managing risk and return



Probabilistic modeling is a key enabler of this process, in particular in three of the steps shown above – steps 1, 3, and 4. First, once the risks that matter most have been prioritized, probabilistic modeling becomes an important tool for combining all available insight on these risks, and for understanding their impact on performance (step 1, “Insight and risk transparency” in the exhibit). Second, the output of the probabilistic model helps decision makers assess how the level of risk matches risk capacity, and decide whether the company is overextended or overinsured (step 3, “Risk capacity and appetite”). Probabilistic modeling is a key input in this step, but it is not the only criterion to use, since the issues relating to “unknown unknowns” (“black swans”) are most important at this point.

Finally, probabilistic modeling is important in step 4, “Risk-related decisions and managerial processes.” Risk-related decisions often involve making explicit trade-offs between risk and return or between different risks, and probabilistic modeling is frequently the tool best suited to quantifying these trade-offs. The “unknown unknowns” issue is still important here, but what is most crucial is an understanding of the impact of each alternative decision. This understanding proceeds, to a greater or lesser extent, from a probabilistic risk profile curve, along which the trade-offs between alternatives are more or less fully reflected in differences in the uncertainties that have already been probabilistically analyzed in steps 1 and 3. Indeed, institutionalizing this type of analysis is often an important part of the risk-informed processes described in step 4.

The nuts and bolts of probabilistic modeling

Companies and decision makers sometimes utilize probabilistic modeling in the context of an integrated risk-return process as discussed above, or in another process for systematically making strategic decisions under uncertainty. In other situations, however, decision makers may use probabilistic modeling in a more focused manner, to support a specific immediate-term decision, perhaps taken in isolation. Probabilistic modeling, however, should always be embedded in a broader framework, no matter what the circumstances under which it is being used. Monte Carlo simulation should not simply be leapt into, because any trust in thoughtlessly gotten results would be misplaced, along the lines of the invalid conclusions discussed above. To pass a baseline Hippocratic-oath-style imperative “to do no harm,” any use of probabilistic modeling should be set up as part of a process which includes at least the following four elements.

- 1 **Risk identification and assessment.** This involves mapping the key value drivers of the business, going deeper and deeper to greater levels of detail where it matters. Based on these value drivers, a comprehensive list of key risks and uncertainties is created. A sequence of workshops in relevant parts of the business can help to rank these uncertainties in several dimensions, usually at a qualitative or very approximate, but nevertheless robust, level. The usual dimensions include at least two of the following: a) probability/frequency of occurrence of this event; b) level of impact, whether purely on financial performance or more broadly on the organization, if the event occurs; and c) level of resilience or organizational preparedness to respond to the event.
 - This workshop-driven ranking typically enhances understanding of the key value drivers, and identifies the 5-10 key risks (upside and downside) that really matter, and should be explored in greater detail. Depending on complexity, this step typically takes a few weeks of focused work, but the highest value is in institutionalizing the approach to be a part of ongoing strategic planning. The workshop methodology also helps generate buy-in to the approach and explain the overall goals of the exercise, so that the next steps become logical.
- 2 **Quantify overall risk exposure.** In this step, the organization more deeply investigates exactly the identified priority risks, harnessing all the tools and information available (as described above) to quantify their probability and impact. It is here where targeted fundamental analysis, expert workshops, information markets, and other ad-hoc tools are most helpful. The results are integrated into an overall probabilistic model that generates probabilistic output on key metrics based on the assumptions made, including best possible assumptions on correlations. This is where the nuts and bolts of probabilistic modeling occurs, but the process is likely to be misguided if the other three elements are performed with insufficient care.
- 3 **Explore targeted scenarios.** At this point, a long list of important, but hard to quantify assumptions, has been generated. These assumptions may include hidden, but important details – what if the price of our special type of plastic resin decouples from ethylene? Or they may be the big elephants in the room – the big questions which have resisted answers from even with the best group efforts. Ten years from now, what will the oil price be? Will our new drug work or not? Regardless of type, a few overarching scenarios should be explored, possibly with other risk factors probabilistically modeled within each scenario, and then the conclusions of each scenario brought up for discussion. This is a form of stress-testing.

- Many die-hard analytic modelers tend to ignore this step, feeling that “residual scenarios” not modeled probabilistically are a symptom of imperfect data or insufficient analysis. One of our insights from doing this in numerous situations, however, has been that decision makers want and need important alternative scenarios laid out for them, rather than folded in. The decision makers want to see things clearly and be able to do some intuitive stress-testing themselves. Probability aside, decision makers need to get comfortable with the world they would be facing in these situations. Management engagement with this can lead to highly productive discussions.
- 4 Derive actionable conclusions**, which is the main goal as discussed earlier. These may well be influenced by the assumptions made and the targeted scenarios explored; e.g., we can afford to continue our growth strategy if oil price stays above \$60, but we need to emphasize more lower-growth stable assets if it goes below, because then the volatility could kill us.

When probabilistic modeling is performed as part of the integrated risk-return approach sketched in the exhibit on page 15, the first three parts of the process described in these paragraphs become a core part of the “Insight and risk transparency” step. These three elements must however be included in all contexts (not only the integrated approach), because they equip the modeler and the decision maker with the right understanding for making any decision based on probabilistic information.

When not to use probabilistic modeling

It is our belief that well-framed probabilistic modeling supports better informed decision making in a very broad range of situations, more broadly than where it is currently used. Nevertheless, it may not be appropriate in several categories of problems.

- **When the tails in the probability curve matter most, not the middle region.** Overconfidence and the clash between objective and subjective probability manifest themselves most strongly at the tail ends of the distribution. Indeed, no reliable probabilities are usually available for extreme events. If those are clearly the cases that need to drive the decision, then the machinery of probabilistic modelling would likely be unhelpful, and targeted scenarios would be the only answer.
- **When the biggest uncertainties arise from a complex web of external and internal events.** Probabilistic modelling is excellent at capturing insight about a handful of key externalities. It can capture relationships between them, and likely managerial response or corporate flexibility to adapt to them. However, in areas where the dominant uncertainties revolve around who will do what in response to whom, and in what order, a decision tree-driven approach, possibly including game theory, is likely preferable. It is likely to be much more important for the decision maker to gain comfort about the necessary sequence of events and decisions than their aggregate probabilities.
- **When the data available on the most important risks are poor.** The largest uncertainties of course dominate the probabilistic output. If data on them are unavailable or confidence in existing data is low, there may be little value in using probabilistic machinery on the remaining factors for which there may be good data, since these are of far less importance. Judgment would have to be exercised to determine whether there was still value in running targeted scenarios on the dominant, intractable uncertain factors and doing probabilistic modelling on the rest. Obviously the choice of going ahead would

be predicated on the helpfulness of having a probabilistic output in each scenario, but the decision should be explicitly considered.

■ **When the impact on management’s decision making ability would be limited.**

Decision makers need to compare options to make decisions. Forcing probabilistic information on decision makers who do not want it, or working out detailed probabilistic information on one decision alternative with no hope of having comparable information (or any similar baseline) on other alternatives has little value, except as a tactical move to demonstrate the potential information gain to ultimately expanding the same approach to more of the alternatives.

* * *

Making strategic decisions under uncertainty will always be challenging. Experience has shown that deep and useful insights come from the appropriate harnessing of the best possible analytic approaches in the context of a robust process, comprehending all sources of information. Probabilistic modeling is optimal in the role of consolidating the insights and providing structure in many situations. The output is a structured management conversation around the insights and experience that have been captured by the model. By thoroughly understanding the impact of the most important known upside and downside risks, decision makers hold the keys both to surviving in a world of uncertainty and to positioning their companies most advantageously for profiting from it.

Martin Pergler is a senior practice expert in McKinsey’s Risk Practice, and **Andrew Freeman** is a Risk Practice senior knowledge expert in the London office.

McKINSEY WORKING PAPERS ON RISK

- 1. The Risk Revolution**
Kevin Buehler, Andrew Freeman and Ron Hulme
- 2. Making Risk Management a Value-Added Function in the Boardroom**
Gunnar Pritsch and André Brodeur
- 3. Incorporating Risk and Flexibility in Manufacturing Footprint Decisions**
Martin Pergler, Eric Lamarre and Gregory Vainberg
- 4. Liquidity: Managing an Undervalued Resource in Banking after the Crisis of 2007-08**
Alberto Alvarez, Claudio Fabiani, Andrew Freeman, Matthias Hauser, Thomas Poppensieker and Anthony Santomero
- 5. Turning Risk Management into a True Competitive Advantage: Lessons from the Recent Crisis**
Gunnar Pritsch, Andrew Freeman and Uwe Stegemann
- 6. Probabilistic Modeling as an Exploratory Decision-Making Tool**
Martin Pergler and Andrew Freeman

EDITORIAL BOARD

Andrew Freeman Managing Editor

Senior Knowledge Expert
McKinsey & Company,
London

Andrew.Freeman@mckinsey.com

Peter de Wit

Director
McKinsey & Company,
Amsterdam
Peter_de_Wit@mckinsey.com

Leo Grepin

Principal
McKinsey & Company,
Boston
Leo_Grepin@mckinsey.com

Ron Hulme

Director
McKinsey & Company,
Houston
Ron_Hulme@mckinsey.com

Cindy Levy

Director
McKinsey & Company,
London
Cindy_Levy@mckinsey.com

Martin Pergler

Senior Expert,
McKinsey & Company,
Montréal
Martin_Pergler@mckinsey.com

Anthony Santomero

Senior Advisor
McKinsey & Company,
New York
Anthony_Santomero@mckinsey.com