Decision Making Under Conditions of Uncertainty: A Wakeup Call for the Financial Planning Profession

by Lynn Hopewell, CFP®

Editor's note: *In honor of the* Journal of Financial Planning's *25th anniversary, during 2004 we are reprinting what we consider to be some of the best content of the* Journal. *This month, we present an article by Lynn Hopewell, first published in the October 1997 issue, suggesting the use of stochastic models such as Monte Carlo simulation as an effective tool for making financial decisions based on future events—more effective, Hopewell says, than deterministic models. This was one of the first articles in the financial planning profession to advocate the use of Monte Carlo.*

Lynn Hopewell, a former editor of the Journal of Financial Planning*, has several financial planning clients, but is now mostly retired. He continues to write, working on family and local history topics. He has six books inprocess. A Virginia Tech and Harvard Business School graduate, he enjoys keeping up with fellow alumni. When this article was first published (October 1997), Mr. Hopewell was president of The Monitor Group, a financial and investment advisory firm in Fairfax, Virginia.*

Most financial planning decisions are fraught with uncertainty. Although the financial planning profession has recognized this by its words, it has not by its actions. The analytical techniques taught and the computer-based analytical tools used in the industry are woefully out of date. They ignore advances of the last 40 years. Oddly enough, academic attention to the use of modern quantitative techniques applied to personal financial planning decision making has been almost nonexistent.

This paper discusses the problem and uses several illustrative examples to show how uncertainty intrinsic to financial planning decisions can be better described, modeled and communicated. The results can offer much more accurate and faithful descriptions of the nature of the dilemmas that clients face and better choices to deal with them. Pointers to literature and computer software tools are provided.

Although the financial planning community is justifiably proud of the progress it has made in advancing toward a profession, planners must demand more from their educational, academic and software suppliers—and from themselves.

Client Problems Fraught with Uncertainty

Predicting future events is always difficult—life is filled with uncertainty. Questions simply posed can be difficult to answer. *How much money should I save to fund a college education for my children?* Such an ordinary question—yet not easy to answer because the major variables used to determine the answer are not fixed, but instead are uncertain. What will be the earnings on the fund as it accumulates? What will be the escalation rate of college costs? Other common issues in financial planning involve similar uncertainties. Insurance needs analysis and retirement needs analysis are two other common issues that planners help clients address. These have even more uncertain variables. These facts are intuitively familiar to all financial planners. Every time a planner addresses one of these issues, he or she has to answer the following questions. What methodologies do you use to perform the analysis? What are the uncertain variables? What quantitative tools are appropriate to carry out the methodologies? How do you express the answers? Each problem may have its own set of assumptions and appropriate methodology. In spite of the continued development and improvement of financial planning analytical techniques and tools over the past 20 years, the basic issue of dealing with the intrinsic uncertainty of financial planning decisions has been sidestepped. It has been sidestepped in both theory and practice.

Existing Analytical Tools of Limited Value

In spite of the increasing improvement of financial planning software since the early 1980s, I know of no tools that explicitly deal with the uncertain nature of problem variables. The tools are deterministic. No matter how well designed and how faithfully the software models a particular problem, it allows you to specify only one value for a variable. Yet, for real-world problems, the essential variables are uncertain; they can cover a wide range of values and each value can have a different probability of occurring. Thus, stochastic tools are needed.

For example, consider educational funding with just two variables: inflation rate of expense and investment returns. Eight different returns and eight different inflation rates leads to 64 possible combinations of variables. Few have the time to input all these combinations, so planners resort to best-case, worst-case approaches. But this approach does not faithfully reveal the true nature of the underlying uncertainty of the answer.

It is not enough to simply explore the range of outcomes. Best- and worst-case analyses do not reveal the most essential information—the likelihood (or probability) of particular outcomes. Such analyses show what is *possible,* but not what is *probable.* Yet the probability of an outcome is perhaps the most essential piece of knowledge necessary for deciding a course of action. Few parents would want to save for college based on the lowest assumed investment return and the highest expense inflation rate if that outcome was of very low probability.

When planners present best-case, worst-case analyses, clients tend to favor the worst-case scenario because they want to take no chances. Yet decision makers usually cannot afford to fund all future capital needs based on worst-case assumptions. Using best-case, worst-case, planners do not correctly communicate the nature of the uncertainty underlying client problems.

Existing Financial Planning Education Is Weak

One peruses the financial planning literature in vain for papers that explicitly apply state-of-the-art techniques for dealing with the problems of uncertainty. Yet tools such as Bayesian probability analysis, decision trees and Monte Carlo analysis techniques were the core subjects in business schools 40 years ago and longer. These tools have been widely used in other industries for years.

The Next Generation of Planning Tools

The second generation of planning tools will explicitly address uncertainty. Instead of deterministic models, stochastic models will prevail. Before the advent of very fast desktop computers, there were practical barriers to the use of stochastic models. Anywhere from 2,000 to 5,000 calculations might be necessary to properly develop the distribution of the output or forecast variable. With slow computation cycles, calculation could take hours. However, with the current generation of computer hardware, computation speed is no longer a limitation. Monte Carlo tools are available now and are easily incorporated into any spreadsheet model by planners. Financial planning software manufacturers can easily add Monte Carlo to their deterministic models. Other second-generation tools include Bayesian inference, decision trees and game theory. Examples of new third-generation tools include fuzzy logic, decision tree influence diagrams and option pricing theory.

The following examples will serve to illustrate the issues and show how planners can begin to use these improved tools.

Rental Apartments Profits

Suppose a client presented you with the following issue. She is thinking of investing in an apartment complex and provides you with the information shown in Table 1.

TABLE 1

Possible Client Venture: Information Provided on an Apartment Complex

Number of Apartments	40
Rent per Apartment	$500
Average Number Rented During a Year	35
Lowest Number Rented During a Year	30
Average Expense for Complex for a Year	$15,000
Highest Expected Expense in a Year	$17,500
Lowest Expected Expense in a Year	$13,500

She wants your assistance in exploring the profit potential of the venture. You first calculate the profit using average figures for the variables. Thirty-five rentals and $15,000 average expenses give an annual profit of $2,500. This is not very revealing, so next you try the worst-case, best-case approach. An analytical model of the possible outcomes is shown in Figure 1.

FIGURE 1
Likelihood of Profit: Best-Case, Worst-Case Decision Tree

This diagram might be called a best-case, worst-case "decision tree." It clearly shows the possible range of outcomes given the best-case, worst-case assumptions, but that is not enough! The client wants to know the *likelihood* of making a profit. If you calculated more outcomes, you might have something to work with.

FIGURE 2
Likelihood of Profit: Many-Points Decision Tree

Figure 2 shows a "many-points" decision tree. Now the true nature of the problem is beginning to reveal itself. How many calculations would be necessary to obtain an accurate description of the possible outcomes? The number of possible apartments rented ranges from 30 to 40, or 11 outcomes. The expenses range from $13,500 to $16,500. Assuming that $100 increments give enough fine detail, then there are 31 possible expense outcomes. Thirty-one times 11 gives 344 possible combinations of expenses and revenue. How many planners would make 344 calculations? How many clients would pay for it?

But wait. Knowing the number of possible outcomes is not enough. We need to know the *probability* of the various outcomes, not just their range. Suppose the client told you that each outcome was equally likely. The frequency distribution of outcomes then would be "flat." By counting, you could come up with the probability that a certain profit would be obtained. It would be laborious, but possible. But suppose some values were more likely than others. Suppose, for example, that rentals and expenses followed a "normal" distribution. To properly model the outcomes, you will have to run the model more often with some variable values than with others. The mechanics of using a deterministic model quickly become overwhelming. It is understandable why analysts fall back on the best-case, worst-case approach.

What is needed is an analytical tool that rapidly calculates all the various possibilities and describes how often each outcome occurs—their probability distribution. Such computer-based tools are inexpensive and readily available. Figures 3 through 5 show the results of using such a tool,[1] a Monte Carlo spreadsheet add-in, commonly available for Microsoft *Excel* and *Lotus 123*, for the rental apartment problem.

The following assumptions are made. First, the distribution of rentals is normal, centered at 35 with a standard deviation of 2 units. Second, the operating costs are normal, centered at $15,000 with a standard deviation of $500. The Monte Carlo simulation gives the data shown in Figure 3.

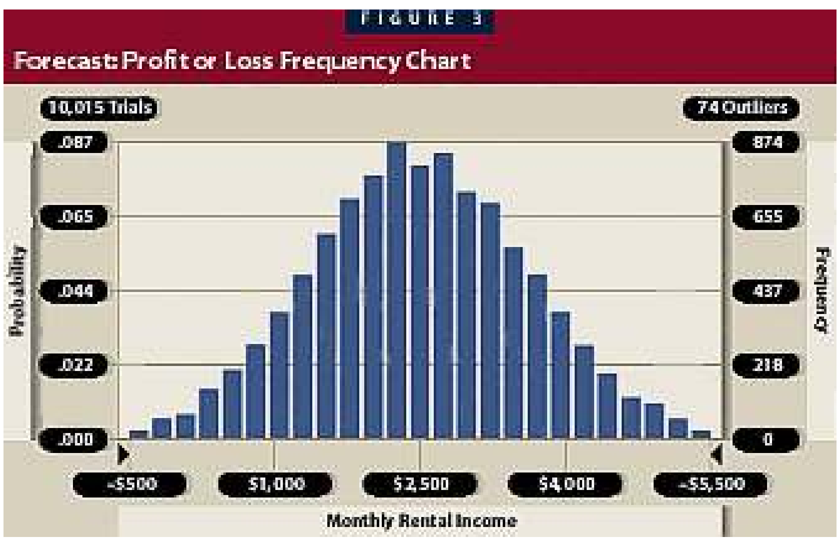


Figure 3 shows the probability frequency distribution of profit outcomes. As expected, most outcomes group around the average outcome. The cumulative distribution of Figure 4 is more useful. It rearranges the information in the frequency distribution to tell us the probability of an outcome being less than a certain value. Table 2 is based on Figure 4. The average profit is still $2,500, but it shows that the probability is only 10 percent that a loss will occur. Figure 4 gives far more information about the distribution of possible outcomes than a calculation using average estimates of variables or best-case, worst-case calculations.

FIGURE 4

Forecast: Profit or Loss Cumulative Chart

TABLE 2

Forecast: Profit or Loss

Normal-Normal

0%	-$1,678.23	60%	$2,785.13
10%	$1,083.35	70%	$3,103.49
20%	$1,566.64	80%	$3,454.43
30%	$1,913.15	90%	$3,937.49
40%	$2,216.00	100%	$7,340.46
50%	$2,512.54		

Education Needs Analysis

Table 3 is a spreadsheet analysis of a much more common problem posed to planners by clients: *How much money should I set aside in a college fund for my children?* This simplified analysis is for one child for four years of college. The spreadsheet calculates the future value of a year of education taking into account inflation of expenses. Then, it discounts the last four years back to the present using the spreadsheet's present value function. For a $15,000 annual expense in today's dollars, an eight-percent expense inflation rate and a six-percent discount rate, $71,671 should be set aside today for the future college expense need. (The problem is similar if the question is how much to save periodically rather than how much to set aside now.) You probably have done many of these analyses, or something like it. I know I have. Yet although this analysis is quite common, *it has a 50-percent chance of being wrong—that they would need more money*. Exactly how much more money they might need is an issue that requires further analysis. Do we really want to recommend strategies that have such a high probability of failure?

TABLE 3

College Expense Projections

College Inflation Rate = 8.0%

Year	Future Cost	PV of Years 8-11 at a Discount Rate
Today	$15,000	6%
1	$16,200	$71,675
2	$17,496	
3	$18,896	
4	$20,407	
5	$22,040	
6	$23,803	
7	$25,707	
8	$27,764	$27,764
9	$29,985	$29,985
10	$32,384	$32,384
11	$34,975	$34,975

Suppose we use Monte Carlo techniques to analyze the problem. Assume that the inflation of education cost is distributed normally around eight percent, with a standard deviation of one percent. Assume that the discount rate is distributed normally around six percent, with a standard deviation of one percent. (These figures are arbitrary for illustration only.)

Figure 5 shows the frequency distribution of the funds required. Figure 6 shows the cumulative distribution, and Table 4 gives the percentiles of the cumulative distribution. From Table 4, we can see that giving the client a figure based on averages ($71,671) has a 50-percent chance of being too little. If the client wants to be 90 percent certain that he will have enough money, he should set aside $81,827, not $71,671. He should set aside $106,888 if he wants to be almost 100 percent sure he has enough. $106,888 is 49 percent more money than the funds calculated by using averages. Surely, this description of the likelihood of the outcomes is more useful to the decision maker than an answer based on average or best-case, worst-case assumptions.

FIGURE 5

Forecast: PV of Future Education Costs Frequency Chart

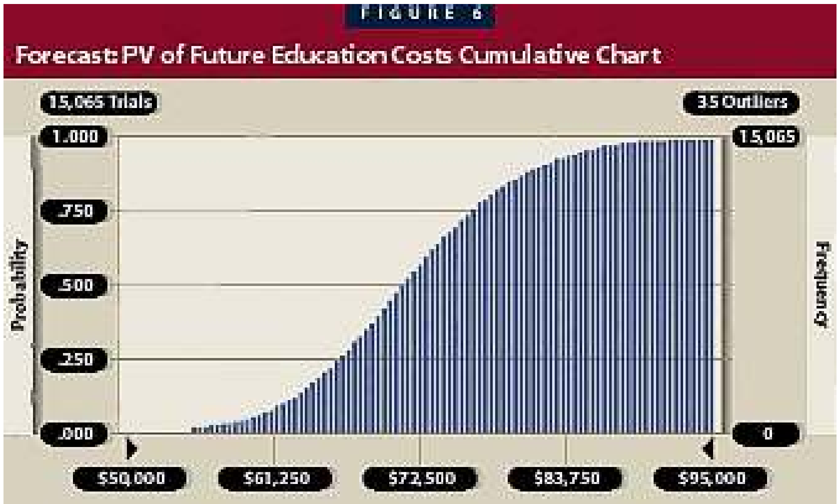


FIGURE 6
Forecast: PV of Future Education Costs Cumulative Chart

TABLE 4

Forecast:
PV of Future Education Costs

Percentile	Value (approx.)
0%	$48,285
10%	$62,873
20%	$65,783
30%	$68,012
40%	$69,895
50%	$71,688 (50% chance of failure)
60%	$73,542
70%	$75,703
80%	$78,154
90%	$81,827
100%	$106,888

Retirement Capital Needs Analysis

Table 5 is a spreadsheet that addresses client questions on another common topic, retirement planning. Clients want to know: How long will my money last? How much can I spend without running out of money prematurely? The spreadsheet model takes a starting capital sum and draws down on it by annual spending and calculates the balance left at any time. Other variables required are the inflation rate of spending, marginal tax brackets and investment returns.

TABLE 5

Retirement Spending Capacity (Taxable Savings)

		Range Name
Starting Retirement Fund	$2,000,000	Save
Average Inflation Rate	4%	Inflation
Tax Rate While Withdrawing	33%	Tax
Average Investment Rate of Return	7%	Invest
Age Now	65	
Years Funds Must Last After Retirement	25	

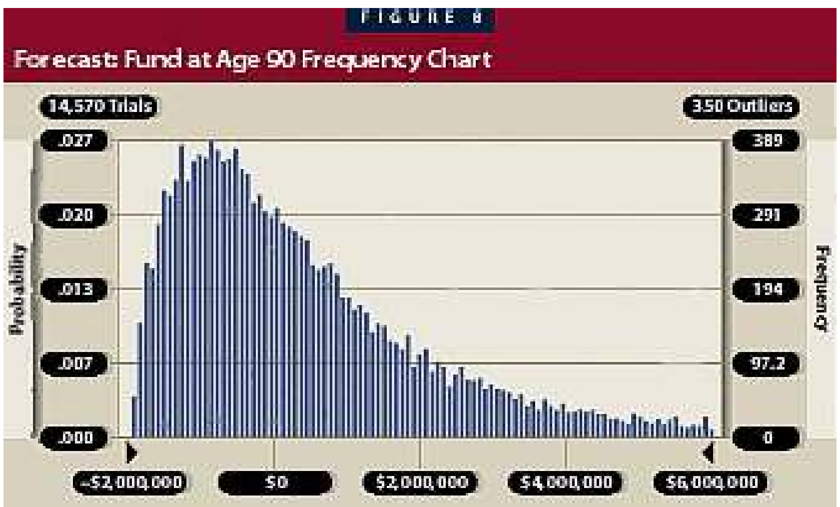
Use "Goalseek" tool to find amount in Cell G17 that makes last figure in Column F go to zero.

Age	Year	Starting Retirement Fund	Accumulated Funds — End of Year: No Tax	After Tax	After Tax & Spending	At Retirement (Beginning of Year After-Tax Dollars Withdrawn)	After-Tax Dollars Withdrawn (Constant Dollars)	Fund Balance After Tax & Spending & Inflation
65	1	$2,000,000	$2,140,000	$2,093,800	$2,006,437	$83,449	$83,449	$1,926,180
66	2		$2,289,800	$2,191,999	$2,009,682	$86,787	$83,449	$1,852,123
67	3		$2,450,086	$2,294,804	$2,009,445	$90,258	$83,449	$1,777,828
68	4		$2,621,592	$2,402,430	$2,005,416	$93,869	$83,449	$1,703,293
69	5		$2,805,103	$2,515,104	$1,997,268	$97,623	$83,449	$1,628,518
70	6		$3,001,461	$2,633,063	$1,984,650	$101,528	$83,449	$1,553,500
71	7		$3,211,563	$2,756,553	$1,967,188	$105,590	$83,449	$1,478,239
72	8		$3,436,372	$2,885,836	$1,944,486	$109,813	$83,449	$1,402,732
73	9		$3,676,918	$3,021,181	$1,916,121	$114,206	$83,449	$1,326,979
74	10		$3,934,303	$3,162,875	$1,881,642	$118,774	$83,449	$1,250,977
75	11		$4,209,704	$3,311,214	$1,840,573	$123,525	$83,449	$1,174,726
76	12		$4,504,383	$3,466,509	$1,792,405	$128,466	$83,449	$1,098,224
77	13		$4,819,690	$3,629,089	$1,736,599	$133,604	$83,449	$1,021,470
78	14		$5,157,068	$3,799,293	$1,672,580	$138,949	$83,449	$944,461
79	15		$5,518,063	$3,977,480	$1,599,740	$144,507	$83,449	$867,197
80	16		$5,904,327	$4,164,024	$1,517,432	$150,287	$83,449	$789,676
81	17		$6,317,630	$4,359,316	$1,424,971	$156,298	$83,449	$711,897
82	18		$6,759,865	$4,563,768	$1,321,628	$162,550	$83,449	$633,857
83	19		$7,233,055	$4,777,809	$1,206,632	$169,052	$83,449	$555,557
84	20		$7,739,369	$5,001,888	$1,079,163	$175,814	$83,449	$476,993
85	21		$8,281,125	$5,236,477	$938,353	$182,847	$83,449	$398,164
86	22		$8,860,803	$5,482,068	$783,283	$190,161	$83,449	$319,070
87	23		$9,481,060	$5,739,177	$612,976	$197,767	$83,449	$239,708
88	24		$10,144,734	$6,008,344	$426,400	$205,678	$83,449	$160,076
89	25		$10,854,865	$6,290,135	$222,461	$213,905	$83,449	$80,174
90	26		$11,614,706	$6,585,143	$0	$222,461	$83,449	$0

The typical analysis makes assumptions about the variables and computes an answer. In Table 5, the client is told that, given the assumptions, spending $83,449 annually and increasing it with an inflation rate of four percent will cause him to run out of money in exactly 25 years. The obvious question occurs. Suppose the investment return is different from seven percent. What starting spending amount will give the client a high assurance that he will not run out of funds before he "runs out"?

On first impulse, the analysis might result in the graph shown in Figure 7. This simply is a plot of the fund balance in 25 years, given various investment returns from four percent to ten percent. The spending rate and other variables remain constant. Visual inspection shows that the fund balance is not linear as a function of investment return. That's because of the compounding effect. The graph is useful only if you believe that all investment returns from four to ten percent are equally likely.

Figures 8 and 9 and Tables 6 and 7 show the results of a Monte Carlo analysis. Only the investment return variable is investigated.



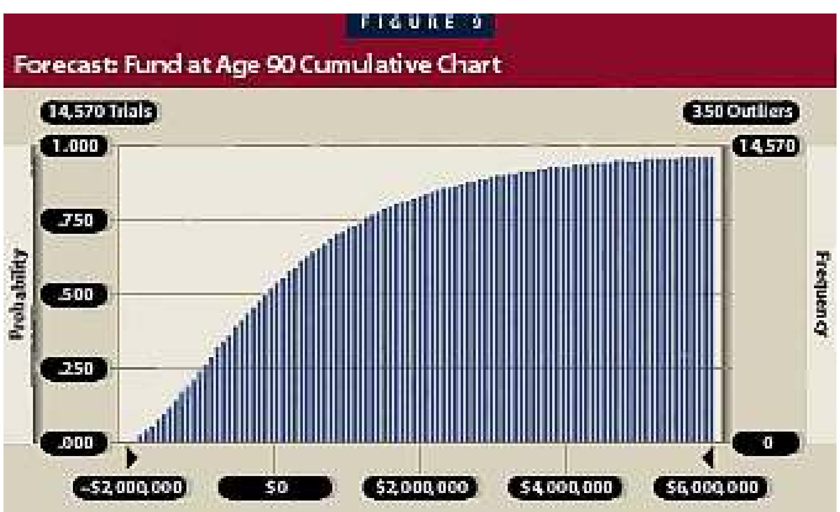


TABLE 6

Forecast: Fund at Age 90

Percentile	Value
0%	-$1,789,920
10%	-$1,305,532
20%	-$971,837
30%	-$661,439
40%	-$343,069
50%	$28,327
60%	$441,551
70%	$953,679
80%	$1,710,410
90%	3,004,037
100%	$35,895,076

TABLE 7

Forecast: Fund at Age 90

Percentile	Value
0%	-$1,001,856
10%	$10,839
20%	$460,872
30%	$920,355
40%	$1,347,358
50%	$1,861,132
60%	$2,400,907
70%	$3,109,855
80%	$4,043,197
90%	$5,652,413
100%	$22,162,737

We assume that the investment return distribution is normal, with a mean of seven percent and a standard deviation of three percent. Figure 8 shows the retirement fund balance frequency distribution. Figure 9 shows the cumulative distribution and Table 6 shows the percentiles of the cumulative distribution. What can we conclude? Again, the retiree has a 50-percent chance of running out of money before he runs out of breath.

But now we can explore alternatives. Suppose we reduce the initial spending ($83,499) until the cumulative probability distribution shows only a ten-percent chance of running out of money. The figure arrived at is $60,000. Table 7 shows the distribution percentiles.

The opportunities to apply the science of decision making under conditions of uncertainty to financial planning are almost unlimited. As an example in insurance, Kelly [1994] showed that at the target funding rate, a vanishing premium variable life insurance policy investing in the S&P 500 had a 36-percent chance of failing and required funding considerably above the target to ensure success. Daily [1993] used simulation to compare alternative estate strategies.

Modeling Concerns

Assumptions about the frequency distribution of variables have to be carefully considered; the proper assumption will not always be clear. In the retirement example above, if the distributions are assumed to be flat (equally likely), then spending must be reduced to about $50,000 to give a ten-percent chance of not running out of funds. (The reason is that the flat distribution allows more possible outcomes at returns below the mean, thus giving more outcomes that result in running out of money.) Planners using Monte Carlo techniques will have to become skilled in the appropriate distributions used to described variables.

Summary

Clearly, to make better decisions about problems filled with uncertainty, clients need better information than that revealed by simple deterministic analyses using mean or best-case, worst-case assumptions. To quote Nobel Prize laureate Milton Friedman, "Never try to walk across a river just because it has an average depth of four feet."

Happily, for problems that can be modeled by spreadsheets, the tools for better decision making have been available for a number of years. (See references for supplier information.)

But more is necessary. Our educational institutions should move out of the Dark Ages and incorporate into their curricula techniques for dealing with decisions under conditions of uncertainty.

Academics should lead the way in applying such techniques to common financial planning problems and publish papers that communicate those techniques and the insights resulting from them to the planning community. For example, there is much yet to learn about the selection of appropriate variable distributions for typical problems. Insurance and estate planning are also ripe for probabilistic analyses. Without such research guidance, these tools could be mindlessly misused by planners.

Software manufacturers should incorporate Monte Carlo techniques into common tools. Planners must become more sophisticated in their understanding of uncertainty, and demand the education and tools to deal with it. Then they will have to become more creative and skilled in explaining the results to clients.

Finally, to ourselves as an emerging profession, we should ask not *whether* we should use these techniques and tools, but rather, why have we not already done so?

Endnote

1. Thanks to Decisioneering, Inc. of Denver, Colorado, for providing the Monte Carlo software to the author.

References

Robert T. Clemen, *Making Hard Decisions: An Introduction to Decisions Analysis.* Second Edition (Duxbury Press, 1996).
Glenn S. Daily, "Does Life Insurance Add Value?" *Journal of Financial Planning*, October 1993.
Paul S. Kelly, "Selecting Vanishing Premiums: Decisions Under Uncertainty," *Journal of Financial Planning*, October 1994.
Craig W. Kirkwood, *Strategic Decision Making* (Prindle Weber & Schmidt, 1996).
Mark Kritzman, "Monte Carlo Simulation," *The Portable Financial Analyst* (Probus, 1995).
Monte Carlo spreadsheet add-ins: Crystal Ball, Decisioneering, Inc., Denver, Colorado, (800) 289-2550; @RISK, Palisade Corporation, Newfield, New York, (800) 432-7475 (U.S. only).

Sidebar: What Is a Monte Carlo Simulation?

Financial planning models are used to predict future outcomes. Models are used to define the relationship between a set of inputs and an output describing the future event. Models that assume a fixed relationship between inputs and outputs are called *deterministic.* A deterministic model produces an unambiguous answer. Models that depend on inputs that are influenced by chance are called *stochastic.* Stochastic models produce many possible answers, described by a distribution. A model that depicts the time of sunset is deterministic because it relies on fixed physical laws. You will not hear a weather report that says there is a 40-percent chance that the sun will set at 5:31 p.m. Other weather models—"there is a 30-percent chance of rain tonight"—are stochastic. The inputs that affect the weather are uncertain. A model variable that is uncertain is called a random variable. In a deterministic model, we assign a single value to a variable. In a stochastic model, a variable is assigned many values. The distribution of variable values often is described by its mean and standard deviation. However, there are many possible variable distributions. A major challenge of modeling is to choose distributions that are appropriate for each variable.

Both deterministic and stochastic models can be solved with a mathematical formula. However, not all stochastic models can be so solved. For those cases, we must resort to numerical techniques. We try out various values for the model variables. If we try enough values for each variable, the answer begins to emerge. If we randomly sample the values according to a defined distribution of the variable, the numerical solution is called a Monte Carlo simulation.

The Monte Carlo simulation determines the outcome distribution of the forecast variable by exercising the model many times (each calculation is called a "trial"). If, for example, a normal distribution is specified for a particular variable, many more trials will be chosen using values close to the mean than would be selected using a flat distribution. Each variable is assigned a distribution appropriate to the nature of the variable. The distribution of the output, or forecast variable, is dependent on the combined effect of the distributions of all the input variables. After a substantial number of trials, the distribution of the forecast variable becomes clear. For the examples used in this paper, only a few minutes were required to calculate 10,000 trials. The Monte Carlo tools discussed in this paper provide the means to randomly select values for many variables according to predefined variable distributions, and produce statistics and graphs of the forecast variable.