Modeling the Future

by Glenn Kautt, CFP, EA, and Lynn Hopewell, CFP

The mathematics behind simulation modeling is not new, but most planners do not have a background in statistics or simulation modeling. With this in mind, the authors demystify the process by taking apart a simple planning model that uses simulation techniques. They review the kind of data that must be used in simulation models to preclude substantial forecasting errors. Finally, the authors discuss how and why planners can and should incorporate simulation modeling into their practices.

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Until recently, planning models that gave a single answer or a string of single answers as the output were state of the art for the planning profession. No commercially available planning tool could model uncertainty. Stated technically, the vast majority of planning models yield a single-point answer and are called "deterministic" models. That is to say, one or more exogenous variables are introduced—such as rate of return or inflation—and the model is run to predict an outcome stated as a single number or set of numbers.

Deterministic modeling of the future carries an inherent problem, however: Conditions of uncertainty in the future make this type of financial planning model inaccurate—not wrong, but inaccurate.

Most experienced planners recognize the inherent inaccuracy of a single-point prediction. These planning models give "average" results, literally. Some try to compensate in their presentation to a client by making comments such as, "This is just a reality check" or "This is a ballpark estimate."

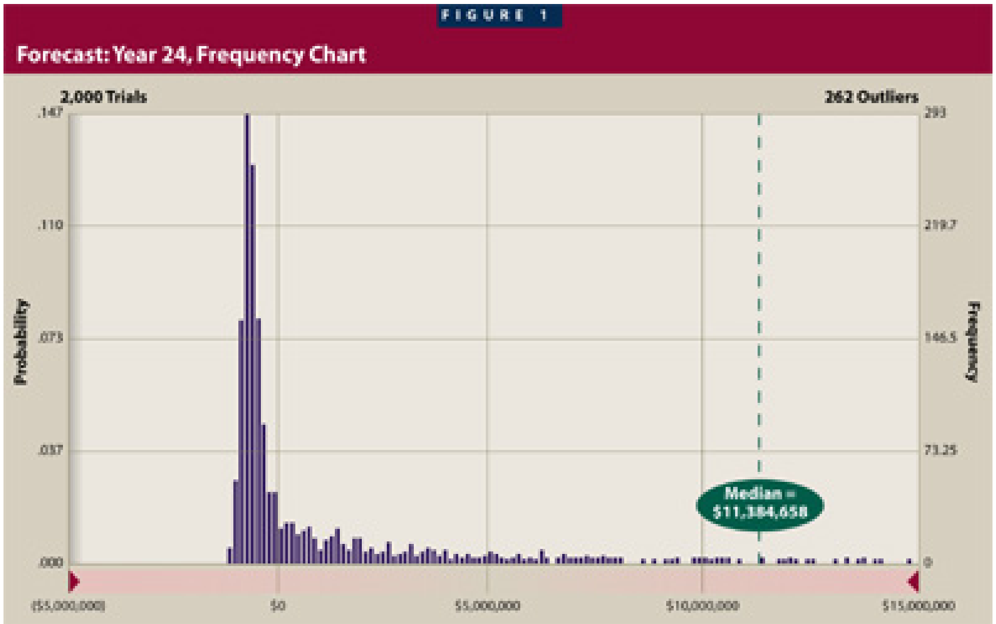
This kind of output is becoming passé for planning and modeling purposes. With the advent of very high-speed processors and memory, making excuses for a model's accuracy is now unnecessary. The advent of new, more sophisticated planning tools gives planners an opportunity to be "above average" in their approach to modeling the future. In 1997, one of the authors urged the use of planning models that account for uncertainty.[1] Since then, other professionals have commented on simulation modeling.[2]

Using appropriate simulation modeling programs, a planner can quantify the uncertainty or probability of an outcome.

The Law of Averages and Statistics, Lite

A study of Swedish male drivers found that 84 percent of respondents think they are "above-average" drivers. By mathematical definition, 84 percent of the drivers cannot be above the average! The "average" is actually the statistical "mean" of a group of numbers. The "median" is the middle number of a group of numbers. The median may or may not be the same number as the mean, depending on the type of distribution. The "mode" is the number of events that occur the most times in a group of results. When a distribution is normal, or "bell-shaped," the mean, mode and median will coincide on a graph. In most non-normal distributions, these measures do not coincide.

Figure 1 illustrates the mean, median and mode using a common lognormal frequency distribution.[3] In this example, the dashed line indicates the position of the median (middle number): $11,384,658. The mean (average) is – $251,200. This occurs when the distribution is not normal. In the lognormal distribution shown in Figure 1, the distribution has a "tail" of possible outcomes skewed to one side. The mode (most frequent) outcome occurs 293 times in this example of 2,000 trials. The chart also indicates 262 "outliers": outcomes outside of the range of the displayed data but that are used in the statistical calculations.



Now that we know a bit more about distributions, let’s examine how to employ simulation tools to model the future to help your clients make better, more informed decisions using answers that encompass an entire range of probable outcomes, not just averages.

What is Simulation Modeling and How Does It Work?

When we use the word "simulation," we refer to an analytical process used to imitate a real-life system. Simulation grew out of the development of probability and statistics, which have their modern mathematical origins in the 19th century.[4] Computational techniques were developed as mathematicians found formulaic analyses of future outcomes too complex to develop or the labor to do the calculations too daunting. Simulation modeling made its first significant contribution using modern computing equipment during the Manhattan Project to answer questions about supercritical nuclear chain reactions. The techniques developed there were given the name "Monte Carlo."

Today, programs are available that use simulation to quickly analyze the effect of varying inputs on outputs of the modeled system. One type of program uses Monte Carlo simulation, which randomly generates values for specific variables over and over to simulate the future. These are called "stochastic" models.

Let’s develop a stochastic model and compare it with a deterministic model. This will allow us to understand how the models differ and how the outputs can be interpreted. We will use a simple Monte Carlo simulation with one input and variations around the expected value of the input.

We will calculate the future value at the end of 20 years of an investment account with a starting value of $100,000. Using historical data from the U.S. equity markets, we assume a nine percent real rate of return distributed normally and with no withdrawals from the account. We also assume yearly volatility—stated as one standard deviation—of 20 percent. For a normal distribution, one standard deviation means that about 66 percent of the time the returns will fall within a range of the stated return plus or minus that deviation. Thus, in our example, 66 percent of the time returns will range from –11 percent to 29 percent in any year. Three standard deviations—99.5 percent of all possible return rates—fall between –51 percent and 69 percent in this example.

Also as part of our modeling assumptions, we assume that the return in any given year is not correlated to the return in any other year. In other words, one "down year" is not necessarily followed by another down year, and so on. Technically speaking, there is no covariance in year-to-year returns. This assumption is different than the assumption of normal return distributions. In actuality, there may be some covariance between annual returns, but we are not assuming this relationship. It is important to the simulation in that it simplifies the model and reduces the calculations considerably.

First, the deterministic solution. Using a financial calculator or spreadsheet, we calculate the return using nine percent each year, yielding an average or mean outcome of $560,441. Table 1 shows the single answer for each successive year. Many models also can show this result as a graph.

TABLE 1

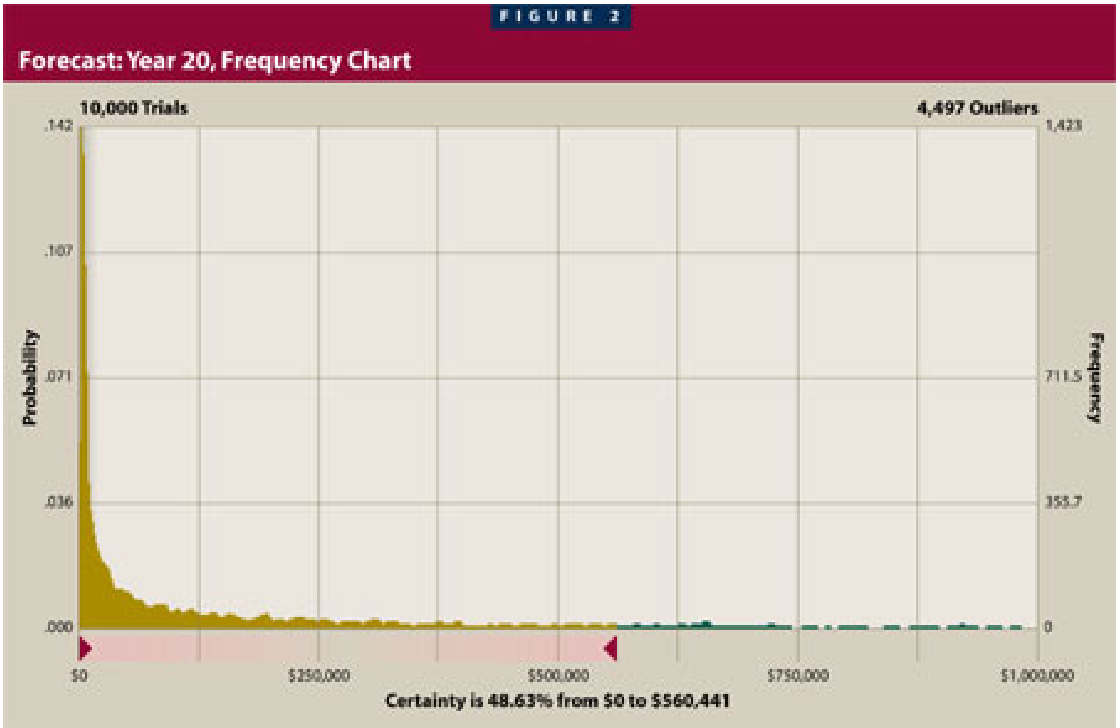
Deterministic Model of Investing $100,000 at 9% for 20 Years

Year	Amount	Year	Amount
0	$100,000		
1	$109,000	11	$258,043
2	$118,810	12	$281,266
3	$129,503	13	$306,580
4	$141,158	14	$334,173
5	$153,862	15	$364,248
6	$167,710	16	$397,031
7	$182,804	17	$432,763
8	$199,256	18	$471,712
9	$217,189	19	$514,166
10	$236,736	20	$560,441

What is the likelihood of this happening? Even though we know the standard deviation is 20 percent, we do not know how likely it is that the investment will total $560,441 in year 20. Even if we try applying a normal distribution to the answer, we still don't know how far the result might deviate from the mean. That's where the stochastic model pays off.

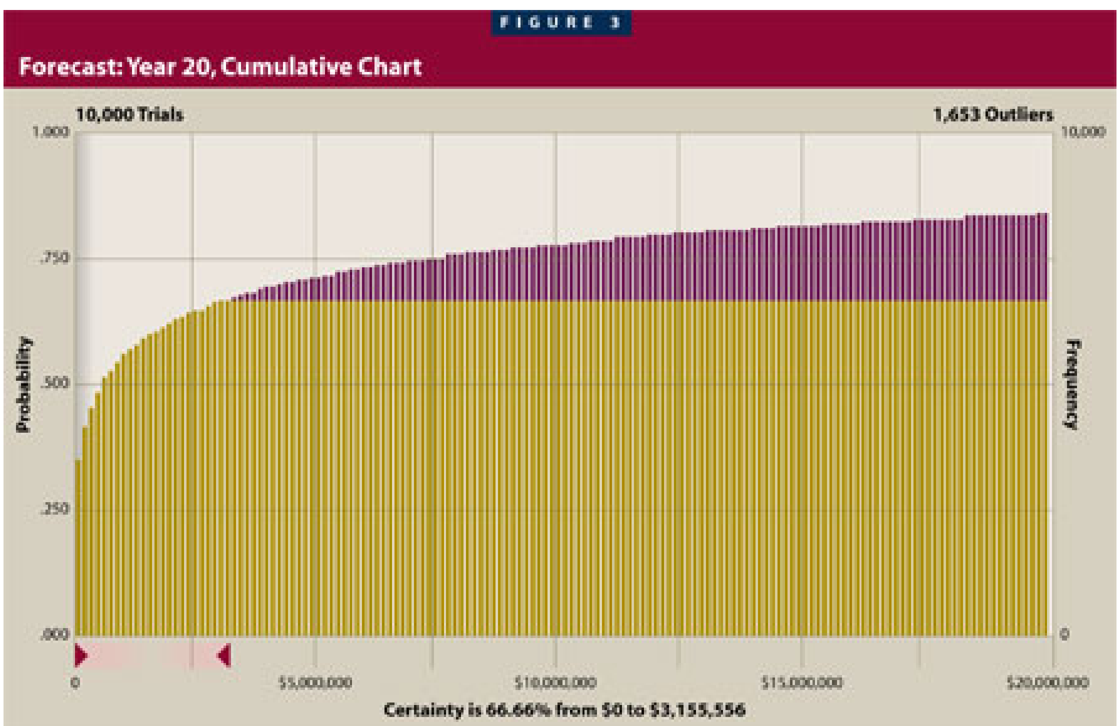
To develop a stochastic model, we have to look at each variable and insert it into the model. Mathematically stated, the model's expected value is P (payoff) = (1 + R1)(1 + R2)…(1 + R20). If we randomly sample normally distributed returns for each of the 20 years, P is generated as a number between $0 (the worst, as negative returns essentially wipe the account out) and over $72 million (the best, with returns at the 99.5 percent probability percentile each and every year).

Figure 2 shows 10,000 trials and the outcomes in a plot called a "frequency distribution." The frequency distribution plots the number of outcomes against the amount of money in the final year of the model.[5] It may surprise you that the payoff is not a normal distribution even when the distribution of the rate of return is normal. Using a simple accumulation investment model, a lognormal distribution is the mathematically expected shape. If we change the amount of the normal standard deviation of the investment returns, the number of years examined or the rate of return, the outcome still results in a lognormal distribution. In other words, the shape of the curve may change slightly with difference assumptions, but the "skewness" does not go away.



The intuitive expectation of a normal distribution around the mean for the returns is incorrect. More practically, assuming a normal distribution of return outcomes could lead to the wrong expectations and recommendations to a client.

Figure 3 shows a different and possibly better way of looking at the results. Instead of the frequency distribution shown earlier, we can look at a cumulative probability distribution. Here we see the final return amount as a probability of occurrence from 0 to 86 percent.



Here’s how to interpret Figure 3. At a cumulative probability of 20 percent, the expected outcome is $18,846. Another way of interpreting this chart: You expect a total investment return better than $18,846 80 percent of the time; better than $631,827 50 percent of the time and better than $3,155,556 only 33 percent of the time. This last is shown as the purple shaded portion of the cumulative curve above.

Table 2 shows the cumulative probability discussed above in decile format. The probability of occurrence is equal to 100 percent minus the cumulative probability. The results look quite different than the deterministic solution shown in Table 1.

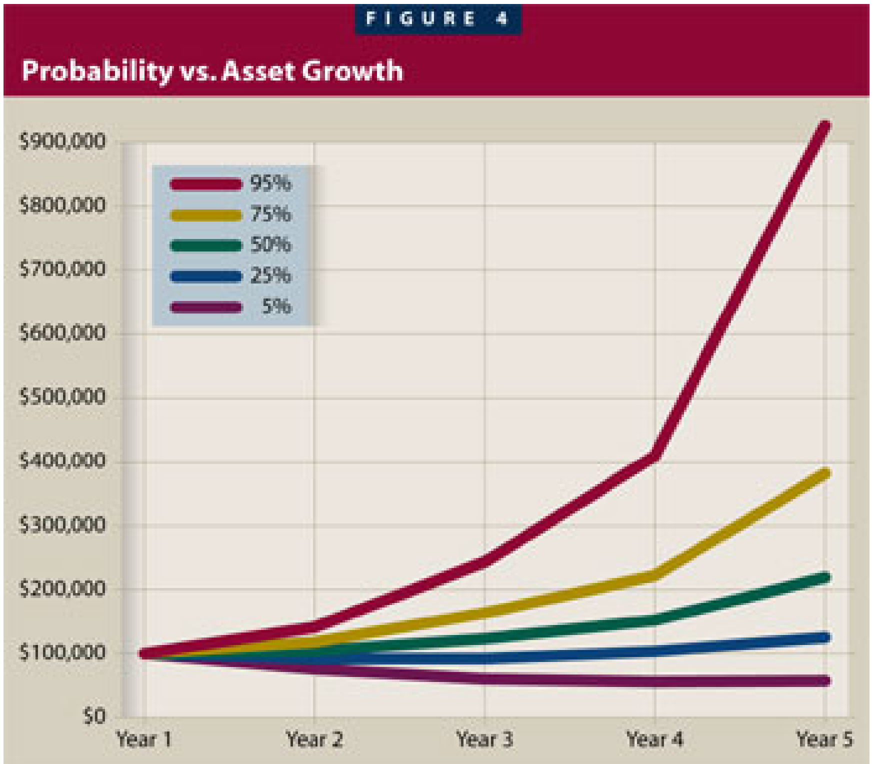
TABLE 2

Cumulative Probability of Investment Return in Year 20

Percentile	Value
0%	$0
10%	$2,291
20%	$18,846
30%	$76,169
40%	$232,527
50%	$631,827
60%	$1,662,983
70%	$4,474,244
80%	$12,970,824
90%	$53,031,995
100%	$25,565,493,590

Another way to portray the probability of occurrence is by plotting specific probability curves against the return (or other outcome) over time, as shown in Figure 4. This chart is a bit more complex as it simultaneously portrays three variables (probability, outcome and time).[6] This way of portraying the outcome sometimes visually helps in conceptualizing the probability distribution. Outcomes plotted this way typically assume a "horn" shape, depending on the probable range of outcomes.

In Figure 4, the assumptions are different so we can clearly see the differences in probable outcomes. These results are interpreted as follows: Given the assumptions of time, return and volatility, there is a 5 percent chance of making $900,000 or more, a 50 percent chance of making $219,000 or more, and a 75 percent chance of making $125,000 or more.



The Importance of Data: The Truth and Nothing But the Truth

No matter how sophisticated the model, if it uses inaccurate data, the results are usually wrong. Not surprisingly, accurate input data is extremely important to stochastic modeling. Every stochastic model requires at least one variable, such as rate of return, and the range and distribution of the variance of that variable. Typically, ranges of variance are stated in terms of a single standard deviation. In most cases, these distributions are normal. Currently, variance/volatility data for inflation, specific indices and certain investments are available. As a result, enough information is available to create credible investment models that give a much better forecast of the future than deterministic forecasts.

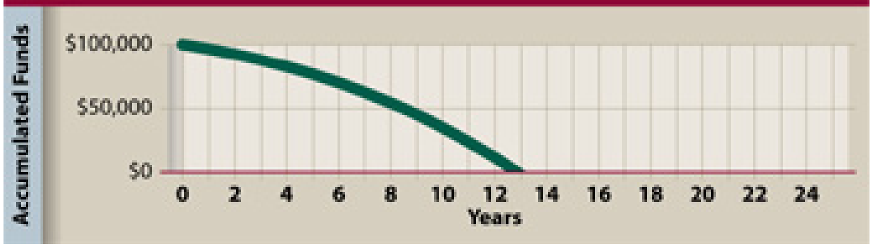
Let's further examine this need and use of accurate data. Occasionally, planners suggest increasing the rate of return of a portfolio in order to meet future financial goals if the initial analysis falls short of the goal. In doing so, however, the planner may have violated a basic law of investing and provided an answer less accurate than the initial analysis.

How can this be? As the planner increases the rate of expected return in the deterministic model, it cannot account for an increase in the volatility of the portfolio. Modern portfolio theory states that if the long-term rate of return of a portfolio increases, so does its volatility. If the volatility increases faster than the rate of return, the final amount may increase enough to satisfy financial goals, but the probability of hitting those numbers may change substantially. For example, by varying the portfolio design, the amount of the final outcome increases, on average, but the probability of hitting that number might decrease. The chance of a larger final amount of money may be offset to such an extent by the lower probability that the recommended investment changes are unacceptable to a client. Only the stochastic model will reveal this.

Let us review how this could occur. Using our original planning model, we will add a spending component of $10,000 annually. We will inflate the spending by 3 percent and will adjust the income taken for taxes at 28 percent. The financial goal is to have the money last for 25 years. In the stochastic model, when we adjust the rate of return, we will also adjust the volatility to correspond to standard deviations we have experienced in our model portfolios over the past 25 years. This gives us a reasonable statistical base when we change rates of return, and a more accurate assessment of the future (see Figure 5).

FIGURE 5

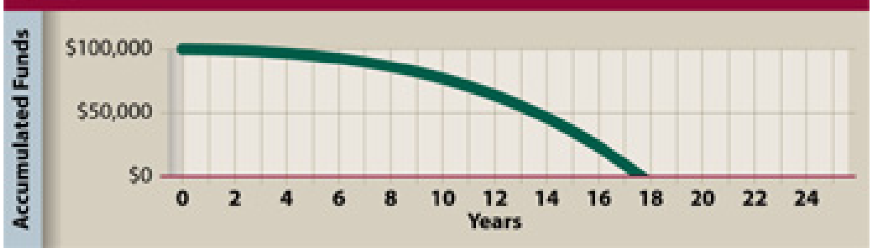
$100,000 in Taxable Funds Earning 9%, $10,000 Is Your First-Year Withdrawal



This deterministic output shows that the investor will run out of money in about year 14, using a nine percent rate of return. Not good enough. Let’s crank up the rate of return to the S&P Index historical average between 1973 and 1997 of 13.5 percent (see Figure 6).

FIGURE 6

$100,000 in Taxable Funds Earning 13.5%, $10,000 Is Your First-Year Withdrawal



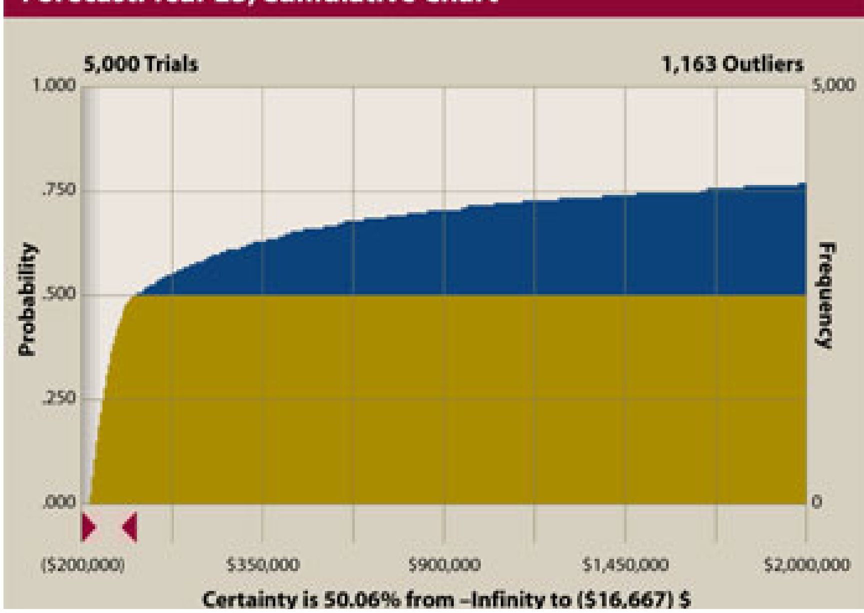
This results in another unacceptable outcome. Let’s increase the return by developing a diversified portfolio that included foreign equities, and small- and large-cap securities. This model portfolio has returned an average ROI of 15.5 percent during the same period (see Figure 7).

FIGURE 7

$100,000 in Taxable Funds Earning 15.5% $10,000 Is Your First-Year Withdrawal

FIGURE 8

Forecast: Year 25, Cumulative Chart



she believed they were within "striking range" in ng the goal? No way to find out unless we model

no adjustment for portfolio volatility. To include the reasonable assumptions. For our model viation for a 9 percent average ROI portfolio was 4 standard deviation was 16.8 percent; for the model standard deviation also was 16.8 percent.

we note there is approximately a 50 percent chance s. As shown in Table 3 (also see Figure 8), there is cent chance of having as much as $861,000.[7]

Is this outcome acceptable to the client? Maybe yes, maybe no. However, the client understands the possibilities better, and both the planner and the client can make more informed decisions about the portfolio design and whether a change in portfolio volatility is appropriate.

A key to the successful employment of stochastic models is accurate variance data on all input variables. Without accurate variability data, a stochastic model may give results even more misleading than its deterministic cousin. Where can planners get this information? Variances on well-known indices, inflation and some investments are available from a number of reporting services. Equally important is an understanding of the volatility of the portfolio the planner builds into the model, and how the volatility of the portfolio changes as returns change. The authors use proprietary data available from an investment consulting firm that has developed volatility data specific to a number of portfolio designs.[8]

What's Out There to Use Now?

While it is beyond the scope of this article to compare and contrast all the programs currently available, here are several programs planners might look at that provide "built-in" simulation.

1. AA Sym forecasts savings available after retirement based on a predetermined set of actuarial tables and return distributions. Investment before retirement and spending after retirement presumably are deterministic variables.

2. Money Tree provides simulation outputs for its popular retirement planning models showing the output graphically as the amount of money over time.

3. Financial Engines is a Web-based program that shows the amount of savings available within a probability range based on a predetermined set of return and volatility data on each investment supplied by the program.

4. T. Rowe Price has a retirement model that they will run in-house. It uses a number of planning inputs and predetermines all the variances.

5. A number of programs from Crystal Ball allow for any number of variables with any type of distribution and more than one simulation technique. This program is clearly the most complex—and the most difficult to learn to use.

Why Me?

Why should any planner consider learning a new and obviously more complex planning process now? Here are some plausible reasons:

1. Inexpensive and widely integrated planning and investment programs such as Quicken Financial Planner provide predictive deterministic modeling. No matter what you might think, these types of models can provide many of the same answers planners tell their clients. Regardless of how inherently inaccurate the results might be, these models are gaining popularity because of availability, convenience and price.
2. A huge new investment-trading paradigm exists. Schwab recently reported that approximately 40 percent of its trades are done electronically. Merrill Lynch now offers electronic trading, designed to shift trading business away from their brokers, forcing them to become advice givers. Add to this the unrelenting trend in increased electronic information gathering, analysis and investing.
3. These strong and irreversible market trends will dilute planners' effectiveness as value-added advice-givers if they use the same models and systems consumers get essentially for free. Planners who do not embrace new, more advanced modeling processes may lose new business because someone else's software now

gives the same answers as planners' programs, but at no cost. Thus, planners' deterministic modeling efforts add no new value.

4. As we have discussed in detail, planners who do not incorporate stochastic modeling in their analyses may suffer from giving inaccurate or misleading advice.

What's Next for Me?

What can planners do to start using this kind of modeling in the face of currently available programs? The authors recently invited their clients to a seminar they gave to explain the concept of simulation modeling and why specific outcomes in the future are uncertain. The seminar described and portrayed different outcome displays, how they were related and what caused the changes. In this fashion, clients have a chance to learn about probability and simulation modeling in a way that is not threatening. In addition, they have time to absorb the concepts before modeling (or remodeling) the future for them.

You may wish to try a demonstration package, such as one from AA Sym, Crystal Ball or Money Tree. Crystal Ball allows you to build your own spreadsheet model, whereas the other two have pre-packaged inputs and outputs. In any case, you must have volatility data. As time goes on, the authors believe more and more planning programs and systems will embrace simulation as a way of measuring uncertainty in the future. By learning more now using simple models, you will have a head start on understanding basic concepts such as normal and non-normal distributions, deviation, and two- and three-variable output charts and graphs. Most important, you will learn how to introduce the concept to your clients.

Endnotes

1. See Lynn Hopewell, *"Decision Making Under Conditions of Uncertainty: A Wakeup Call for the Financial Planning Profession,"* *Journal of Financial Planning*, October 1997.
2. See Thomas J. Connelly, *"Is Non-normal Normal?" Journal of Financial Planning*, August 1998, and Ed McCarthy, "*Monte Carlo Simulation: Still Stuck in Low Gear*," *Journal of Financial Planning,* January 2000.
3. Results from Crystal Ball Pro 2000, Decisioneering Inc., 1515 Arapahoe St., Suite 1311, Denver, CO 80202, (800) 289-2550.
4. For a good non-technical historical discussion of the origins and modern development of probability and financial statistics, see Peter L. Bernstein, *Against the Gods, The Remarkable Story of Risk* (New York: John Wiley and Sons Inc., 1996).
5. Results from Crystal Ball Pro 2000.
6. Results from AA Sym, Macey-Holland & Co., LLC, 4200 Northside Parkway Bldg., Atlanta, GA 30327 (877) 566-4786.
7. Results from Crystal Ball Pro 2000.
8. Callahan and Associates, San Francisco, California.