Finance and Monte Carlo Simulation

by David Nawrocki

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"Those who cannot remember the past are condemned to repeat it."
George Santayana (1863–1952)

Monte Carlo simulation has enjoyed a resurgence in financial literature in recent years. This paper explores the reasons why implementing Monte Carlo simulation is very difficult at best and can lead to incorrect decisions at worst. The problem is that the typical assumption set used in Monte Carlo simulation assumes normal distributions and correlation coefficients of zero, neither of which are typical in the world of financial markets. It is important for planners to realize that these assumptions can lead to problems with their analysis. Financial planners will find that exploratory simulation provides equivalent or better answers and is simpler to implement without assumptions.

A New Toy, Again

It was a wonderful time. Everybody had brand new computers that were more powerful than anything that had come before. With the increase in computational power came the new toys with which to play. Linear programming, nonlinear programming, integer programming, goal programming, queuing theory, Box-Jenkins ARIMA models, Almon distributed lags and Monte Carlo simulation were among the many toys under the tree. However, just like the day after Christmas, some of the toys still worked, some were ignored and some were broken. And the parents learned which toys not to buy in the future.

Unfortunately, the parents turn into grandparents with foggy memories, and the children into parents who don't remember the toys that broke. So several generations later, the old toys are back under the tree waiting to break again.

If this Christmas story sounds like the 1980s and 1990s with the microcomputer, think again. The 1980s and 1990s are just history repeating itself. It is actually the story of the universities in the mid 1960s, who were taking delivery of the first mainframe computers that had the computational power to do something useful. These multi-million dollar machines were not under the tree for most businesses, let alone for a small child. Only the universities with their research and instructional funds could afford them. It was here that all of the quantitative toys were played with and tested—including Monte Carlo simulation, which is the topic for this paper.

It was 1964 when Hertz [1964] first suggested using Monte Carlo simulation in business applications. This paper created an explosion of usage in all business disciplines, including finance. It was covered in textbooks and in courses where professors were almost giddy with their new toys. Everything was going great when Lewellen and Long [1972] provided the wakeup call. They stated that Monte Carlo simulation failed to provide pertinent information and that the information that it did provide could just as easily come from single point estimates.

Monte Carlo simulation requires that the analyst set up a mathematical model of the process. This setup can be very time consuming and provides the simulation a very low benefit-cost ratio. Philippatos [1973] notes that while some dynamic properties can be obtained through simulation, there are other techniques that can achieve the same purpose. He concludes by advising that future converts should use the technique sparingly and, perhaps, only after everything else fails. Myers [1976] also agrees with the Lewellen and Long position, though he points out that Monte Carlo simulation would be appropriate if the analyst has no other idea how a variable may work.

Rubinstein [1981] echoes Myers' sentiments and develops a set of criteria to be used in deciding whether it is appropriate to use Monte Carlo simulation. Monte Carlo simulation is appropriate when

- It is impossible or too expensive to obtain data
- The observed system is too complex
- The analytical solution is difficult to obtain
- It is impossible or too costly to validate the mathematical experiment

A more recent study by Rees and Sutcliffe [1993] confirms the above criteria. Essentially, Monte Carlo simulation is useful only when nothing else will work. It has proved to be useful in academic financial and statistical research, but only when the data or the analytic solution is not available. This is not the case in the investment decisions typically faced by financial planners. Financial market data is plentiful and cheap. Analytic models are available to quickly analyze the data and provide the same or better answer than Monte Carlo simulation. Chau and Nordhauser [1995] provide a good overview of articles using Monte Carlo in accounting and capital budgeting research. They found that Monte Carlo simulation has been found useful wherever data are not available, but they found no articles supporting its use with financial market returns.

There was a recent article on Monte Carlo simulation in this journal by Abeysekera and Rosenbloom [2000] where the answer to the authors' problem became evident as soon as they stated their assumptions for the Monte Carlo model. Obviously, there is no need to run the model when we already know the answer.

TABLE 1

Rubinstein Criteria	Abeysekera and Rosenbloom	Kautt and Hopewell	Appropriate Use of Monte Carlo
Are data available?	Yes	Yes	No
Is analytic model available?	Yes[1]	Yes[2]	No
Is mathematical experiment validated?	Yes	Yes	No

Notes:
1. Modern portfolio theory
2. Geometric mean criterion. See Gressis, Hayya and Philippatos [1974].

Monte Carlo simulation is also the focal point for another recent article in this journal by Kautt and Hopewell [2000]. Let's apply the Rubinstein criteria to both articles. The appropriate use of Monte Carlo simulation would require a "no" answer to the three questions in Table 1. Given that both data and analytic models are available, Monte Carlo simulation is not appropriate in either article.

TABLE 1 HERE

Today, history is repeating itself with nifty spreadsheet add-ons that do all of the heavy lifting for Monte Carlo simulation and with the converts thrilled with their new toy. Rekenthaler [2000] states in his Morningstar.com column that he sees an article every couple of weeks that explains how the new technique of Monte Carlo simulation improves upon conventional math. After discussing the fact that Monte Carlo simulation has been around for a while, Rekenthaler points out that you can arrive at the same answer with a mathematical formula and with Monte Carlo simulation, except that the formula is slightly more accurate and is quicker in getting you the answer. He concludes that Monte Carlo simulation would be appropriate whenever the mathematical formula cannot be solved. Déjà vu all over again, only 25 years later.

Evensky [2001] gets to the heart of the matter—that is, risk versus uncertainty: "The problem is the confusion of risk with uncertainty. Risk assumes knowledge of the distribution of future outcomes (i.e., the input to the Monte Carlo simulation). Uncertainty or ambiguity describes a world (our world) in which the shape and location of the distribution is open to question. Contrary to academic orthodoxy, the distribution of U.S. stock market returns is far from normal."

Evensky continues by examining the assumption set used by planners, which includes normal distributions and the expected returns and variances for stocks and bonds. He cites a survey of experts for their forecast of future returns given the current economic environment. Their forecasts for stock returns ranged from negative returns to positive returns of 11 percent for the next five to ten years, making it difficult to decide on the mean of the distribution for the Monte Carlo simulation. Evensky notes that Monte Carlo simulation is an effective way of educating people regarding the uncertainty of risks, but rather than reducing uncertainty, it increases the guesswork manyfold because of its assumption set. The two articles that have appeared in this journal include both normal distributions and zero correlations in their assumption sets. It is important for planners to realize that these assumption sets can lead to incorrect decisions and that the implementation of Monte Carlo simulation is going to take a great deal of care. It is not an easy implementation.

At this point, Monte Carlo simulation

is not generally used by financial planners [McCarthy, 2000] nor has there been a strong case put forward to encourage such use. One could accept the judgment of the numerous authors cited above, but there isn't a clear picture as to why so many authors recommend against the use of Monte Carlo simulation. The problem is that it is very difficult to implement an assumption set that matches the real world when using Monte Carlo simulation. The purpose of this paper is to discuss various problems that are inherent in the assumption set of a Monte Carlo application. The next section provides a short and rather narrow description of simulation modeling. Later sections present a description of potential problems with simulation and provide an example demonstrating some of these problems.

Simulation Models

Philippatos [1973] provides a useful definition of simulation. Simulation is the use of a model to approximate the behavior of a real-world system within an artificial environment. The artificial environment is where the analyst attempts to model the real-world system. In finance, we usually are working with an accounting model of cash inflows and cash outflows. Therefore, a model could be a simple definitional model:

$$Y = W + X \qquad (1)$$

We might also use linear models such as (2) or nonlinear models as in (3).

$$Y = a + bW + cX \qquad (2)$$

$$Y = a + bX + cX2 \qquad (3)$$

In all cases, Y is the result of the model. It may be the answer to a problem, or it may be the forecast of the future. In any event, we want to know Y. W and X are known as exogenous variables because their values are determined outside of the model. We have to have values for W and X in order to get an answer for Y. How the values are determined for the exogenous variables, W and X, determines the type of simulation model. Monte Carlo is just one type of simulation used to generate values for the exogenous variables. There are four general types of simulation.

Monte Carlo (random number generator). This is used when it is not possible to obtain sampling data but we have some knowledge about the population. Actual sampling is either impossible or uneconomical to use in order to generate values for the exogenous variables. Monte Carlo simulation could also be used to model the error process in a regression relationship. In equation (4), the error term, e, is assumed to be normally distributed and can be simulated using Monte Carlo.

$$Y = a + bW + cX + e \qquad (4)$$

Tactical (sensitivity analysis). Here we study behavior of the model as changes are made in parameters and assumptions. For example, we would ask how changes in a, b and c in equations 2 and 3 affect the results.

Strategic or exploratory. Exogenous variables are changed to reflect certain courses of action. This is the famous "what if" simulation technique. What if we implement this action? What if that happens? This type of simulation generally relies on a model built from historical data and sometimes may be called historical simulation. However, it can be used with other types of models including Monte Carlo simulation. The key is to set up a model of how the world works and then test different policies or decisions through the model to see what works.

Interactive. A human decision process determines the exogenous variables. In addition, an artificial intelligence or mechanical decision process could determine the exogenous variable. This type of simulation is typically played in real time.

A simulation model may include several simulation techniques. For example, playing a game of Monopoly is an example of Monte Carlo simulation and interactive simulation. Rolling the dice is an example of the former. Deciding to buy Boardwalk is an example of the latter. Kautt and Hopewell [2000] provide another example in their paper, which combines exploratory simulation and Monte Carlo simulation.

In finance, exploratory simulation is generally the most useful. It doesn't create a large computational burden and is relatively easy to implement. The use of historical data provides as realistic a model of real-world behavior as can be achieved. Monte Carlo simulation is generally an oversimplification of the real world. As pointed out by Evensky [2001], the problem is with the assumption set used in Monte Carlo simulation. In the typical Lake Wobegon world of Monte Carlo simulation, all distributions are normal and all correlations are zero. It doesn't capture the complexity of interrelationships that are contained in the historical data. Monte Carlo variables assume that the processes being studied are independent of each other and that each value is a random draw from a distribution, or serially independent. Proponents of Monte Carlo simulation point out that the available computer programs can handle dependent relationships between exogenous variables. However, the problem is that the interrelationships between two or more variables are generally quite complex, and it is difficult to determine the correct relationships and distributions.

Using Correlation Coefficients to Measure Interrelationships Between Variables

FIGURE 1

Computation of Cross Correlations Between S&P and Nasdaq Indexes Using Observation Pairs—1970 to 1994

Using daily returns, the correlation is 0.79

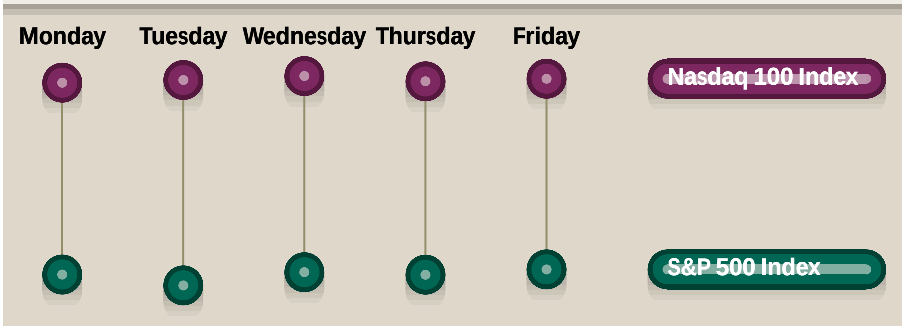


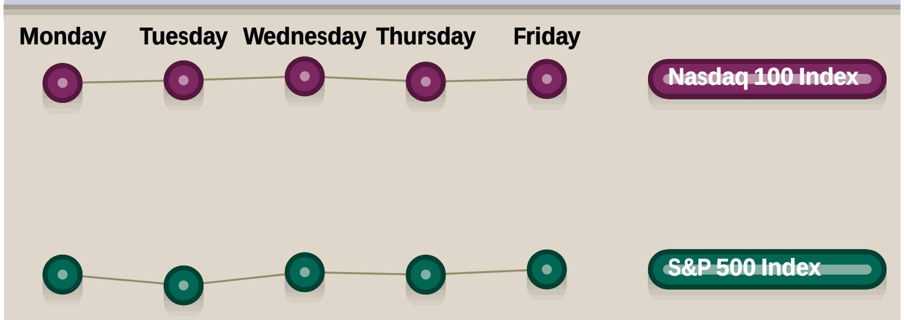
FIGURE 2

Serial Correlations for Nasdaq and S&P Indexes—Daily Data 1970 to 1994

Using daily returns, the correlation is 0.79

- **Pairwise observations are for a one-day lag**
- **Serial correlation for Nasdaq = 0.13 (5.47)**
- **Serial correlation for S&P 500 = 0.01 (0.62)**

T-test in Parentheses



The relationship between two variables can be described by a correlation coefficient that tells how strong the relationship is between two variables and whether the relationship is a positive or negative relationship. However, more than one correlation is needed in order to provide a realistic model of the relationship. Figure 1 demonstrates how a correlation is computed using paired observations of the two variables over time. Since the relationship is across the two variables, it is called a cross correlation. Using daily returns for the Nasdaq composite and the S&P 500 index from 1970 to 1994, the cross correlation is computed to be 0.79, which is a significant positive relationship.

FIGURE 1 HERE

At this point, Monte Carlo is still in the game. Most spreadsheet add-in packages can model this relationship. Unfortunately, there is still the relationship over time or serial dependence. Rolling a fair pair of dice represents an independent process over time—that is the result of the current roll cannot be used to predict the next roll of the dice. When serial dependence occurs, the result of the current roll can be used to predict the next roll. In this case, the dice will not be fair. Serial dependence is measured with a serial correlation. Note that in Figure 2, the observation pairs used for the computation of the correlation coefficient is across time, not across the two variables. The two variables each have their own serial correlation.

FIGURE 2 HERE

The Nasdaq has a significant serial correlation coefficient and therefore cannot be modeled using an independent Monte Carlo simulation process. The S&P, on the other hand, could be modeled using Monte Carlo simulation, as it is not serially correlated over time. Unfortunately, this isn't the only serial dependence that occurs between two variables. Figure 3 demonstrates the concept of a cross-serial correlation. A cross-serial correlation captures a lagged correlation between the two variables. Note that the observation pairs represent both a serial correlation and a cross correlation process.

FIGURE 3

Figure 3 demonstrates a cross-serial correlation between the Nasdaq and the S&P lagged one day. Note that there is significant cross-serial correlation in both cases where the S&P is lagged and when the Nasdaq is lagged. By now, the model required by the Monte Carlo simulation in order to capture all of the cross, serial and cross-serial correlation coefficients is quite complex. To make matters worse, there is only a one-day lag at this point. As we go

FIGURE 3

Cross-Serial Correlation Between the Nasdaq 100 Index And the S&P 500 Index Lagged One Day— Daily Data 1970 to 1994

- **Correlation Nasdaq and S&P lagged one day = 0.0863 (3.64)**
- **Correlation S&P and Nasdaq lagged one day = 0.0474 (1.99)**

T-test in Parentheses

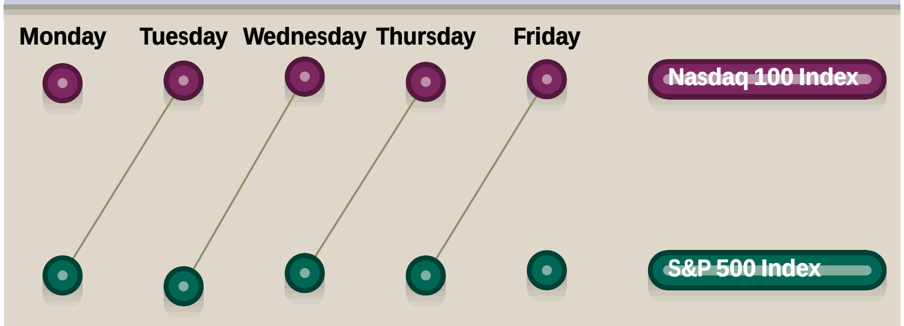
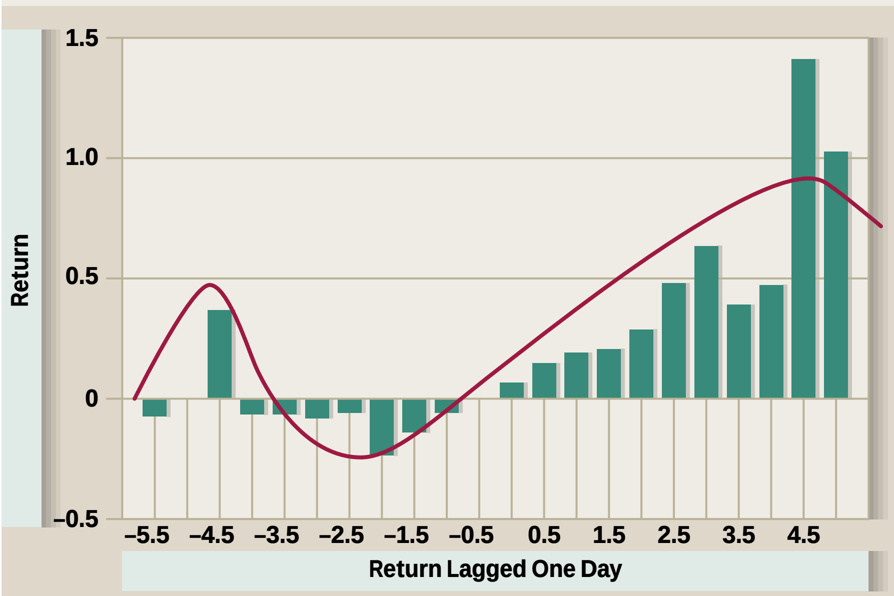


FIGURE 4

Nonlinear Serial Correlation S&P 500

1970–August 2000



Serial Correlation = 0.09
Annual Return = 9.78%

to longer lags such as a week, month, quarters and years, the model becomes even more complex.

Nonlinear Relationships

There is even more bad news. All of the correlation coefficients that we have just described represent linear relationships between variables. They may be nonlinear, which is very likely with stock market data. Figure 4 provides a graphical view of the nonlinear serial correlation for the S&P 500 index computed from daily data from January 1970 to August 2000.

FIGURE 4 HERE

The linear serial correlation for the S&P 500 in this case (daily data from 1970 to 2000) is not very impressive (0.09). However, there is a clear nonlinear pattern to the graph. Generally with stock market data, the linear serial correlation is close to zero, but at the same time there is significant nonlinear serial correlation. Figure 5 demonstrates a perfect linear serial correlation for the data. A comparison of the two graphs provides a visual picture of the differences between linear and nonlinear serial correlation.

FIGURE 5 HERE

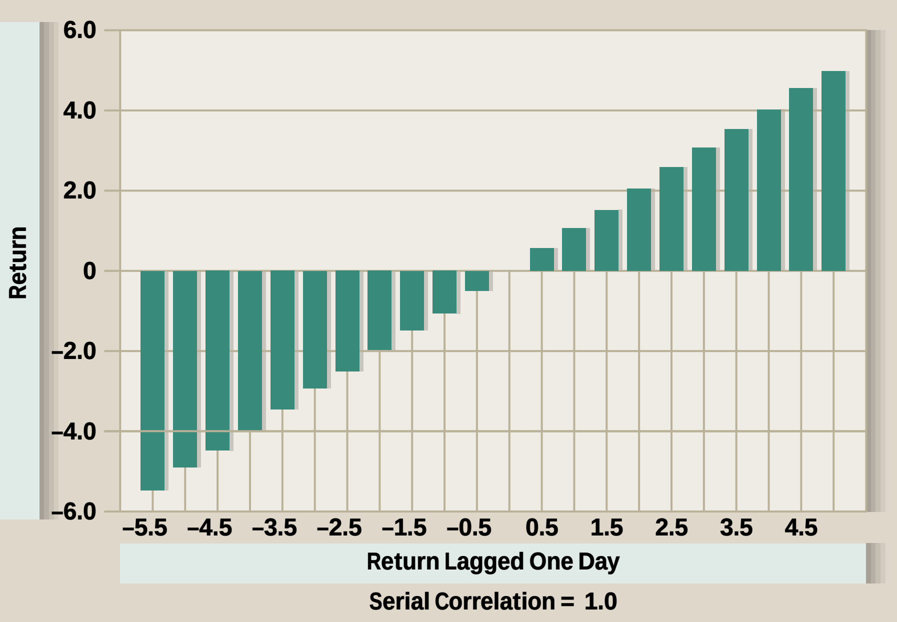
An analyst attempting to formulate a Monte Carlo simulation model is going to be overwhelmed by all of the lagged relationships going back into time. Adding nonlinear relationships just makes the burden unbearable.

Nonstationary Distributions

This is another area of interest when modeling market returns. Monte Carlo simulation assumes that the market decides on one distribution with one mean and one standard deviation and that the market will continue to follow that distribution until the end of time. To be honest, we do hear about mean reversion where everyone is conjecturing that the market will be reverting to its long-term mean sometime

FIGURE 5

Perfect Linear Serial Correlation



in the next ten years. This may be comforting to an analyst; unfortunately, the economic conditions that generate financial market returns are constantly changing. Thus, the mean and standard deviation of the market returns are constantly changing. Recent empirical work by Whitelaw [1994] and Perez-Quiros and Timmermann [2000] indicate that means and standard deviations vary throughout the business cycle. There isn't a stable distribution to hang your hat on. Again, nonstationary distributions are very difficult to model for inclusion into a Monte Carlo simulation.

Fortunately, there is a simple alternative to Monte Carlo simulation: exploratory simulation using historical data. The data represents the model or laboratory that is used in exploratory simulation and it contains all linear and nonlinear correlations, all normal and nonnormal distributions and all stationary and nonstationary distributions. There is no need to try to model them as with Monte Carlo simulation. In addition, it is an unfortunate fact that most analysts are not going to model these relationships. They will use Monte Carlo simulation with linear correlations of zero and normal distributions as did the two papers that appeared recently in this journal. This simplification can lead to incorrect answers, especially with financial market data. Financial market data is quite complex with nonlinear relationships and strangely shaped return distributions.

A Demonstration Case Study

Table 2 provides the results from a demonstration study using exploratory simulation and Monte Carlo simulation. An investment fund is currently equally invested into stocks and timber. The manager wants to know whether to sell some or all of the timber and increase the amount invested in stocks. The data consists of semiannual returns from 1960 to 1998. The results are summarized in Table 2. It is easy to see that timber has a lower return, a higher standard deviation and a higher downside risk (semideviation) than the stock investment. So it seems to be a clear decision to invest solely in stocks, yet there is the matter of the low correlation between the two investments. It is slightly negative but not significantly different from zero. However, a zero correlation is still able to contribute considerable diversification to a portfolio.

TABLE 2 HERE

The next step is to study the performance of the portfolio that has an equal allocation between the two investment alternatives. Using Monte Carlo simulation, the following assumptions are made.

The distributions for stocks and timber are normally distributed. The cross correlation between the two investments is effectively zero. All serial correlations are zero as are all cross-serial correlations. Finally, all relationships are linear.

The portfolio performance generated by Monte Carlo simulation to model the portfolio is lackluster. It does have reduced risk compared with an all-stock portfolio but with a lower return. The lower return results in poor risk-reward performance as evidenced in a lower reward to semivariability (R/SV) ratio. (The reward to variability (R/V) ratio is also lower. The R/V ratio uses the standard deviation as the risk measure while the R/SV ratio uses the downside risk measure, semideviation.) The manager, given this analysis, is likely to shift funds from timber to stocks. In fact, an optimal allocation (from an optimizer that maximizes the Roy reward-to-variability ratio) would allocate 96 percent to stocks and 4 percent to timber.

The alternative is exploratory simulation, which uses historical data to simulate the performance of the portfolio over a rel-

TABLE 2

Investment Results from Monte Carlo Simulation and Exploratory Simulation of an Investment Portfolio

1960 to 1998

		Semi-Annual					
Investment	**Annual Return**	**Std. Dev.**	**Semidev.**	**R/SV Ratio**	**R/V Ratio**	**Skewness**	**Kurtosis**
Equity (S&P)	12.26	11.6883	6.2129	0.5612	0.2983	0.1972	3.5348
Timber	5.06	16.1417	8.6058	0.0019	0.0035	2.1890*	5.9212
Simulation of 50-50 Portfolios							
Monte Carlo	8.55	9.9830	6.1201	0.2806	0.1721	0.1517	3.0987
Exploratory	10.48	9.0052	4.3520	0.6065	0.2931	0.7646*	5.0010

	Correlation	**T-Test**
Cross-Correlation S&P—Timber	–0.1196	–1.0502
Cross-Serial S&P—Timber Lagged 1 Period	–0.0747	–0.6485
Cross-Serial Timber—S&P Lagged 1 Period	0.2158*	1.9137

*Significant at five percent confidence interval
R/SV Ratio = (Semiannual Portfolio Return – T-Bill Rate)/Semideviation
R/V Ratio = (Semiannual Portfolio Return – T-Bill Rate)/Standard Deviation
Monte Carlo—10,000 iterations using semiannual returns
T-Bill Rate = 5.00%

evant historical period. The portfolio resulting from this analysis includes all dependent relationships, all nonlinear relationships and does not assume a normal distribution. Note that the exploratory simulation portfolio with equal allocation to timber and stocks has a higher return than the Monte Carlo simulation. The standard deviation is lower, and although the semideviation is higher, the R/SV ratio is higher than the R/SV ratio for stocks by themselves. The timber-stock portfolio provides a better risk-return performance than the stocks-only portfolio.

How can the return be higher for the exploratory simulation portfolio as compared with the Monte Carlo simulation portfolio? Simply stated, the exploratory simulation portfolio return is the actual economic return of the portfolio. The Monte Carlo return is a calculated return assuming normal distributions, serial independence and linear relationships. The exploratory simulation technique makes none of these assumptions.

The Monte Carlo simulation suffers from a number of problems, which are demonstrated in Table 2 and Figure 6.

The first problem is that the distributions for timber returns and stock returns are not normal distributions. The stock distribution has a higher kurtosis than would be expected if the distribution was normal. The timber distribution is significantly skewed and has a higher kurtosis. Second, there is a significant lagged relationship between timber and the S&P lagged six months.

Finally, there is the problem of nonlinear relationships. Figure 6 demonstrates that the cross-correlation relationship of the S&P and timber is nonlinear. The graph indicates that there is a negative relationship between timber and stocks in the –3 percent to +4 percent range. However, the linear correlation coefficient

FIGURE 6

Nonlinear Correlation Between S&P and Timber

1960–1998

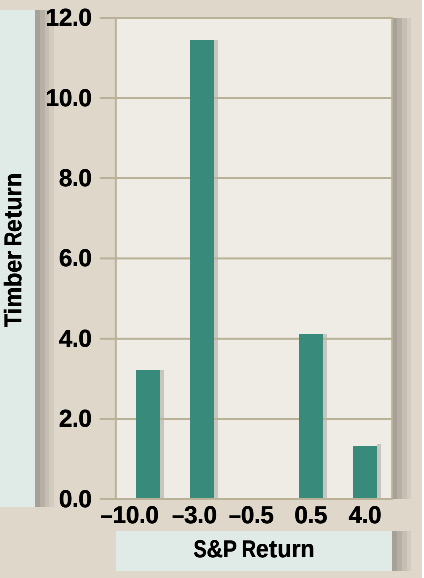
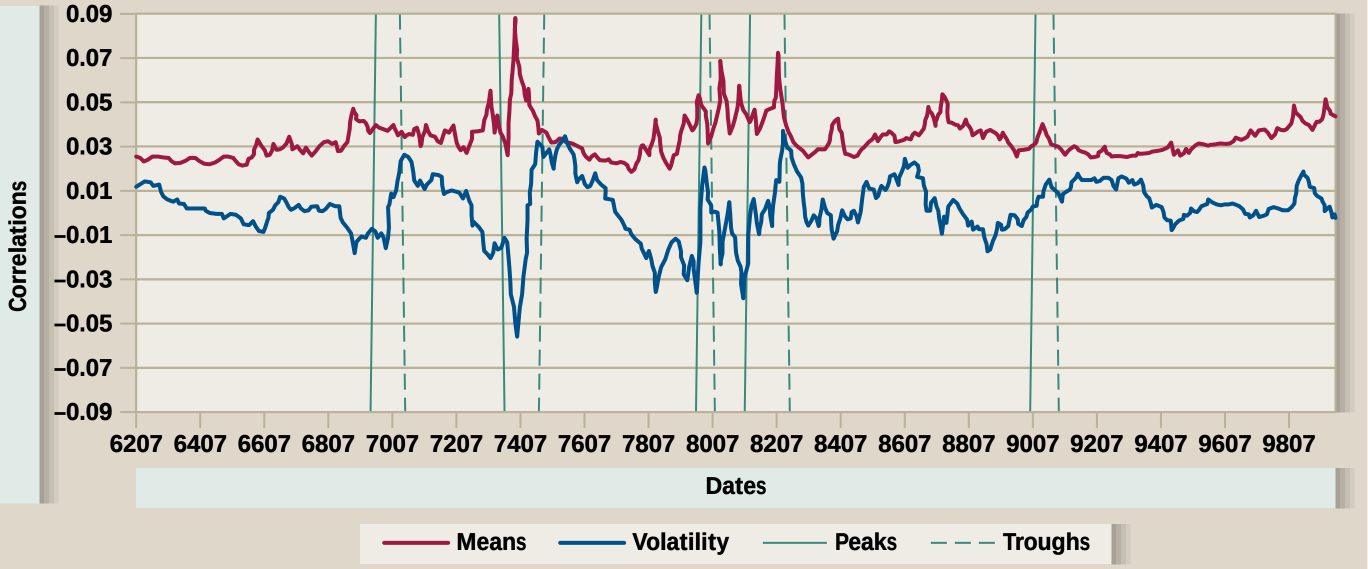


FIGURE 7

Whitelaw 1994 JF Graph with CRSP Value Weighted Index Updated to December 1999



underestimates the strength of the relationship. The computed correlation is close to zero and is not statistically significant. All of these problems conspire to provide the wrong decision—that is, sell the timber investment.

FIGURE 6 HERE

Forecasting

A recently received e-mail about economists included the four golden rules of econometric forecasting: (1) think brilliantly, (2) be infinitely creative, (3) be outstandingly lucky and (4) otherwise, stick to being a theorist.

As investment literature is fond of pointing out for legal reasons, past performance is not a guarantee of future returns. This counsel applies equally to both exploratory simulation and Monte Carlo simulation. Picking historic periods for an exploratory simulation that are equivalent to the current situation is problematic. However, even more so is picking a distribution to use in a Monte Carlo simulation. It should be noted that we are not forecasting per se when we use exploratory simulation. We are trying different policies to find out which one will best meet our needs. We are stress testing the policy with data that includes all of the nonnormal, nonlinear and nonstationary interrelationships.

Historic data has suffered from a poor reputation because of straight-line extrapolations of expected returns and variances. Exploratory simulation with historic data is not a straight-line extrapolation. In addition, it includes the factors that drive stock market returns. Monte Carlo simulation homogenizes away the factors that drive stock returns. Can you forecast stock returns without bringing forward a forecast for any financial variable? Monte Carlo simulation lets you do this by simply specifying the distribution for stock returns. Exploratory simulation requires that you have some idea of what is currently happening and what could happen next in the financial markets. Then, you pick a comparable period in history and test different investment strategies throughout that period. Next, you select the strategy that worked best in the period and you hope for the best because you are dealing with uncertainty.

The goal in the equity-timber case study is simply to see which strategy performed best during the various economic conditions that existed in the past 40 years. Did the portfolio run into liquidity problems during these decades that included recessions, high inflation, market crashes, credit crunches, wars and energy shortages? It is important that the selected strategy be able to deal with these scenarios, as it is doubtful that any of these have been banished from our future. It is important to study these periods as timber and equities perform differently during recessions and during periods of high inflation. As a result of studying these periods, the investor should give timber a higher allocation in the portfolio. We are not forecasting that the portfolio will return the 10.48 percent annually obtained in Table 2. Rather, it is a forecast that this strategy will provide the best results given different economic conditions over the years.

The probability results from Monte Carlo simulation may look impressive to a client. However, if that number is derived from assumptions that are not realistic, there is no value to the number. It does provide a good excuse: "Well, the Monte Carlo model did tell us there was a 15 percent chance of this happening." The real question is whether it provides a good policy decision. Recent research in the Journal of Finance by Whitelaw [1994] and Perez-Quiros and Timmermann [2000] indicates that the stock market mean returns and volatility are different between peak-to-trough and trough-to-peak periods in the business cycle. In the current environment (January 2001), would an investment advisor be comfortable making a recommendation using Monte Carlo simulation based on some normal distribution derived from the last 75 years? The alternative would be to set up an exploratory simulation that looks at recent history (the last 30–40 years) for previous peak-to-trough periods in order to see which asset mix provides the best results after the economy has reached a peak.

The Whitelaw [1994] study is particularly interesting. He uses a smoothing technique to filter out the noise that occurs in the stock market data. The resulting means and standard deviations are varying over time and are related to the business cycle. Note that the greatest variations occur during recessions. There is also the unsettling tendency for the risk to increase while at the same time returns are decreasing. Rarely does increased volatility lead to increased returns. Portfolio theory tells us that increased risk leads to increased returns, but this refers to an optimized outcome from a subset of market data while the market itself has never been optimized. It can do whatever it pleases, and does.

FIGURE 7 HERE

When should a financial planner use Monte Carlo simulation? Whenever a variable in the problem cannot be estimated or is not available. Appropriate variables might include a person's life span or irregular cash flow needs for a retirement problem. Rekenthaler [2000] discusses Hopewell's problem of in-retirement planning with irregular cash-flow needs. This seems to be an appropriate application for Monte Carlo simulation, but only for those variables where the data are not available. Monte Carlo simulation gives up information through its assumption set whenever variables with readily available data are used.

Summary

Monte Carlo simulation is useful for those cases where data and analytic models simply are not available. Otherwise, it requires more work and does not result in a demonstrably better answer than other analytic techniques. The benefit/cost ratio just is not there.

The problem with Monte Carlo simulation is the assumptions that have to be made in the model in order to easily deploy Monte Carlo simulation. Since few planners have formal training in operations research, they will tend to make these assumptions without understanding their implications. Other forms of simulation, exploratory and tactical, do not make these assumptions and are easier to deploy. Monte Carlo simulation implies we are operating under conditions of risk and we know the underlying distributions. However, the financial markets are really operating under conditions of uncertainty where we don't know the distribution. Under these conditions, the best policy is one that adapts to the uncertain conditions. It is important to stress test policies to see which have proved the most adaptable under severe conditions. This is the role of exploratory simulation with historic data.

Finally, McCarthy [2000] notes that financial planners have been slow to employ Monte Carlo simulation. Proponents of Monte Carlo simulation have to demonstrate the additional benefits of using Monte Carlo simulation before it can be recommended for wider use within the profession. Its benefits do not lie in the area of analyzing aggregate market returns. However, it could prove useful in other areas of a financial planning practice where data are not readily available. Proponents of Monte Carlo should explore those areas for it to become a valuable addition to financial planning.

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Monte Carlo Simulation—Challenging the Sacred Cow

by John D. Kingston, CFP

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These days you can find a number of Web sites and financial planning software programs that suggest to clients that they should feel comfortable that their objectives will be met because their financial plans have been run through thousands of random mathematical simulations using historical asset class returns.

Supporters of Monte Carlo simulation say it helps investors choose the most attractive course of action, providing information about a range of outcomes such as best and worst case scenarios and the probability of reaching a specified target. They believe it's a better alternative to using "one" blended rate-of-return assumption in the financial planning process and then projecting that by 20 or more years.

If "one" blended rate of return is the only option in financial planning, then Monte Carlo may yet serve a purpose in helping consumers understand the risk of missing their objective. If not, the profession may find this exercise is little more than hype developed by mathematicians and promoted by financial planning software companies. Monte Carlo simulations might only be a tool to show clients how technical we are, giving them one more piece of evidence why they should place their trust in us financial planners in the first place. In many cases, the amount and predictability of a client's retirement income (such as Social Security and pensions) and lifestyle changes make the uncertainty of investment returns a less important issue in the overall financial plan.

A Common Trait Among Bear Markets

Monte Carlo simulations may provide insight regarding investment returns over a limited period of time, but when used to analyze an overall financial plan, there are several problems. First, the longer the time period in question, the closer the deviation of returns should converge on the long-term average—that is, of course, if the analysis properly takes into account the historical distribution of returns and doesn't cluster all the poor (or good) years together. A totally random approach fails to replicate the effects of a significant bear market. I'm not talking about the short-term greater-than-20-percent hiccups that technically qualify as a bear market, but the prolonged ones that go into the second year posting even greater losses, where investors become so fed up with repeated bear market sucker rallies that they don't ever want to see a stock again. Bottoms of significant bear markets occur when the financial journals can only see and report on the worst of a negative investing environment, further encouraging investors as they throw in the towel. The 1973–74 bear market, for example, saw losses in the S&P 500 of almost 50 percent and the Valueline index by more than 70 percent. It then took approximately seven years for the market to recover to break even.

While many observers believe that bear markets exhibit some degree of randomness in their occurrence (and I'm not one of them), there is one thing all bear markets share. They all have a second significant down year followed by a longer recovery period of higher-than-normal returns. Only two bear markets lasted longer than 24 months (1929 and 1938), but the bulk of their losses were sustained in two years. At a minimum, it's this sharper than normal post-bear market recovery period that teaches us that bear markets are not clustered together. Significant bear markets pose the greatest financial risk to investors and they cannot be adequately duplicated by a random approach.

Financial planning is inherently more complex than an analysis of investment returns, while Monte Carlo surrounds the client with a range of investment outcomes so broad that the client may easily lose sight of the real goal. If the client's financial plan has a five-year horizon and he or she is overweighted in large-cap stocks, then knowing the range of returns for that asset class over any five years might be of interest. The longer the time period the greater the uncertainty that other lifestyle factors will affect the plan, and the less useful Monte Carlo becomes.

What is it you want to test? If the client has significant exposure to certificates of deposit or other short-term fixed income securities, then Monte Carlo should be adjusted to the inflation environment linked to those rate-of-return probabilities. There is a linkage between interest rates and expected future inflation rates, and short-term fixed income securities have a higher correlation to current inflation rates than do longer-term fixed income investments. If one variable offsets another variable (even partially), you shouldn't count one while ignoring the other. Therefore, Monte Carlo doesn't seem to provide substantially improved rate-of-return information for long-term financial plans, and the short-term is flawed by ignoring the correlation of inflation rates to different asset classes in the computation.

What may be worse is that Monte Carlo masks the client's worst case and most likely scenarios with a range of outcomes so large that it distorts reality. The randomness of Monte Carlo simulation, by its nature of clustering the good times or bad times in its range of scenarios, may potentially turn a planner's client into a professional liability.

For a retired client living off his or her investments, a significant bear market beginning immediately is probably a worst-case scenario. The software used at our firm allows us to model a client's financial plan as close to his or her projected circumstances as possible, before looking at the impact of different rates of return (including the ultimate bear market example above), to see how they may affect the client's objectives. We can input both rate of return and duration for a bear market, the recovery period and post-recovery period depending on the client's specific investment allocation, and then show the client a graphical comparison with more normalized scenarios. Our software allows for multiple qualified and nonqualified plan accounts so that we can provide individualized treatment, showing continuing deferral of employment income if applicable, or using different asset classes or investment styles that may logically suggest using different rate-of-return assumptions. Distributions are taxed appropriately (Roth or regular) and can be accelerated in years that cash flow is needed. Additions or outflows such as stock options, sale of property, divorce transactions, major expenditures and gifts can be modeled as taxable or untaxable based on their character and calculated with other income each year.

Lifestyle expenditures are adjusted for inflation and can be changed in any year. If refinancing is not chosen, the software will automatically show sale of the primary residence when liquidity is exhausted, showing the client how much longer the assets will last if he or she rents or purchases a smaller residence.

In the end, Monte Carlo simulation seems to clash with the continuing development of a holistic approach that allows changes in the client's investment allocation over time, with the corresponding changes of anticipated rate of return over the same time periods. Modern software can and should incorporate greater flexibility within the financial planning model, making random rate-of-return simulations even less relevant.

While the profession quietly questions Monte Carlo simulation, the benefits are being loudly proclaimed by the software industry as the hottest new innovation in financial planning in decades. Marketing hype touts this new information as one more item of value in a client's financial plan, while opponents say that when we extend client expectations out 20 or 30 years, identifying factors such as lifestyle expenditures, tax rates, inflation and investment preference based on risk may be more important. Chaos theory teaches us how small errors in the early years of a financial plan can make dramatic consequences when compounded over a long period of time, so let's not make our real problems any bigger than they are. Some "what if" scenarios are necessary, but let's do it right and do it often. The real answer is to make the plan as representative as possible under the circumstances and to update it regularly. The benefit that Monte Carlo simulation promises to provide might be better achieved by using common sense in the financial planning process.

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