Retirement, Market Uncertainty, and Monte Carlo

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1. Monte Carlo in Financial Planning

Twenty years ago, Monte Carlo probability based methods found a place in the financial planning profession as advisors began to use these stochastic simulation models to show clients how different retirement strategies might be expected to perform under dynamic stresses of many varied potential economic and market driven futures. The advantage of probability based analysis over straight line deterministic illustrations lay in Monte Carlo's ability to convey risk and volatility as unpredictable facts of financial life, and offer a technique to contrast and compare the risks and benefits of various planning options.

a. Deterministic vs. Monte Carlo Financial Planning Models

Deterministic, or constant based, financial planning creates a single forward looking financial illustration based on the assumption that the future is essentially predictable and average each year. Deterministic results represent the most common, or the mean, expected planning result that would occur if the average rate of return occurred each year. Deterministic results are simple, easy to read, and easy to explain. As long as everyone understands the assumptions and limitations, deterministic planning models are valuable tools to examine complex financial interactions. Deterministic models are also the essential fundamental underpinnings of advanced Monte Carlo Simulations.

Monte Carlo Simulation, or Stochastic Analysis, runs hundreds or thousands of plan models utilizing changing return assumptions for each year within each simulation. These simulations create collections of planning outcomes that might occur in hundreds and thousands of changing potential future real world market environments. The annual rates of returns used within the simulations are randomly selected based on expected average return and an expected return volatility.

Chaos Theory and the Law of Large Numbers are statistical concepts that support the Monte Carlo Simulation technique. By applying large numbers of simulations based upon specifically randomized market behavior modeling, a range of probable and potential financial plan projections can help demonstrate, measure, and compare expected future results and plan reactions under conditions of uncertainty.

Box–Muller Transform – Trigonometric Randomization Method

$$Z_0 = R\cos(\Theta) = \sqrt{-2\ln U_1}\cos(2\pi U_2)$$
$$Z_1 = R\sin(\Theta) = \sqrt{-2\ln U_1}\sin(2\pi U_2).$$
$$R^2 = -2\cdot\ln U_1$$
$$\Theta = 2\pi U_2.$$

b. Goals, Practice & Application

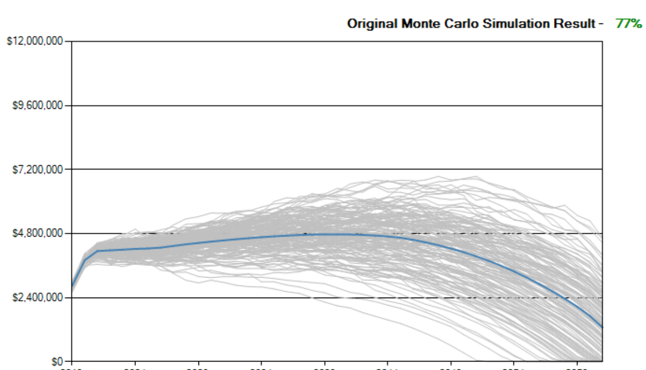
The primary goal of Monte Carlo in financial planning is to model how clients' financial condition might change under a range of potential market conditions. Simulation results help advisors measure and explain retirement sustainability risk. More importantly, simulation helps compare and contrast planning decision options.

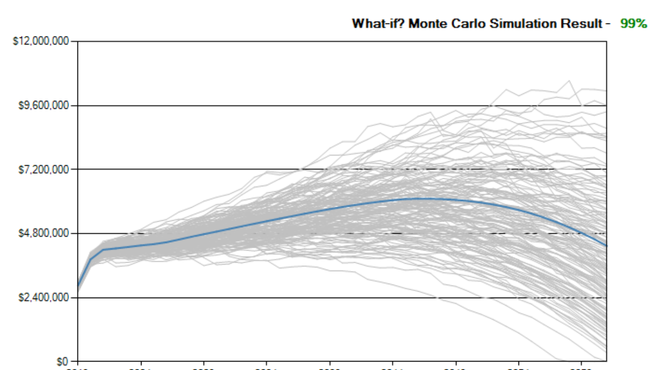
Monte Carlo is a uniquely powerful modeling process that helps advisors understand, evaluate, and illustrate how clients' financial plans are likely to behave if exposed to volatile rates of return. The collection of simulation results may be analyzed to demonstrate how market volatility affects potential capital growth and consumption trends. Monte Carlo can be useful illustrating the risks and dynamics of accelerating capital depletion brought about by unfortunate loss timing.

Monte Carlo Simulation requires two primary systems: an accurate financial planning calculation and projection system that accepts sequential return information, and a statistically appropriate random return generator. How we define 'accurate' and 'appropriate' is the heart of the Monte Carlo modeling discussion.

Monte Carlo Simulation exposes a financial plan to a series of dynamically changing annual return sequences mathematically modeled to represent thousands of potential economic futures. The randomly created possible return sequences attempt to include the full range of potential market fluctuations; ups and downs in all possible combinations in a way that mimics how real financial portfolios might behave over time. How these sequences are selected, and what they imitate, fundamentally affect the Monte Carlo Simulation results.

In practice, Monte Carlo random sequences are created parametrically using "normal" and "log-normal" probability density curves and measures of volatility such as standard deviation to describe how client portfolios are apt to behave. Most current models and illustrations of portfolio behavior are designed to be easy to understand and explain. These techniques have been useful and valuable in planning tools, but more advanced statically accurate models such as "Fat Tail" log-normal may better mimic real world financial conditions.





2. Expectations and Uncertainty

If markets were predictable and stable, financial planning would be much easier. We could plan for a known future, and wouldn't need Monte Carlo. Reliable ten percent returns would allow planners to tell exactly when clients could retire, and precisely how much they could safely spend. In reality we know from experience to expect market fluctuations, and that returns are not only uncertain, but sometimes even substantially negative.

a. Measuring Historic Returns

Interpreting huge amounts of raw financial data and arriving at usable information about what really happened is fraught with problems for the statistically inclined.

For financial modeling purposes and to examine the historic return measurement issue, let's start by using daily S&P 500 return information. Adjusting the return raw data to reflect the daily value percentage change allows us to isolate price out of the sequence and focus on relative daily volatility.

Combining the returns arithmetically gives us a daily average return of .0XX%. If we look at total return over the time range geometrically, we obtain a daily average return of .0YY%. These relate to X.X% and Y.Y% percent annually. This demonstrates one of the hazards of measuring historic returns.

b. Modeling Return Probability

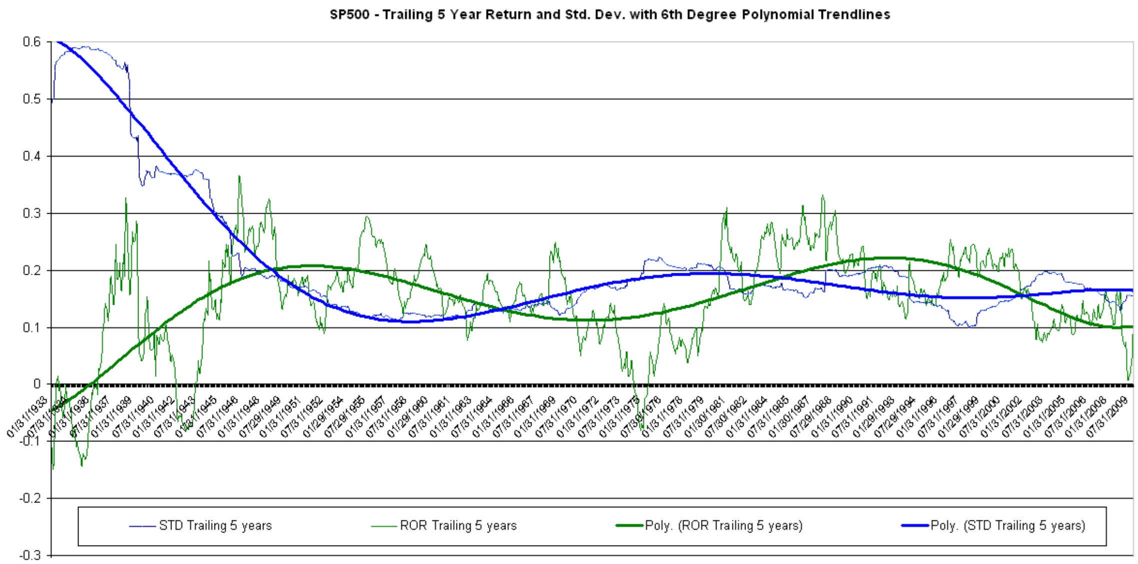
Knowing an average expected return is the first step in statically modeling future return. The next requirement is making collection of various returns that in aggregate, on average, offer the expected return and doing so in a way that is similar to how markets perform. This means varying each random annual return above and below the average so that most are relatively close to the average, some are a ways away from the average, and a very few are pretty far from average.

A good model will produce a collection of random returns that averages the expected return, is distributed the same as market returns, and has the same kind of occasional return extremes as the market experiences.

Creating a model that creates distributions and extremes that are both similar to reality is tricky, due to some of the common mathematical practices in place in our industry. Using the entire set of historical return information available, allows us to know the average and cumulative returns, and allows us to measure historic distribution using Standard Deviation measurement. Unfortunately, these techniques can deliver a misleading model that does not accurately illustrate financial experience.

c. Volatility & Standard Deviation

Volatility is a moving target. We can measure volatility for a range of time and obtain a Standard Deviation that represents the entire data set. However, when we examine the data, we may observe that there are quiet times and active times. One single measure of volatility, encompassing both quiet and active markets, is a simplification that does not really accurately represent either kind of market.

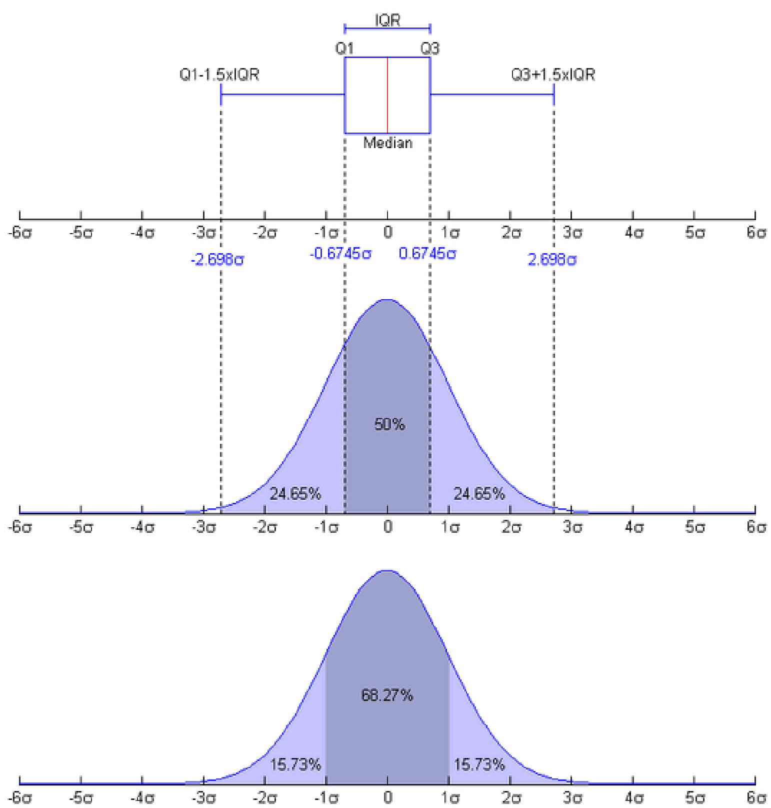


Return and volatility trend variance over time

3. Probability Assumption Options

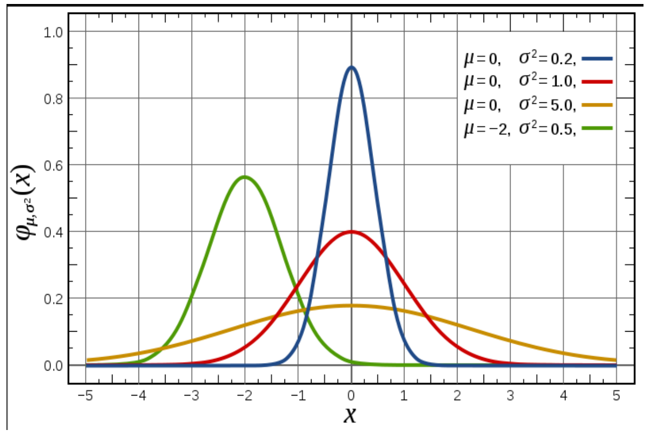
a. Probability Density Functions

In probability theory, a random variable's density function describes the likelihood it will occur at any given point in the outcome range. The function is just a mathematical way of describing the probability of an outcome occurring.



b. Normal, Log-Normal & Skewed Distributions

One very common and useful probability density function is the standard normal. It is an example of the well-known 'bell curve'.



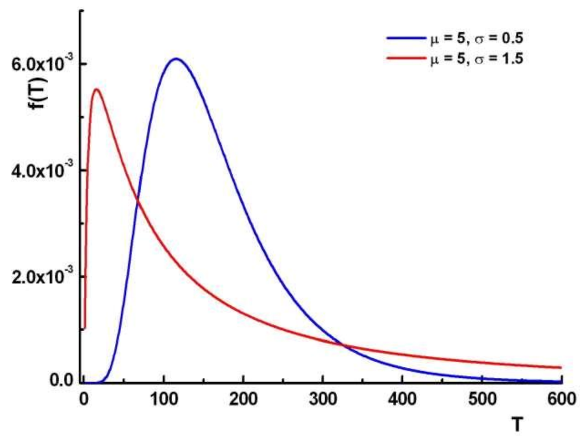
Normal distribution, describes many situations where variables tend to cluster around a mean. For example, the heights of adult males in the United States are roughly normally distributed, with a mean of about 70 in (1.8 m). Most men have a height close to the mean, though a small number of outliers have a height significantly above or below the mean. Normal distributions are used throughout statistics, natural and social science as a simple model that approximates complex phenomena.

The standard normal distribution probability density function is:

$$\phi(x) = \frac{1}{\sqrt{2\pi}}\, e^{-\frac{1}{2}x^2},$$

Log-Normal

Lognormal distributions describe many physical, chemical, biological, financial, and statistical results. Mathematical processes of multiplying a series of random variables will produce a new random variable (the product) which tends to be Lognormal in character.



The standard log-normal distribution probability density function is:

$$f_X(x;\mu,\sigma) = \frac{1}{x\sigma\sqrt{2\pi}} e^{-\frac{(\ln x-\mu)^2}{2\sigma^2}}, \quad x > 0$$

Conclusion

Monte Carlo simulation, also known as Stochastic Modeling, is a method of testing a complex system for potential probable outcomes over a range of possible conditions and sequence of variables. Monte Carlo evaluations can offer a kind of stress test. Results can help advisors evaluate, illustrate, compare, and contrast clients' financial future under various retirement ages, withdrawal levels, and portfolio strategies. Most importantly, Monte Carlo is used in comprehensive retirement planning to measure the probability that clients will successfully enjoy a chosen level of retirement income through life expectancy.

Using Monte Carlo simulation in Silver, Easy Money, or Golden Years is fundamentally about building the representative financial plan that best models clients' current and expected financial condition. All the basics of financial planning apply: Client financial positions, retirement ages, withdrawal intentions, return expectations, inflation rates, and life expectancy used impact not only the nominal financial plan results, but the Monte Carlo results as well.

Monte Carlo probability outcomes should be considered relative to the inputs and variables used. Advisors can change saving amounts, spending levels, portfolio returns, inflation, retirement age, and time horizon to see how each affects probability of success. By making modifications, advisors can learn how each variable impact's Monte Carlo results.

Monte Carlo simulation models are an important way to show future portfolio returns, and order of returns are unknown and quite variable. Monte Carlo illustrates potential outcomes over a wide combination of possible market conditions, and can measure a client's exposure to risk.

The advisor's goal is to find and illustrate a combination of strategies that offer a high probability of success. Levels of savings, differing investment strategies, risk profiles, retirement ages, and social security claiming ages all contribute to Monte Carlo outcomes. Including Monte Carlo simulation in the planning process demonstrates to clients how their financial decisions impacts long term results, and can help them make better, more informed choices.