Innovative approaches to putting asset allocation into practice

Building on more than 15 years of asset-allocation research, Paul D. Kaplan, who led the development of the methodologies behind the Morningstar Rating™ and the Morningstar Style Box™, tackles key challenges investor professionals face when putting asset-allocation theory into practice.

Table of Contents

Foreword
Introduction
Part I: Equities
1. Purity of Purpose: How Style-Pure Indexes Provide Useful Insights
2. Investing in Europe With Style: Why Investors in Europe Would Benefit From Constructing Portfolios Through the Prism of Style
3. Why Fundamental Indexation Might—or Might Not—Work
4. The Fundamental Debate: Two Experts Square Off on the Big Issues Surrounding Fundamentally Weighted Indexes
5. Collared Weighting: A Hybrid Approach to Indexing
6. Yield to Investors? A Practical Approach to Building Dividend Indexes
7. Holdings-Based and Returns-Based Style Models
8. Estimates of Small Stock Betas Are Much Too Low
9. A Macroeconomic Model of the Equity Risk Premium

Part II: Fixed Income, Real Estate, and Alternatives
10. Good and Bad Monetary Economics, and Why Investors Need to Know the Difference
11. Inflation, Gilt Yields, and Economic Policy
12. Reverse Mean-Variance Optimization for Real Estate Asset-Allocation Parameters
13. The Long and Short of Commodity Indexes
14. Less Alpha and More Beta Than Meets the Eye
15. Venture Capital and its Role in Strategic Asset Allocation

Part III: Crashes and Fat Tails
16. One and a Quarter Centuries of Stock Market Drawdowns
17. Stock Market Bubbles and Crashes: A Global Historical and Economic Perspective
18. Déjà Vu All Over Again
19. Déjà Vu Around the World
20. Getting a Read on Risk: A Discussion With Roger Ibbotson, George Cooper, and Benoit Mandelbrot on the Crisis and Risk Models

Part IV: Doing Asset Allocation
21. Does Asset-Allocation Policy Explain 40%, 90%, or 100% of Performance?
22. Asset-Allocation Models Using the Markowitz Approach
23. Asset Allocation With Annuities for Retirement-Income Management
24. MPT Put Through the Wringer: A Debate Between Steven Fox and Michael Falk
25. Updating Monte Carlo Simulation for the 21st Century
26. Markowitz 2.0
27. What Does Harry Markowitz Think? A Discussion With Harry Markowitz and Sam Savage

Afterword
About the Author
Index

Available at www.wiley.com/buy/9781118115060 and wherever books and eBooks are sold.
When the Wright Brothers pioneered powered flight in 1903, their genius lay in conquering the three axes of control: pitch, yaw, and roll. Over the years, technologies advanced, planes crashed, and aviation evolved to compensate. By 1952, the Wrights’ original airplane was barely recognizable in a world of jets and supersonic aircraft, which nonetheless were still governed by the same three principles of control.

In 1952, another pioneer, Harry Markowitz, invented portfolio optimization.¹ His genius was also based on three principles: risk, reward, and the correlation of assets in a portfolio. Over the years, technologies advanced and markets crashed, but portfolio-optimization models did not evolve to compensate. This is surprising. Markowitz himself was a pioneer of technological advancement in the field of computational computer science. Furthermore, he did not stand idly by in the area of portfolio modeling; he continued to improve his models and to influence the models of others. Few of these improvements, however, were broadly picked up in practice.

Because Markowitz’s first effort was so simple and powerful, it attracted a great number of followers. The greater the following became, the fewer questioners debated its merits. Markowitz’s original work is synonymous with Modern Portfolio Theory; it has been taught in business schools for generations and, not surprisingly, is still widely used today.

¹Morningstar Advisor, April/May 2010. © 2010 Morningstar. All Rights Reserved. Used with permission. The appendix was added for this book.
Then came the crash of 2008, and now people are starting to ask questions. The confluence of the recent economic trauma and the technological advances of the past few decades make today the perfect time to describe the supersonic models that can be built around Markowitz’s fundamental principles of risk, reward, and correlation. We assert that Markowitz’s original work remains the perfect framework for applying the latest in economic thought and technology. We dub our updated model Markowitz 2.0.

**THE FLAW OF AVERAGES**

The 1952 mean-variance model of Markowitz was the first systematic attempt to cure what Savage (2009) calls the flaw of averages. In general, the flaw of averages is a set of systematic errors that occurs when people use single numbers (usually averages) to describe uncertain future quantities. For example, if you plan to rob a bank of $10 million and have one chance in 100 of getting away with it, your average take is $100,000. If you described your activity beforehand as making $100,000, you would be correct, on average. But this is a terrible characterization of a bank heist! Yet, as Savage writes, this very mistake is made all the time in business practice. It helps explain why everything is behind schedule, beyond budget, and below projections, and it was an accessory to the economic catastrophe that culminated in 2008.

Markowitz’s mean-variance model attempted to fix the flaw of averages by distinguishing between different investments with the same average (expected) return, but with different risks, measured as variance or its square root, standard deviation. It was a breakthrough that ultimately garnered a Nobel Prize for its inventor. The use of standard deviation and covariance, however, introduces a higher-order version of the flaw of averages, in that these concepts are themselves versions of averages.

**ADDING AFTERBURNERS**

By taking advantage of the very latest in economic thought and computer technology, we can, in effect, add afterburners (more thrust) to the original framework of the Markowitz portfolio optimization model. The result is a dramatically more powerful model that is more aligned with twenty-first century investor concerns, markets, and financial instruments (such as options).

Traditional portfolio optimization, commonly referred to as mean-variance optimization, or MVO, suffers from several limitations that can
easily be addressed with today’s technology. Our discussion here will focus on five practical enhancements:

First, we use a scenario-based approach to allow for fat-tailed distributions. Fat-tailed return distributions are not possible within the context of traditional mean-variance optimization, where return distributions are assumed to be adequately described by mean and variance.

Second, we replace the single period expected return with the long-term forward-looking geometric mean; this takes into account accumulation of wealth.

Third, we substitute conditional value at risk, which only looks at tail risk, for standard deviation, which looks at average variation.

Fourth, the Markowitz model used a covariance matrix to model the distribution of returns on asset classes; we replace this with a scenario-based model that can be generated with Monte Carlo simulation and can incorporate any number of distributions.

Finally, we exploit new statistical technologies pioneered by Savage in the field of probability management. Savage invented the Distribution String, or DIST, which encapsulates thousands of trials as a single data element or cell. It eliminates the main disadvantage of the scenario-based approach—the need to store and process large amounts of data.

**THE SCENARIO APPROACH**

One of the limitations of the traditional mean-variance optimization framework is that it assumes that the distribution of returns for the assets in the optimization can be described simply by mean and variance alone. The most common depiction of this assumption is to draw the distribution of each asset class as a symmetrical bell-shaped curve. As illustrated in Figure 26.1, however, the return distributions of different asset classes don’t always follow a symmetrical bell-shaped curve. Some assets have distributions that are skewed to the left or right, while others have distributions that are skinnier or fatter in the tails than others.

Over the years, various alternatives have been put forth to replace mean-variance optimization with an optimization framework that takes into account the non-normal features of return distributions. Some researchers have proposed using distribution curves that exhibit skewness and kurtosis (that is, ones that have fat tails), while others have proposed using large numbers of scenarios based on historical data or Monte Carlo simulation.

The scenario-based approach has two main advantages over a distribution-curve approach. One, it is highly flexible. Nonlinear instruments such as options, for example, can be modeled in a straightforward
FIGURE 26.1 Skewed Returns. The return distributions of different asset classes do not always follow a symmetrical bell-shaped curve.


*The 1933 small-company stocks total return was 142.9%.

manner. Second, it is mathematically manageable. For example, portfolio returns are simply weighted averages of asset-class returns within the scenarios. In this way, the distribution of a portfolio can be derived from the distributions of the asset classes without working complicated equations that might lack analytical solutions; only straightforward portfolio arithmetic is needed.
FIGURE 26.2 Skewed Returns. As the area to the left of the gray vertical line shows, the smoothed scenario approach does a better job of estimating the probability of tail events than the mean-variance model. Source: Morningstar (2009).

In standard scenario analysis, there is no precise graphical representation of return distributions. Histograms serve as approximations, such as those shown in Figure 26.1. We augment the scenario approach by employing a smoothing technique so that smooth curves represent return distributions. Figure 26.2 shows the distribution curve of annual returns for large-company stocks under our approach. Comparing Figure 26.2 with the large-company-stock histogram in Figure 26.1, we can see that the smooth distribution curve retains the properties of the historical distribution while showing the distribution in a more aesthetically pleasing and precise form. Furthermore, our model makes it possible to bring all of the power of continuous mathematics (previously enjoyed only by models based on continuous distributions) to the scenario approach.

In Figure 26.2, the solid line is what we get when we use mean-variance analysis and assume that returns follow a lognormal distribution. The dotted line is what we get when we use our smoothed scenario-based approach. The area under the solid line to the left of the gray vertical segment shows that the 5th-percentile return under our model is negative 25.8 percent, meaning
there is 5 percent probability of a return of less than negative 25.8 percent. Under the lognormal model, however, the probability of the return being less than negative 25.8 percent is only 1.6 percent. This illustrates how a mean-variance model can woefully underestimate the probability of tail events.

As Kaplan et al. (2009) discuss, tail events have occurred often throughout the history of capital markets all over the world. Therefore, it is important for asset-allocation models to assign nontrivial probabilities to them.

**REWARD OVER THE LONG TERM**

The second enhancement we make to MVO is to use geometric mean. In MVO, reward is measured by expected return, which is a forecast of arithmetic mean. Over long periods of time, however, investors are not concerned with simple averages of return; rather, they are concerned with the accumulation of wealth.

We use forecast long-term geometric mean as the measure of reward, because investors who plan on repeatedly reinvesting in the same strategy over an indefinite period would seek the highest rate of growth for the portfolios as measured by geometric mean.

**DOWNSIDE OF STANDARD DEVIATION**

Our third enhancement deals with risk. Much has been written about how investors are not concerned merely with the degree of dispersion of returns (as measured by standard deviation), but with how much wealth they could lose. Many downside risk measures have been proposed to replace standard deviation as the measure of risk in strategic asset allocation. While any one of these could be used, our preference is to use conditional value at risk.

Conditional value at risk (CVaR) is related to value at risk (VaR). VaR describes the left tail in terms of how much capital can be lost over a given period of time. For example, a 5 percent VaR answers a question of the form: Having invested $10,000, there is a 5 percent chance of losing $X or more in 12 months. (The “or more” implications of VaR are sometimes overlooked by investors, with serious consequences.) Applying this idea to returns, the 5 percent VaR is the negative of the 5th percentile of the return distribution. For example, as we mentioned, the 5th percentile of the distribution shown in Figure 26.2 is negative 25.8 percent, so its 5 percent VaR is 25.8 percent. This means there is a 5 percent chance of losing $2,850 or more on a $10,000 investment. CVaR, however, accounts for possible losses beyond VaR; it is
the expected or average loss of capital should VaR be breached. Therefore, CVaR is always greater than VaR. The 5 percent CVaR for the distribution shown in Figure 26.2 is 35.8 percent, or $3,580, on a $10,000 investment.

**SCENARIOS VERSUS CORRELATION**

Next, we model the distribution of returns differently. In mean-variance analysis, a single number, the correlation coefficient, represents the covariation of the returns of each pair of asset classes. This is mathematically equivalent to assuming that a simple linear regression model is an adequate description of how the returns on the two asset classes are related. In fact, the R-squared statistic of a simple linear regression model for two series of returns is equal to the square of the correlation coefficient.

For many pairs of asset classes, however, a linear model misses the most important features of the relationship. For example, during normal times, non-U.S. equities are considered to be good diversifiers for U.S. equity investors. But during global crises, all major equity markets move down together.

Furthermore, suppose that the returns on two asset-class indexes were highly correlated, but instead of including direct exposures to both in the model, one was replaced with an option on itself. Rather than having a linear relationship, we now have a nonlinear relationship that cannot be captured by a correlation coefficient.9

Fortunately, these sorts of nonlinear relationships between returns on different investments can be handled in a scenario-based model. For example, in scenarios that represent normal times, returns on different equity markets could be modeled as moving somewhat apart from each other while scenarios that represent global crises could model the markets as moving downward together.

**ULTRASONIC STATISTICAL TECHNOLOGY**

Finally, we make use of new technology. Because it could take thousands of scenarios to adequately model return distributions, a disadvantage of the scenario-based approach has been that it requires large amounts of data to be stored and processed. Even with the advances in computer hardware, the conventional approach of representing scenarios with large tables of explicit numbers remained problematic. That is, until recently.

The phenomenal speed of computers has given rise to the field of probability management, an extension of data management to probability
distributions rather than numbers. The key component of probability management is DIST—Savage’s Distribution String, which can encapsulate thousands of trials as a single data element. The use of Distribution Strings greatly saves on storage and speeds processing time—a Monte Carlo simulation consisting of thousands of trials can be performed on a personal computer in an instant. While not all asset-management organizations are prepared to create the Distribution Strings needed to drive the geometric-mean-CVaR optimization, some outside vendors, such as Morningstar’s Ibbotson Associates, can fulfill this role.

Another facet of probability management is interactive simulation technology, which can run thousands of scenarios through a model before the sound of your finger leaving the Enter key reaches your ear. These supersonic models allow much deeper intuition into the sensitivities of portfolios and encourage users to interactively explore different portfolios, distributional assumptions, and extreme events often mistakenly called black swans.¹⁰

A working sample of such an interactive model is available for download from www.ProbabilityManagement.org.¹¹

**THE NEW EFFICIENT FRONTIER**

Putting it all together, we form an efficient frontier of forecast geometric mean and CVaR as shown in Figure 26.3,¹² incorporating our scenario approach to covariance and new statistical technology. We believe that this

![Figure 26.3 A Markowitz 2.0 Efficient Frontier](image-url)
efficient frontier is more relevant to investors than the traditional expected return versus standard deviation frontier of MVO because it shows the trade-off between reward and risk that is meaningful to investors; namely, long-term potential growth versus short-term potential loss.

**APPENDIX 26A: TECHNICAL DETAILS OF MARKOWITZ 2.0**

This appendix can be found on pages 333-347 of the full book.

**NOTES**

2. I discuss fat-tailed distributions in Chapters 18 and 19 of this book.
3. Ranking investment strategies by forecasted geometric mean, an idea promoted by William Poundstone (2005), is sometimes described as applying the Kelly Criterion. Markowitz explored the idea in Chapter 6 of Markowitz (1959) and currently advocates it. (See Markowitz 2010.) For a discussion on the differences between the arithmetic mean (or expected return) and the geometric mean and when to use which one, see “A Note on Expected Return and Geometric Mean” at the beginning of this book.
4. Also known as Expected Shortfall. See Chapter 19 of this book.
5. Morningstar Direct’s asset allocation module provides several return distributions for Monte Carlo simulation and optimization. See Note 6 in Chapter 27 for details.
7. Chapters 16 and 17 of this book present much of the data and content of Kaplan et al. (2009).
8. In Morningstar Direct’s asset allocation module, conditional value at risk is one of six choices of risk measure. See the appendix for a complete list.
9. See Figures 25.3 and 25.4 for examples.
10. Taleb (2004), who popularized the term, defines a black swan as an extreme event that has never occurred before, has major consequences, and can be explained after the fact. However, as documented throughout Part III of this book, extreme events have repeatedly occurred repeatedly through capital market history. Somewhat tongue-in-cheek, Larry Siegel (2010) suggests calling such events “black turkeys.”
11. The core of Morningstar Direct’s asset allocation module is a fully functional, highly interactive implementation of Markowitz 2.0. See the appendix for details on the methodology.
12. Other researchers have also proposed using geometric mean and CVaR as the measures of reward and risk in an efficient frontier. See, for example, Sheikh and Qiao (2010).

REFERENCES


