Asset Allocation in a Crash-Prone World

By Nathan Lee, CFA®, Kyle Cox, and Patrick R. Morris

Modern portfolio theory and its principal application, mean-variance optimization, have been essential and time-tested tools for many a consultant in devising asset allocations for clients. Without them, one might imagine myriad complicating factors affecting each asset class that may not add any additional clarity to what the "best" allocation ultimately would be. Instead, mean-variance optimization offers a helpful albeit highly simplified framework. However, the applicability of mean-variance optimization can be limited when quality forecasts are not available, which is always the case in highly uncertain times. In these instances, asset allocation decisions can be aided by risk-based scenario analysis.

Mean-Variance Optimization

Modern portfolio theory states that three critical attributes determine whether an asset class should make it into the final allocation: expected return, expected correlation to existing assets, and expected risk, as measured by volatility. The goal of mean-variance optimization is efficiency, that is, an overall allocation with the maximum expected return per unit of risk. This goal frequently is achieved by diversification—investing in low to negatively correlated assets. Even if an asset class has the same expected return and volatility as the current portfolio, modern portfolio theory still would prescribe an allocation to that asset class so long as it has low to negative correlation to the existing portfolio. Investing in that low to negatively correlated asset makes the final portfolio more efficient (Markowitz 1990).

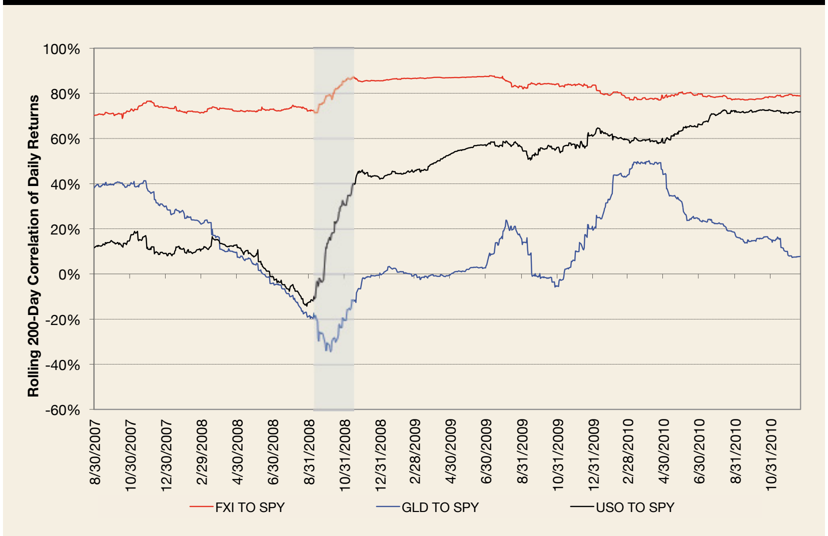
With the credit crises of 2008 and the ongoing sovereign credit issues in Europe, the effectiveness—if not the relevance—of mean-variance optimization has been attacked by several outspoken critics (e.g., Taleb 2010). Admittedly portfolio theory is a model and therefore a simplification of reality. And mean-variance optimization, like any model, follows the garbage in-garbage out rule. But mean-variance optimization often fails because forecasts that drive the model are questionable at best, not because the math underpinning the model is invalid. Forecasts often are reliably unreliable because forecasters mechanically extrapolate from historical returns, and from too-brief a period, especially in forming actuarial assumptions that guide future long-term allocations (Arnott 2004). Forecasts are possible only in steady-state environments, and at other times the crystal ball is cloudy at best.

VIX Index and Correlations

To illustrate how easily a crisis can dispose of a forecast, we need to go back to December 31, 2007. The VIX Index, commonly referred to as "the fear gauge," measures the volatility that market participants expect in the S&P 500 Index in the near-term. The VIX reflects the price investors are willing to pay to hedge or insure portfolios against market declines. The level that day was 22.5. Because the S&P 500 often can be used as a proxy for the U.S. equities asset class, the VIX can be used to form risk forecasts for a tactical allocation. Yet after the Lehman crisis, the VIX hit an intraday high of 89.5 on October 24, 2008, more than four times the initial expectation, as panicked investors paid any price to insure their portfolios against market risk.

In addition, correlations can spike in a crisis as higher volatility triggers margin calls and investors sell not what they want but what they can. When correlations rise between asset classes, investors rudely discover they are not as diversified against a market decline as they initially thought. For example, when risks—especially geopolitical risks—are high, gold and oil often rally as equity markets sell off. Oakley (2009) and others have theorized about "decoupling," where an investor can best diversify an exposure to a developed market such as the United States, which has moderate growth, a shrinking middle class, high national debt, and large trade deficits, by investing in a developing, high-growth economy such as China, which has a burgeoning middle class, large currency reserves, and trade surpluses. Hence, gold, oil, and China are popular candidates for diversifying U.S. equity exposure. In figure 1, the rolling correlations of these candidate diversifiers to U.S. stocks are modeled by using the GLD exchange-traded fund (ETF) as a proxy for gold, the USO ETF as a proxy for oil, and the FXI ETF as a proxy for the investable portion of the Chinese equity market. The Lehman-induced panic is shaded in gray and figure 1 shows a sharp increase in correlations across all three diversifiers. Correlations for gold and oil, once negative, grew positive by the time the S&P 500 hit bottom in March 2009. Instead of decoupling, the Chinese ETF correlation to the United States increased to nearly 90 percent.

FIGURE 1: ROLLING 200-DAY CORRELATION TO SPY (S&P 500 ETF)



What can an asset allocator do then when a reliable forecast is not possible and therefore mean-variance optimization is not an option? The alternative is twofold. First, expand the asset classes beyond traditional stocks and bonds to include alternative investments such as market-neutral strategies. Second, instead of relying on prediction-based models, use a risk-based scenario analysis to understand the potential losses of individual asset classes and asset mixes, which in turn should help an allocator better anticipate the ability to meet near-term liabilities.

Market-Neutral Strategies

Expanding beyond the traditional asset classes of stocks and bonds to include market-neutral strategies can dramatically improve the return per unit of risk achieved in a portfolio. This is the case because a market-neutral strategy, when properly constructed of both long and short securities, is inherently nondirectional by design. It therefore has lower volatility and lower correlation to buy-and-hold, long-only equity strategies such as indexing, which have a big directional or "beta" component of risk. Asset mixes including market-neutral strategies should have more robust diversification even in a rising-correlation environment.

Why? As correlations across stocks rise, the stocks sold short will become more correlated to the stocks held long, making them even more effective as hedges in a market decline. This is not the case, for instance, in a mix of international and domestic stocks held long; any diversification benefit of the international stocks proves fleeting as correlations rise in a declining market.

Risk-Based Scenario Analysis

Next, analyze your asset classes and different asset mixes under different risk scenarios. As of this writing, debate continues about the likelihood of near-term deflation or inflation, both of which can have significant effects on markets and the economy. The deflationary camp will point to a lower velocity of money, higher lending standards, high unemployment, lower consumer spending, and high corporate cash levels to argue its case. The inflationary camp will mention rising commodity prices (especially in agricultural goods), the immense liquidity resulting from record monetary easing and fiscal stimulus, and creeping protectionism.

If there were a high probability of inflation or deflation, what would the impact be on different asset classes? To sketch out an answer, mean-variance optimization would be a rather blunt tool, because it requires single estimates of an asset's return, volatility, and correlation that are assumed to be static for the investment horizon, regardless of whether the economy swings between deflation and inflation in the interim. For example, if assets were modeled under the expectation of deflation, and inflation was to actually occur, then the asset mix would prove too-heavily allocated to bonds. If estimates assumed inflation and deflation actually occurred, then the mean-variance optimization could be significantly overallocated to stocks—a devastating outcome if current or soon-to-be retirees are involved.

Monte-Carlo Simulation

In contrast, Monte Carlo simulation does not assume static estimates; it uses computers to simulate a range of values for key variables such as interest rates and equity returns, first in a deflation scenario and then in an inflation scenario. Monte Carlo simulation allows the allocator to see a distribution of potential gains and losses for different asset mixes in both the inflation and deflation scenarios. For an allocator who thinks the odds of inflation or deflation are 50–50 at best, the asset mix with the smallest losses in either scenario would be very interesting.

To illustrate, we ran an historical Monte Carlo simulation where periods of high expected inflation were defined as periods where the yield curve slope (the yield spread between the 10-year and 90-day Treasuries) is more than 3 percent (Bodie et al. 1999). A period where the slope of the yield curve is negative was defined as a period where deflation is expected. We simulated thousands of periods by sampling historical monthly returns of U.S. stocks (proxied by the Russell 1000), U.S. bonds (proxied by the Lehman/Barclays Aggregate Bond Index), and market-neutral strategies (proxied by the Hennessee Market Neutral Index).

A high probability of inflation was modeled by sampling more frequently from periods where the yield curve has a slope greater than 3 percent. A high probability of deflation was modeled by sampling more frequently from periods where the yield curve has a negative slope. For example, in a scenario where the probability of inflation is 100 percent, we exclusively sampled returns from months where the yield curve slope is more than 3 percent. The Value-at-Risk (VaR) measure (90-percent confidence level) of each asset class was computed under each scenario and charted in figures 2 and 3. In figure 2, if the probability of inflation increases, the VaR return of U.S. bonds decreases, intuitively. This is seen in the decreasing red bars reading from left to right. Stocks do not have as regular or as persistent an increase in losses even as the probability of inflation increases. However, the VaR levels are more severe for stocks, which may be surprising for those who think stocks are effective inflation hedges. Stocks also will struggle in periods when the Federal Open Market Committee raises rates to stem inflation and corporations may not be able to preserve margins by automatically passing cost increases to customers. Market neutral is the asset class that has the lowest VaR levels, even if the probability of inflation is high, and this could be a relative haven for incremental allocations.

Figure 3 shows a relationship of increasing losses for equities as the probability of deflation increases. Bonds have decreasing losses as the probability of deflation increases, but again market neutral ranks best.

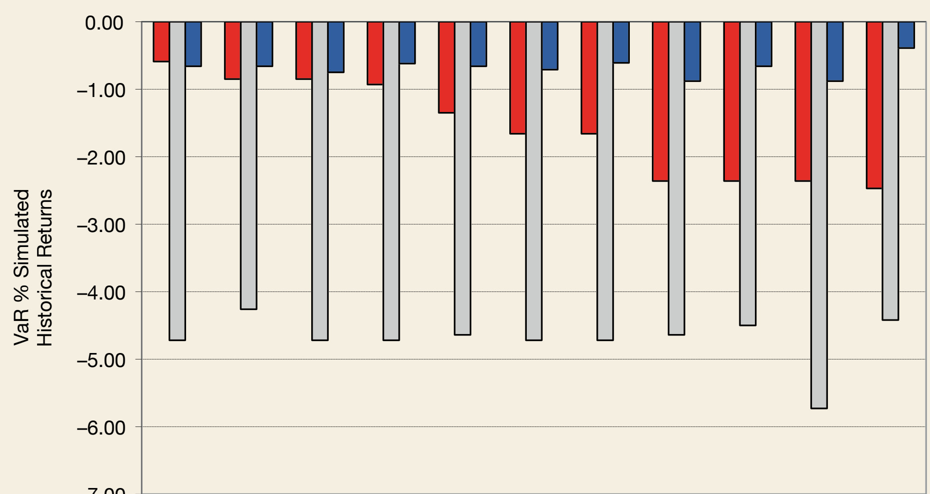
Asset Allocation

After all of this analysis, how is one to allocate cash then? Regardless of whether one thinks deflation or inflation is probable, or is completely neutral on the question, allocating incremental cash to market-neutral strategies should blunt the impact of any crash on portfolios heavily overweight in stocks and bonds.

Scenarios aside, where have actual, significant allocations gone in the period leading up to the tumultuous months of May and June 2010, when sovereign credit risks and the flash crash caused a –12.7-percent decline in the S&P 500? Bloomberg reported on April 13, 2010, "Speculative-grade bond funds had $417 million of inflows last week, the seventh-straight increase, and loan funds had $290 million of inflows, the 19th in a row and the longest stretch ever" (Detrixhe and Peker 2010). The allocation to junk bonds is not surprising in the context of behavioral finance theory, where humans are observed to mechanically rely on heuristics such as simple averages, be overconfident in their ability to predict returns and time risk, and anchor expectations to the recent past, often

FIGURE 2: EXPECTED 90% VAR VALUES FOR ASSET CLASSES AS LIKELIHOOD OF INFLATION INCREASES

If probability of above trend inflation ≥50%, market-neutral losses significantly less severe than stocks and bonds simulated monthly returns for the Russell 1000, Lehman Aggregate, and Hennessee Market Neutral Index (December 31, 1992–November 30, 2008)

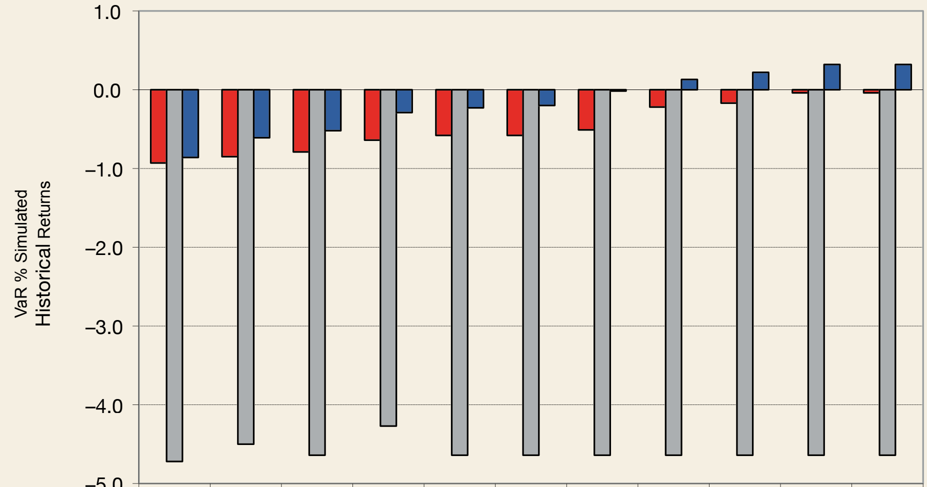


	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Lehman Aggregate Bond Index	–0.59	–0.85	–0.85	–0.93	–1.35	–1.66	–1.66	–2.36	–2.36	–2.36	–2.47
Russell 1000 Stock Index	–4.72	–4.26	–4.72	–4.72	–4.64	–4.72	–4.72	–4.64	–4.50	–5.73	–4.42
Hennessee Market Neutral	–0.66	–0.66	–0.75	–0.62	–0.66	–0.71	–0.61	–0.88	–0.66	–0.88	–0.39

Probability Yield Curve > 3

FIGURE 3: EXPECTED 90% VAR VALUES FOR ASSET CLASSES AS LIKELIHOOD OF DEFLATION INCREASES

If probability of deflation ≥50%, market-neutral losses significantly less severe than stocks and bonds
simulated monthly returns for the Russell 1000, Lehman Aggregate, and Hennessee Market Neutral Index
(December 31, 1992–November 30, 2008)



	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Lehman Aggregate Bond Index	–0.93	–0.85	–0.79	–0.64	–0.58	–0.58	–0.51	–0.22	–0.17	–0.04	–0.04
Russell 1000 Stock Index	–4.72	–4.50	–4.64	–4.27	–4.64	–4.64	–4.64	–4.64	–4.64	–4.64	–4.64
Hennessee Market Neutral	–0.86	–0.61	–0.52	–0.29	–0.23	–0.20	–0.01	0.13	0.22	0.32	0.32

Probability Yield Curve < 0

TABLE 1: MEAN-VARIANCE OPTIMIZATION INPUTS FOR JNK AND SPY ETFS

One Year Ending April 13, 2010	JNK (U.S. High-Yield ETF)	SPY (S&P 500 ETF)
Annualized Average Return	26.8%	35.0%
Annualized Risk	14.3%	17.9%
Correlation to S&P 500	56.1%	100.0%

extrapolating short-term results far into the future (Shefrin 2007). The JNK ETF, which tracks the Lehman/Barclays High Yield Index, is a reasonable proxy for junk bonds as an asset class. Table 1 shows mean-variance optimization inputs using the near-term one-year period ending April 13, 2010, for the JNK ETF and the SPY ETF.

With these inputs, an investor targeting a final portfolio volatility of 15 percent per annum would achieve an optimal portfolio by allocating roughly two-thirds of cash to stocks and one-third to high-yield bonds. Such a portfolio would have outsized cumulative losses of –10 percent in only two months, May and June 2010, as credit concerns resurfaced. The Hennessee Market Neutral Index was down only –0.31 percent for those two months and related strategies would have done a better job mitigating losses. Unrealistic inputs and a very limited menu of asset class options resulted in a counterintuitive outcome: Buy junk bonds with recent less-than-perfect correlation to stocks and lower volatility to diversify the risk of an equity portfolio. However, in a simultaneous liquidity and credit crisis, junk bonds hardly will prove to be diversifiers.

Conclusion

Mean-variance optimization is formulaic; scenarios instead are more open-ended. Perhaps therein lies the great advantage of risk-based scenario approaches to asset allocation. The open-ended nature of scenarios compels allocators to ask questions to identify the pertinent risks as well as the likelihood of their occurrences. Allocators today have a much tougher job than those of 20 years ago. In 2008, two of the largest investment banks failed in the same year. In 2010, the Dow index of blue chips plunged 10 percent in a single day, entire governments saw their debts come under pressure, and the Federal Deposit Insurance Corporation seized more than 150 U.S. banks. Have we entered a new era where markets in general are more prone to crashes? Even if this should prove to be the case, a risk-based scenario approach to asset allocation should help financial planners better navigate uncertain markets that are beyond the reach of conventional tools and defy forecasting. I&W

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Nathan Lee, CFA®, is the lead portfolio manager at HAGIN Investment Management. He earned an AB in cell biology from Cornell University, and an MBA in finance with distinction and an MS in statistics, both from New York University. Contact him at nlee@haginim.com.

Kyle Cox is an associate portfolio manager at HAGIN Investment Management. He earned a BA in economics from Trinity College and is a CFA Level III candidate. Contact him at kcox@haginim.com.

Patrick R. Morris is chief executive officer of HAGIN Investment Management. He earned a BA from Syracuse University and an MS in political communication from Emerson College. Contact him at pmorris@haginim.com.

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