Modeling Fund and Portfolio Risk: A bi-modal Approach to Analyzing Risk in Turbulent Markets

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ABSTRACT

Following the financial crisis of 2008, it has been argued that Value at Risk (VaR), and risk analysis in general, failed to alert risk managers of the turbulence on the horizon. This is a misguided view that should not have come as a surprise because many widely circulated academic papers and discussions suggested, well before the crisis, that simple VaR results could easily be misinterpreted if the circumstances for its proper use are not fully understood. This paper addresses some ways in which VaR concepts may be applied more effectively. Non-standard Monte Carlo simulations are utilized. Whereas standard mean-variance defined methodologies using Monte Carlo analysis may not capture how “fat” a lower tail may actually be, a bi-modal switching structure between assumed normal periods and possible turbulent economic periods may help resolve the problem. Lower boundaries (worst case paths) of the different (normal versus bi-modal) processes are mapped to illustrate implied riskiness of portfolios if turbulence occurs. The analysis implies that no mechanical risk analysis is sufficiently divorced from a judgment call about possible market disruptions; however, a bi-modal approach allows quantification of said judgment in conjunction with empirical observations from history.

JEL Classification: G11, G12, G13, G17

Key Words: Risk Analysis, Monte Carlo, Portfolio Diversification, Commodity Futures
Following the financial crisis of 2008 and 2009 it has been argued that Value at Risk (VaR), and risk analysis in general, has failed the profession and the economy by misleading professionals to underestimate the risks in the system. Its usefulness is in doubt and major “fixes” have been suggested. Interestingly, arguments against VaR are not new. Many widely circulated papers and discussions argued well before the crisis that simple VaR could be very misleading. As such the degree to which rating agencies and regulators were wedded to a simplistic approach to risk analysis is even more troubling. Claims became commonplace that Markowitz approaches to risk diversification and supposed failures of VaR like methodologies created the crisis.

With respect to Markowitz these claims seem totally unfair. When a Dean of a major Business School denounced Markowitz contribution suggesting that he give back his Nobel prize in economics, it underscored how poorly these basic theories that Markowitz introduced were understood. The misperceptions led to dependence on simplistic risk modeling, resulting in simple-minded approaches that would no doubt lead to false conclusions. It was not the fault of Markowitz theory nor was it for a lack of academic material suggesting how that theory and risk analysis should be utilized correctly that triggered the crisis.

The culprits most accused of “causing” the crisis by the media were the mortgage back securities (MBS) industry, hedge funds, structured investment vehicles (SIVs), and of

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1 See, among others, Alexander and Sheedy (2008), Pritsker, M. (2006), Putnam, et al. (2002), Taleb (2008), and Angelidis, and Degiannakis (2007). These references discuss shortcoming and/or provide good background to show that the issues of misapplication of VaR approaches were known well before the crisis in the literature.

2 Wilford (2012) discusses the issue of misinterpretation of Markowitz portfolio optimization at length as well as some of the dangers of a simplistic application of the basic tenants to risk analytics.
course the banks. At the heart of the crisis was home mortgages. So what role then did VaR play, even in simple form?

Following the LTCM (Long Term Capital Management) crisis of 1998, many managers (in particular those familiar with both MBS management and Markowitz theories) argued that a simplistic VaR, based upon a normal distribution, would lead to false estimates of actual risk of MBS funds, certain debt portfolios, debt-inked hedge funds and other similar financial structures. The logic was simple. Debt is effectively an option on the value of the firm (or houses) and as such entities that buy the debt are writing said options. History based return estimations utilized to calculate the risk associated with any structure that is debt-based will inherently underestimate the structure’s actual risk. SIVs incorporated almost all of the characteristics of simple option writing, allowing the easy inference that VaR or Monte Carlo simulations based solely on historical observations would underestimate risk of the structure. As such other risk measurement systems would be needed to correctly judge the risk associated with such a structure. Certainly for debt in a leveraged or hedged (short repos or treasuries) fund an options theoretic approach was well entrenched in the literature as a way of determining the probability of default.

MBS-related markets were not the only ones affected by the 2008 crisis. All markets reacted violently. Risk rose dramatically. Although debt’s option-like characteristic led to underestimation of risk such mis-measurement was not isolated to debt (non-treasury) markets. It permeated all markets. In retrospect it is easy to say that one should have understood that all markets are affected in a crisis. As they were in 1987 Black Monday stock market shock crash, the Fed tightening in 1994, the 1998 – 99 LTCM and Asian contagion crises and that followed the 9/11/2001 attack on New York. The degree and duration of these events varied, but a major change in risk occurred in most markets at every crisis point. If crises are not unusual, the methodology utilized to measure risk should reflect this fact.

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3 During 2006 and 2007 and even up until the emergence of the crisis itself with the demise of Lehman personal experience with investors demonstrated the lack of understanding of this type of bias. When discussing information or Sharpe ratios with investors one could easily be confronted with an investor that claimed to have opportunities with information ratios of 2.5 or 3 or better. The persons usually had a MBA from a major university and actually had no clue that such information ratios were useless measures (the flip side of VaR underestimating risk would be an ex post overestimation of the information ratio). There was no basic understanding of the underlying assumptions necessary for an information ratio to actually provide useful information. In almost all of these cases the funds that they cited as having very high information ratios were based upon high yield debt, ABS or MBS structures.

4 In particular Smithson and Hayt (2001) discuss the inappropriate nature of simplistic MPT and management of debt instruments.

5 See Wibaut and Wilford (2012) for several examples that demonstrate the implications for non-treasury debt during the period of heightened uncertainty and dramatic declines in the value of the firm during the recent crisis.
With evidence that a crisis occurs every 5 to 10 years, risk modeling, even when applied to funds that have “good” underlying risk and return measures, must consider jumps in risk and therefore the probability of significant shifts in returns from those expected turbulences. Doing so implies a bi-modal type risk analysis for any fund, not just those that are based upon embedded options.

I. Crises are Normal

Some justification of the 5 to 10 year “crisis” approach can simply be argued by observing a graph of the S&P since 1980. Chart I below calculates the percentage change in the S&P on a 6-month rolling basis. Since a recession is officially calculated as six straight months of negative growth, a similar time period was utilized in calculating the graph. Monthly data are used with the methodology in equation 1.

\[
\text{Percentage Change} = \frac{S&P_{t+6} - S&P_t}{S&P_t}
\]  

(1)

where \( S&P \) is the value of the S&P 500 stock index.

The negative six-month rolling periods are highlighted in red. A casual glance supports the idea that there were 8 or more periods of significant disruption over the past 30 years. This is more than sufficient to suggest that there is some 20% or more probability of a disruption occurring. Other methods will argue for a greater probability while some may argue for something less, although a probability of a
turbulent period occurring less than 20% of the time seems unlikely. There are several years of no serious disruptions, especially during the ’90s, but with the tech wreck bursting the dot com bubble and the Asian contagion the wondrous period came to a screeching halt. Similar arguments are apropos to the post 9/11 recovery. It was long and solid until it ended in a severe crisis. Estrada (2007) argues that if we look longer across many markets, it becomes even more apparent that such periods of disruptions should be expected. Rutledge (2015) builds a case of turbulence when various marketplaces get out of “time sync” once there is uncertainty introduced by, say, unexpected policy changes.

We start with a probability of 20% that there will be sufficient turbulence to significantly affect the markets and disrupt expectations. In turn these lead to large price and volatility changes, as well as significant changes in the correlations not only of the prices of the underlying assets but also the errors in forecasts of expected returns.6

II. Creating Diversified Portfolios

Putnam (2012) points out that markets which are linear in individual risk (such as a forward foreign exchange contract) can exhibit periods where options-type approaches to risk are more appropriate. That is, inherent in these markets are periods when jump processes, which in and of themselves, cause large shifts in volatility and return expectations. As such, portfolios that utilize these instruments should consider such possibilities and attempt to measure risk accordingly. If markets that tend to fit a Markowitz optimal world (eliminating the most blatant processes which would skew a Markowitz related risk measure) can be affected by these processes, then a standard optimization may be used to examine whether a bimodal approach to risk management deals with disruptions more effectively than traditional approaches. The portfolios that are utilized in this paper are based upon in-sample forecasting and volatility estimation, thereby maximizing the likelihood that they prove to be “better” portfolios (in the mean variance sense of better); that is, the resulting information and Sharpe ratios should have more meaning than, say, ones derived from MBS portfolios.

To provide enhanced diversification we will consider portfolios that contain several unrelated commodities, thereby providing more of a mix of performance possibilities during a jump process, if it is to occur. These portfolios will be long-short, optimized with a risk target in mind, unconstrained, and in excess return space; they are not useful for managing money, however, due to the bias built into them via in-sample measures of return, risk and correlation. One portfolio considered is forced to be long only, not via constrained optimization, but rather through a process of adjustment of expected returns.7

6 Markowitz focused on the correlation in errors in forecasting. We often forget this fact when casually using correlation of prices, ex post.
7 These portfolio summaries are taken from research reported in Wilford (2014).
Primary to the purpose of the exercise is to consider in what manner bi-modal distributions may, or may not, be better ways of examining risk for all, including strongly (positively) biased, portfolios. As such, the portfolios themselves may be thought of as stand-ins for individual funds that could be considered by any investor. Fund of funds managers, pension funds, and foundations, as examples, all tend to make allocation decisions based upon track records and information or Sharpe ratios. An end goal of the exercise is to raise awareness of the implications for leverage when investing in such a fund or structure, hypothetical as in this exercise, or real.

IIa. Proxy Portfolios

Four portfolios are created utilizing the asset classes shown in table 1.

<table>
<thead>
<tr>
<th>Asset</th>
</tr>
</thead>
<tbody>
<tr>
<td>S&amp;P 500 Index</td>
</tr>
<tr>
<td>U.S. Treasury 10-year</td>
</tr>
<tr>
<td>Cash (US Dollar)</td>
</tr>
<tr>
<td>Oil</td>
</tr>
<tr>
<td>Natural Gas</td>
</tr>
<tr>
<td>Gold</td>
</tr>
<tr>
<td>Copper</td>
</tr>
<tr>
<td>Corn</td>
</tr>
<tr>
<td>Wheat</td>
</tr>
</tbody>
</table>

All are created in excess return space, allowing for leverage to be built into the portfolio if needed. Estimated standard deviations are all approximately the same at 10%. Portfolios are designed to include commodities, both hard and soft, to provide diversification characteristics that differ from standard asset allocation models. The optimizations are unconstrained and thus by definition long-short. A long only portfolio is created artificially by adjusting expected returns, while utilizing the variance covariance matrix apropos for the post crisis period.

Portfolios are created based upon four recent periods: Pre-Crisis, Crisis, Post-Crisis and Post Crisis Long Only. Excellent summary characteristics are derived from each portfolio. Each portfolio has information ratios, resulting from in sample estimation; the optimizer “believes” that a factual Markowitz set of assumptions are at play. In fact, with in-sample estimations one has essentially broken a key assumption of portfolio optimization, negating confidence that these could be useful portfolios for investment. For our purposes, the strong summary statistics provide the basis for comparison of the portfolios from a risk modeling perspective.
The periods covered are: 2005 through September of 2008 for the pre-Crisis. The Crisis period is 2008 October through March 2009 and the post crisis period goes from March 2009 through 2011. Table 2 presents the Summary Data. Post Crisis data were utilized when building the Long-Only Portfolio.

<table>
<thead>
<tr>
<th>Period/Statistic</th>
<th>Pre-Crisis</th>
<th>Crisis</th>
<th>Post-Crisis</th>
<th>Long only</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expected Excess Return</td>
<td>14.65%</td>
<td>13.30%</td>
<td>19.62%</td>
<td>16.29%</td>
</tr>
<tr>
<td>Expected Variance</td>
<td>1.05%</td>
<td>1.02%</td>
<td>1.01%</td>
<td>1.12%</td>
</tr>
<tr>
<td>Expected Standard Deviation</td>
<td>10.23%</td>
<td>10.11%</td>
<td>10.03%</td>
<td>10.60%</td>
</tr>
<tr>
<td>Information Ratio</td>
<td>1.43</td>
<td>1.31</td>
<td>1.96</td>
<td>1.54</td>
</tr>
<tr>
<td>Implied Leverage</td>
<td>0.00%</td>
<td>0.00%</td>
<td>188.13%</td>
<td>152.04%</td>
</tr>
</tbody>
</table>

Please note that the Post-Crisis and long-only portfolios are leveraged. Risks are designed to be similar, with returns allowed to vary.

IIb. Simplistic Risk Analysis

The first measure one would consider if these were five-year track records of, say, a hedge fund operator would be the information ratios. Based on these information ratios one would assume that each of the management styles was more than acceptable (of course they were biased by in-sample estimations). Given the Markowitz diversification process utilized to generate these ratios, the implicit bias in the ratios does not come from the type of fund itself (a la MBS or high yield), something one must always consider in actual practice. The second line of analysis would consider the fact that two of the funds are leveraged to obtain the returns that they have – since all of the styles are similar the information ratio will not change with leverage, just the return prospects – so for Monte Carlo simulations, with similar leverage, this may or may not matter. Standardization above was based upon risk levels, not return levels. Though potentially hazardous, this type of comparison analysis is not unusual. Given that the distribution of risk has been generated with an optimization procedure, one may stop here in the analysis or perhaps generate Monte Carlo boundaries from the data. Obviously we believe doing so would be naïve.

IIc. Paths of Actual Performance of Proxy Portfolios

Before simulating the return possibilities of these four proxy portfolios we examine the actual performance of each of these over the entire period. To do so first assume that $10,000 is invested in each portfolio in January of 2008. Below is a graph of the actual performance of each portfolio. As would be expected a portfolio that is designed to perform well during the pre-crisis period, as well as the long only portfolio and the post crisis portfolio, lost between 25% to 40% during the crisis. The portfolio designed for the crisis did well, again as would be expected. The
performance paths are interesting since these same proxy portfolios performed well after the crisis. And, as would be expected, the best performance after the crisis was the Post-Crisis portfolio in-sample optimization. The bias of in-sample optimizations clearly shows up in these comparisons.

The stark differences in the portfolios’ performance shown in Chart 2 can be attributed to the usual suspects (well defined in-sample optimizations and thus biased measures of expected returns and volatility estimates). What is not so obvious, but a huge factor, is the radical differences in the variance covariance matrices between the crisis portfolio and the rest. In many ways this lies at the heart of the risk measurement problem. During shocks, correlations change dramatically; some flip signs, some tend toward extremes, and basically relationships change significantly. Typical Monte Carlo modeling does not fully consider this reality, which tends to occur during a crisis.\(^8\) Table 3 contrasts the correlations of the Pre-crisis period with that of the crisis as an illustration.

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\(^8\) See Chapters 8 – 11 in Haslett (2010) for a discussion of this issue. Also see Putnam and Wilford (2000) for a general discussion of this issue as it relates to portfolio management.
Table 3: Correlations during Pre-crisis and Crisis periods of S&P to Alternative Assets

<table>
<thead>
<tr>
<th>Asset</th>
<th>Correlation to S&amp;P Pre-Crisis</th>
<th>Correlation to S&amp;P Crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td>US Treasury 10-Year</td>
<td>-0.3372</td>
<td>-0.4875</td>
</tr>
<tr>
<td>Cash (USD)</td>
<td>0.0111</td>
<td>-0.0249</td>
</tr>
<tr>
<td>Oil</td>
<td>-0.0336</td>
<td>0.3318</td>
</tr>
<tr>
<td>Natural Gas</td>
<td>0.0225</td>
<td>0.21</td>
</tr>
<tr>
<td>Gold</td>
<td>-0.1149</td>
<td>-0.0163</td>
</tr>
<tr>
<td>Copper</td>
<td>0.1371</td>
<td>0.308</td>
</tr>
<tr>
<td>Corn</td>
<td>0.0309</td>
<td>0.2774</td>
</tr>
<tr>
<td>Wheat</td>
<td>0.0311</td>
<td>0.3622</td>
</tr>
</tbody>
</table>

The sign flip in oil and cash to the S&P should be noted. During the crisis, cash had a negative correlation to almost everything, a significant change from pre-crisis for most assets. The magnitude changes we see above are also interesting. Gold became almost zero correlated with the S&P, all of the commodities became much more correlated, losing much of their traditional value of being close to zero correlation with stocks. Wheat and corn exhibited very large changes. Further, commodity correlations moved dramatically with respect to treasuries. For example, oil’s correlation to treasuries went from a near zero negative correlation to a positive 43% correlation. This is a massive change and reflects the instability of even average daily correlations.

Swings in correlations do not occur in isolation. Changes in volatility are often the reason for such significant changes as pointed out by Putnam, et. al. (2002). To see how greatly volatility changed consider Table 4. Most standard deviations at least doubled during the crisis. Only one did not (natural gas). The S&P index volatility rose almost 4 times, extreme by any measure and oil volatility almost tripled.

Table 4: Standard Deviation of each asset class for each time period

<table>
<thead>
<tr>
<th>Asset Class</th>
<th>Period</th>
<th>Pre-Crisis</th>
<th>Crisis</th>
<th>Post-Crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td>S&amp;P500 Index</td>
<td></td>
<td>16.13%</td>
<td>57.55%</td>
<td>18.88%</td>
</tr>
<tr>
<td>US Treasury</td>
<td></td>
<td>6.25%</td>
<td>12.02%</td>
<td>6.85%</td>
</tr>
<tr>
<td>Cash (USD)</td>
<td></td>
<td>0.09%</td>
<td>0.09%</td>
<td>0.00%</td>
</tr>
<tr>
<td>Oil</td>
<td></td>
<td>34.25%</td>
<td>95.92%</td>
<td>30.09%</td>
</tr>
<tr>
<td>Natural Gas</td>
<td></td>
<td>61.03%</td>
<td>54.74%</td>
<td>45.13%</td>
</tr>
<tr>
<td>Gold</td>
<td></td>
<td>16.99%</td>
<td>38.25%</td>
<td>18.21%</td>
</tr>
<tr>
<td>Copper</td>
<td></td>
<td>28.29%</td>
<td>69.56%</td>
<td>27.79%</td>
</tr>
<tr>
<td>Corn</td>
<td></td>
<td>25.64%</td>
<td>51.48%</td>
<td>33.03%</td>
</tr>
<tr>
<td>Wheat</td>
<td></td>
<td>28.99%</td>
<td>49.24%</td>
<td>37.97%</td>
</tr>
<tr>
<td>S&amp;P500 Index</td>
<td></td>
<td>16.13%</td>
<td>57.55%</td>
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</tr>
</tbody>
</table>
Instability in correlations as well as dramatic changes in volatility and expected returns garnered from the sampling process, while building the portfolios, led to the dramatic performance shifts of the portfolios, with respect to the three periods considered. Said swings in correlations and volatilities are inconsistent with a standard normal Monte Carlo simulation, arguing for the use of one that considers shifts in the distribution of risk during periods of crisis. 9

III. Simulations and Boundary Conditions

First, simulations using a standard VaR type approach will be modeled and lower boundary conditions estimated; two forms are considered: an expected return of the fund itself and a standard deviation of 10% as well as a 0% expected return with a 10% standard deviation. In all of our portfolios we targeted approximately a 10% standard deviation. Second, we allow for the probability of a recession. In this case the bi-modal distribution of risk is modeled. 10

IIIa. Methodology

We model the fund using the following stochastic process:

\[ S_{t+\delta t} = S_t \times e^{\left( (r - \frac{1}{2} \sigma^2)\delta t + \sigma \sqrt{\delta t} \varphi \right)} \]  

(2)

where, \( S \) is the starting value of the fund, \( r \) is the fund return, \( \sigma \) is the fund’s volatility, \( \delta t \) is the time step (1 month), and \( \varphi \) is a random variable with a standard normal distribution.

The simulations are run for a period of 5 years (60 months). We run 10,000 trials for each simulation. Each fund’s possible paths is derived from its expected excess return (see table 2) and volatility of 10%. We also simulate a fund with 0% expected return (zero-return portfolio) and 10% volatility. In the naive bi-modal simulation the scenario of 0% expected excess return and 10% volatility, occurs with 80% probability. Twenty percent of the time the return distribution changes to one with an expected return of -10% and volatility of 20% (we call this the recession state).

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9 One more issue needs consideration before considering Monte Carlo simulations. Two of the portfolios, albeit with the targeted risk of approximately 10% are heavily leveraged (given the perceptions of risk in the modeling). Adjusting these portfolios for risk inherent in the leverage is always open to question. In considering the true danger in any program of investment that one attempts to do with a Monte Carlo simulation the inherent leverage should be considered when observing boundary conditions and probability of default from further leverage.

10 This process follows Norland and Wilford (2002).
When this happens (occurrence of recession state) the fund’s distribution of returns changes (we enter a recession period). With 50% probability the expected return is 0% and volatility is 20% (good recession state) and with 50% probability the return is -10% and volatility is 20% (bad recession state). If we get the good recession state for four months in a six-month period then we assume a switch back to the non-recession state of the world where the fund’s return distribution $r=0\%$ and $\sigma=10\%$ with 80% probability and $r=-10\%$ and $\sigma=20\%$ with 20% probability. When we apply this bi-modal simulation approach to the portfolios below the expected return used in the good state of the world and applied 80% of the times is each fund’s expected return (e.g. 14.65%, 13.30%, 19.62%, 16.29%) and not 0% as in the naïve bi-modal. Everything else remains the same.

After all 10,000 trials are run in each simulation we record the lowest return for each of the 60 periods and we use these observations to plot the lowest possible return boundary noted in the next section. On the y-axis of Chart 3, 1.00 denotes the original investment amount and can be scaled to the principal utilized in the simulations throughout the paper.

### IIIb. Lower Boundaries

Lower boundaries for basic Monte Carlo simulations are calculated based upon monthly observations. By considering the stated expected returns in the simulations we note that the downside risk is mitigated over time (12-month periods given the way we have specified the system). A leveling out is observed in Chart 3. This is representative of what one would expect in a normal world in a 5-year period, given the effective information ratios embodied in the Monte Carlo simulations.

The same standard deviation, again assuming a normal distribution, but with an expected return of 0% is mapped. Doing so provides little or no information. That is, with a standard normal distribution the mapping is simply the bottom side of the cone of outcomes of any standard normal based upon the standard deviation. These data are also presented in Chart 3.11

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11 In the Charts note that the horizontal axis is number of months implied by the simulations and the vertical axis shows the lower boundaries of returns such that a boundary of 1.00 will imply a 100% of return of the investment while a .60 implies a point that implies only a 60% return of investment. Or, 0.40 implies a 60% loss of investment at this point on the boundary.
Next assume that there is a mechanism for a disruption in the markets and some turbulence per Rutledge. In these cases the simulations follow assumptions that there are two possible states of conditions as laid out in section IIa. These simulations provide a very different picture of possible outcomes. With the probability of a transition to a shocked state for the markets of 20 per cent and an expected return of zero under this scenario, the lower boundary conditions are suggestive of the potential for large losses, if a period of turbulence does arise. If a simple VaR or a simple Monte Carlo does not provide sufficient information about downside risk, it is also logical to argue that periods of turbulence do not last forever. That is, normalcy does return. If one did not believe this to be the case then any confidence in an investment strategy would not be logical. As such, allowing both for a disruptive mechanism and also a recovery mechanism is necessary if the risk measurement is to provide useful information.

Hence the quality of these estimations of potential downside are very much dependent on the assumption of how easy it is to snap back to a normal period. Once having switched to the turbulent period, this methodology assumes that it must be clear that the turbulence is over and that the markets have returned to normality. To accomplish this the simulations must show positive returns 4 out of 6 months in Switching Rule (SR) 1 in Chart 4, while SR 2 imposes a rule that there must be at least 3 consecutive months before the switch is made to a normal period of returns and risk. At this point the simulations return to the distribution reflecting the risk and a return of the normal period. In the two simulations in Chart 4, the normal period has $r=10\%$ and $\sigma=10\%$, the good recession state $r=0\%$ and $\sigma=20\%$ and the bad recession state $r=-10\%$ and $\sigma=20\%$. The difference between the two curves reflects the difference in the switching rule mechanism.
Note, however, that the downside may be overstated. If we assume a quick comeback to the “normal” economy, which has an 80% chance of remaining intact once it occurs, and the overall expected return is rather high, these lower boundaries will look different. Under these conditions the expected return overwhelms the downside possibilities.

Next, consider the same switching mechanisms applied to the optimized portfolios highlighted in Charts 5a and 5b which are based upon estimated portfolios noted in Chart 3. The difference in the two charts is stark. Choice of a switching mechanism is critical to the information that is ascertained when examining an investment style, as well as the environment when an investment is made. A judgment call by the user of the bi-modal approach is implied; we believe that this is part of the art of successfully applying any risk management technique.
From a practical standpoint, this type of analytics provides a good sense of what may occur with a successful (ex post) program when considered ex ante with (under an assumption of) potential turbulence. In addition, it highlights the duration one should consider that turbulence could last.

Focusing upon the Pre-Crisis portfolio, simply to narrow the discussion, Chart 6 presents a comparison of the bi-modal distribution lower boundary results using SR 1 versus the Simple estimate of the lower boundary. This example highlights the immediate effect on the lower boundary of allowing for a shock.
For analytical purposes several variables can be adjusted in this methodology. First, consider a probability of a disturbance adjustment. Based upon one’s concerns, it can be adjusted upward or downward just as the expected increase in volatility can be adjusted upward or downward. Chart 7 below maps the lower boundaries for three different simulation setups. The first one is the bi-modal simulation where the probability of the recession state is 20% (exactly the same as Bi-Modal SR 1 in chart 6). The second is a simulation where the probability of the recession state is 30% (all other distribution parameters stay the same). Finally, in the third setup the probability of the recession state is 30% but the volatility of returns is now also 30% (compared to \(\sigma=20\%\) in the previous two cases); interestingly a tripling of volatility of the underlying return series is not at all unusual during periods of market turbulence. Again, this graphic assumes SR 1.
Once the methodology is understood, then adjustments in switching mechanisms probabilities, volatilities, and time periods needed for adjustment are decisions that must be made by the user to approximate the fears that should be considered. This mechanism is very different from that used in a naïve VaR approach, or by basing one’s investment decision on a Sharpe Ratio or Information Ratio. Judgment is needed; price history is not enough.

IV. Applying the methodology to Fund Investment

Investment in funds based upon information ratios (summary statistics), especially those that could have market behavior similar to that mapped above (pairs trading, bond spread trading, any long-only fund, credit funds, as well as equity long-short), “normal” period expectations may provide little or no information concerning performance during periods of serious stress. The degree to which one should

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12 Another experiment also proved very interesting. If one assumed that in a recession the portfolios would remain in the lower area of the bi-modal approach then the lower boundaries are much lower and should concern anyone actually fearful of a more serious turbulent period. For those that think such a possibility is far removed, consider that many of the world’s markets have witnessed periods of non-existence. One of the reasons that the FTSE and the US markets are utilized in long term studies is that they are the only ones not significantly interrupted; thus they are the only ones that truly long dated and not biased the discontinuity that is inherent in almost every other market in the world.

model the probability of the disruption should be driven by the nature of the fund itself. Is it already leveraged? Will a general rise in volatility of the individual components of investment lead to offsets, leaving the actual volatility unaffected? As risk rises what happens to correlations of the components being traded?

These factors will all combine (offset) in a manner that will suggest the correct implication for a turbulence to cause significant losses (or outsized gains) for the investment. In the approaches above no consideration was taken for leverage; however, both the post-crisis portfolio and the long-only portfolio are already leveraged. In applying this methodology to investment in a fund, once the above factors are considered, the leverage factor must be analyzed.

Structured Investment Vehicles (SIVs) of MBS assets are a prime example of underestimation of the potential for a turbulent event to “knock-out” the investor before there is a chance for “normalcy” to return. If the above methodology were applied to a typical SIV, what probability would one consider for turbulence occurring? Perhaps one similar to what was assumed above. Focusing on the lower boundary of Chart 5a, one could ask the question, “at what leverage ratio would each methodology suggest that all the equity would be lost in a tail event?” Depending on the expected return (various models above) such a catastrophic loss would occur more easily with a much lower leverage as illustrated in Chart 8. The implications are clear. Using a straightforward asset allocation and leverage based upon historical information ratios will underestimate the risk of total loss (being knocked out). In our examples, default risk may be underestimated by a factor of 5 for the Post-Crisis portfolio. More simply put, given a leverage factor of 1, the probability of any of our models under a typical mean variance analysis of the likelihood of losing all of one’s capital is negligible. If the switching methodology suggested is applied, the probability increases to near certainty.

Chart 8: Degree of Leverage to Engender a Default
V. Conclusions

Most would agree that Monte Carlo measured VaR, while a powerful tool, is an often misapplied methodology. Thus, many conclude it should simply be discarded to the dustbin of elegant, but useless, economic tools. We beg to differ. VaR in its simplistic form or in a straight-forward Monte Carlo form, or any analytics that are mean-variance based, which only consider past performance sampling, must be suspect. However, if modified to fit the potential of a turbulent environment it can be a very positive tool for better understanding the actual risk of an investment process.

Application of a bi-modal Monte Carlo approach to risk measurement will provide a much more robust measure of the potential pitfalls of investing based on history, simplistic Sharp Ratio measurements, or the belief that past performance is a good forecast for future performance. The last point is stated in every prospectus provided to investors. Unfortunately investors jump right past the statement and use historical performance criteria to measure the risk that is being taken. Doing so can be hazardous to the health of the investor’s portfolios.

Our analysis suggests that each investment strategy must be examined for the potential of a disturbance scenario. Doing so will reflect cognizance of the risk of turbulence and its implications. Given that markets enter into turbulent periods, a bi-modal distribution of return possibilities will present potential outcomes that highlight the risks that are inherent in any strategy while simultaneously incorporating active judgment into the empirical quantification of risk.

If SIVs, for example, had been analyzed using the bi-modal approach for Monte Carlo simulations, surely no financial institution’s board would have invested in the leveraged forms that became commonplace. The misapplication of risk measurement tools certainly contributed to the massive losses due to underestimating said risk, and given the regulatory application of “accepted VaR processes” turned mistakes into a global crisis. Application of a simplistic bi-modal Monte Carlo approach to VaR type analysis would have highlighted the potential for significant losses at the leverage levels many institutions comfortably (blindly) assumed. Use of this analysis would have forced the decision makers to consider what the behavior of the investments actually could be under a market disturbance, no matter the regulatory boxes checked.

Finally, this approach should be present in any fund investor’s toolkit so awareness of hidden risks are better examined and a realistic picture of the risks of any process is provided to investors.
Bibliography


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