Adaptive Asset Allocation: A Primer

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Abstract:

The paper addresses flaws in the traditional application of Modern Portfolio Theory related to Strategic Asset Allocation. Estimates of parameters for portfolio optimization based on long-term observed average values are shown to be inferior to alternative estimates based on observations over much shorter time frames. An Adaptive Asset Allocation portfolio assembly framework is then proposed to coherently integrate portfolio parameters in a way that delivers substantially improved performance relative to SAA over the testing horizon.

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Introduction

Practitioners, academics, and the media have derided modern Portfolio Theory (MPT)

over much of its history, but the grumbling has become outright disgust over the past ten

years. This is largely because the dominant application of the theory, Strategic Asset

Allocation, has delivered poor performance and high volatility since the millennial

technology crash, and the traditional assumptions of MPT under the Efficient Markets

Hypothesis offer no explanation or hope for a different outcome in the future.

Strategic Asset Allocation probably deserves the negative press it receives, but the

mathematical identity described by Markowitz in his 1967 paper is beyond reproach. The

math is the math.

Modern Portfolio Theory requires three parameters to create optimal portfolios from two

or more assets:

1. Expected returns

2. **Expected volatility**

3. Expected correlation

The trouble with Strategic Asset Allocation is that it applies MPT using long-term

averages of these parameters to create diversified portfolios. Unfortunately for SAA

investors, long-term averages turn out to be poor estimates of returns, volatility and

correlation over the 5, 10 or even 20-year horizons that are meaningful for most

investors.

This paper will highlight the flaws inherent in the use of long-term averages as estimates

for portfolio optimization for each of the three parameters, and offer methods of

generating more meaningful estimates using simple measurements of nearer-term

observations.

Garbage In: Garbage Out (GIGO)

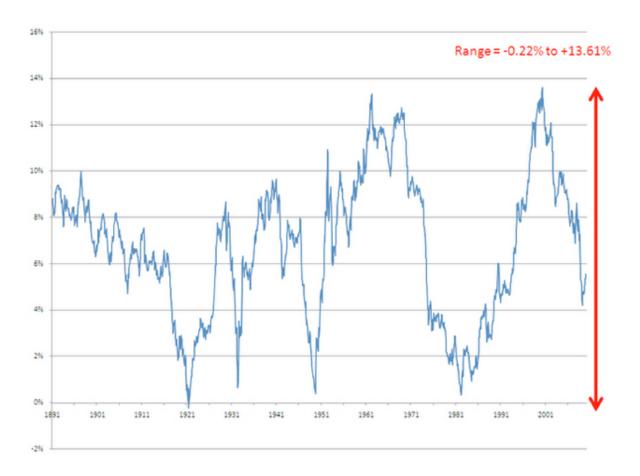
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The Flaw of Averages

GIGO: Returns

The magnitude of errors in long-term return assumptions cannot be overstated. Consider the following chart, which shows the range of real returns to U.S. stocks over rolling 20-year periods from 1871 through 2009. While 20 years or so approximates a typical retirement investment horizon, it exceeds, by multiples, the average psychological horizon of most investors, which is much closer to 3 or 4 years (Dalbar, 2012).

Chart 1. Rolling real total returns to the S&P500, 1871 - 2010



Source: Shiller

You will note that, even over horizons as long as 20 years, annualized real returns to stocks range from -0.22% immediately prior to the Great Depression crash, to 13.61% during the 20 years subsequent to the 1982 low.

This amount of variability in returns means the difference between living on food stamps after 10 years of retirement and leaving a deca-million dollar legacy for heirs. For endowments, this means the difference between persistently missing funding obligations and accelerating generosity. In other words, constructing portfolios through the use of long-term average return estimates is analogous to a game of Russian Roulette, where luck alone decides your fate.

While many investors behave as though there is no alternative to long-term averages for return forecasting, and allocate based on these static assumptions via a SAA framework, a large proportion of investors and institutions do bias portfolios tactically in an effort to generate better returns. Overwhelmingly, these investors apply a long-term value approach to provide a better estimate than long-term averages, such as that proposed by Sharpe (2009). Typically, these methods bias portfolios toward equities as equities fall in price (get cheaper), and reduce exposure as equities become expensive.

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80.0 E(R) Forecast Horizon U-Curve 75.0 High frequency arms race Forecast Accuracy (Percent) Value (long-term mean-reversion) Momentum 60.0 sweet spot 55.0 50.0 45.0 28 124 220 268 253 265 277 289 Forecast Horizon (Weeks)

Chart 2. Return factor estimates over various horizons.

Source: Darwin Funds

As shown in the diagram above however, there are alternatives to long-term value for biasing return estimates. At the extremely short-term horizon, from intra-day to several days, high frequency traders take advantage of myriad factors related to correlation, trend and mean-reversion to generate return estimates. The incredible track-records of firms like GETCO and Renaissance Technologies offer abundant evidence of the efficacy of these types of very short-term estimates. Unfortunately, anomalies at these horizons are fleeting, non-structural and subject to extreme levels of arbitrage. As a result, this end of the estimate horizon has become a virtual arms race where all but the most well funded and technologically adept investors will eventually die off.

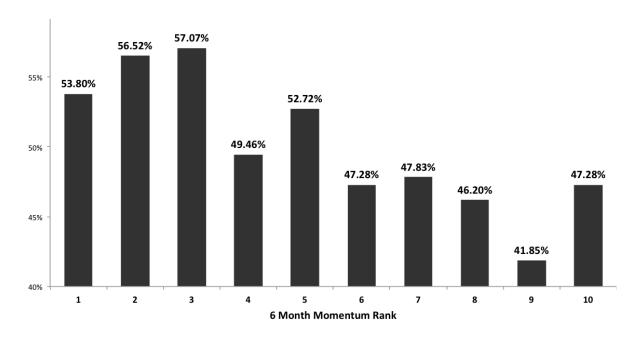
Moving out the investment horizon from daily to weekly, another factor begins to exert a powerful influence: momentum. In the same way physical objects keep moving in the same direction until friction intervenes, security prices tend to continue moving in the same direction for several weeks subsequent to any observation period. In other words,

at the start of any period the securities – stocks, asset classes, art, real estate, etc. – that are observed to have performed best over the recent past will tend to continue performing best over the near future. The first formal analysis of this phenomenon among stocks is generally held to have been done by Jagadeesh and Titman (1993), and it was first put forth as an excess return factor by Carhart (1997). Since then a mountain of evidence has identified this factor in virtually every conceivable asset, including residential real estate (EconomPicData, 2012), art (Mei & Moses, 2010), and asset classes themselves (Asness, 2008 and Faber, 2009)

The following chart demonstrates the tendency for assets that rank in the top half of a group of 10 global asset classes based on 6-month momentum to persist within the top half of performers over the following month. On average, the probability that a top half 6-month performer will deliver returns in the top half over the subsequent month is 54% versus 46% for a bottom-half performer using a sample period from January 1995 to the present.

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Chart 3. Probability that top n ranked assets by 6 month momentum will perform in the top half the following month.



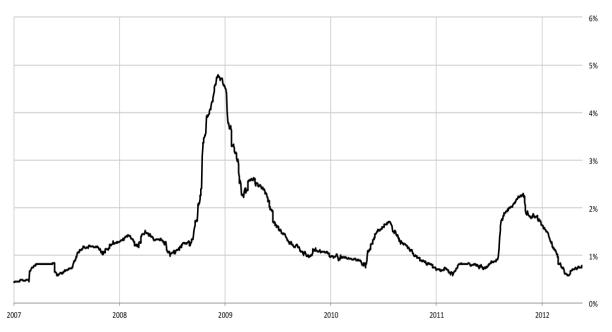
Source: Darwin Funds

Given that such a high probability bias exists at the monthly time frame, it makes little sense to neglect this evidence in favor of long-term average returns for portfolio construction.

GIGO: Volatility

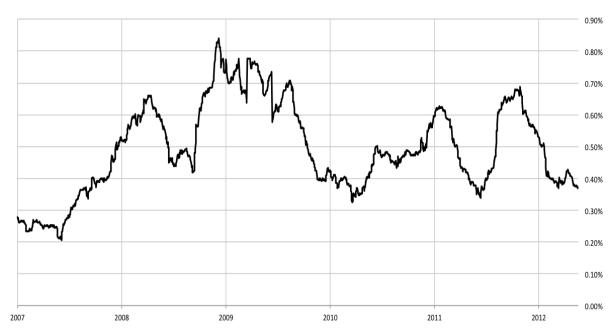
There is a great deal going on under the surface with volatility estimates too. For example, while long-term daily average volatility is around 20% annualized for stocks, and 7% for 10-year Treasury bonds, the following two charts show how realized volatility fluctuates dramatically over time for both stocks and bonds.

Chart 4. 60-day rolling volatility of the S&P 500.



Source: Yahoo Finance

Chart 5. 60-day rolling volatility of the Barclay 7-10 Year Treasury Index



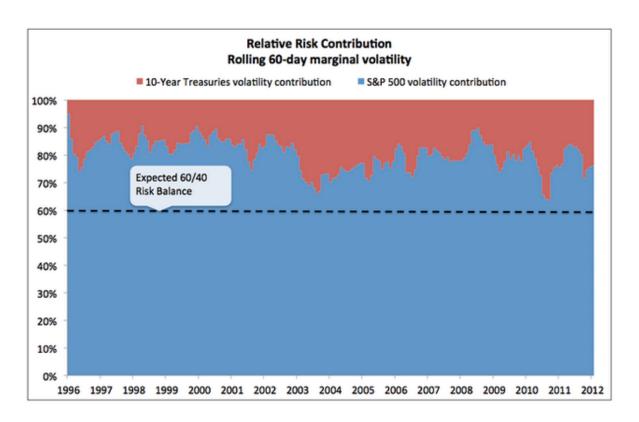
Source: Yahoo Finance

Incredibly, you can see that the volatility of a bond portfolio can fluctuate by over 400% over a 60-day period, and the volatility of a U.S. stock portfolio can fluctuate by almost 1000%.

This has a dramatic impact on the risk profile of a typical balanced portfolio, and therefore on the experience of a typical balanced investor. Most investors believe that if a portfolio is divided 60% into stocks and 40% into bonds, that these asset classes contribute the same proportion of risk to the portfolio.

However, as the next chart shows, for a portfolio consisting of 60% S&P500 and 40% 10-year Treasuries, the stock portion of the portfolio actually contributes over 80% of total portfolio volatility on average, and over 90% of portfolio volatility about 5% of the time. In late 2008 for instance, a 60/40 portfolio generally behaved as though it was over 90% stocks.

Chart 6. Relative risk contribution from stocks and bonds in a 60/40 S&P500 / 10-Year Treasury portfolio.



Source: Yahoo Finance

One of the most basic axioms in the study of time series data is that the most unbiased estimate of tomorrow's price is today's price (Black & Scholes, 1973). In the same way, the most unbiased estimate of tomorrow's *range* of prices is the range of prices observed over the recent past; in other words, the observed recent volatility. If recent volatility is a good estimate of near-term future volatility, it makes sense to use this estimate instead of the long-term average volatility.

Chart 6 illustrated how fluctuations in the volatilities of stocks and bonds led to unstable risk contributions in a balanced portfolio. To maintain stable risk contributions, one only need observe recent volatility for each asset and apportion risk accordingly. For example, if we target equal risk contribution from both stocks and bonds, but the recently observed volatility of stocks is 200% the observed volatility of bonds, the appropriate allocation would be computed as follows:

allocation to stocks x volatility of stocks = allocation to bonds x volatility of bonds

volatility of stocks / volatility of bonds = allocation to bonds / allocation to stocks

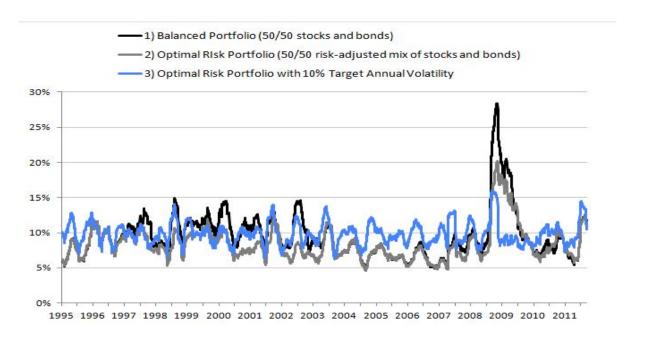
Given that the ratio of the volatility of stocks: bonds is 2:1, the allocation would equal 1:2, or 1/3 stocks and 2/3 bonds.

Once the allocation ratios of individual assets has been calculated in order to distribute risk equally at each rebalance period, one can also measure the total risk of the combined portfolio. Taking it one step further, once the portfolio level volatility has been calculated, one might choose to target a certain volatility level in order to keep the total portfolio risk constant over time. If observed portfolio volatility is above the target, total portfolio exposure is reduced in favor of cash.

Chart 7 shows three time series:

- The black line is a standard 50/50 allocation to stocks and bonds, rebalanced monthly
- The grey line is a 50/50 risk allocation to stocks and bonds, rebalanced monthly
- The blue line is a 50/50 risk allocation to stocks and bonds, rebalanced monthly to a target portfolio risk of 10% annualized

Chart 7. Rolling 60-day volatility of a 50/50 balanced, risk-balanced, and risk-target stock and bond portfolio.



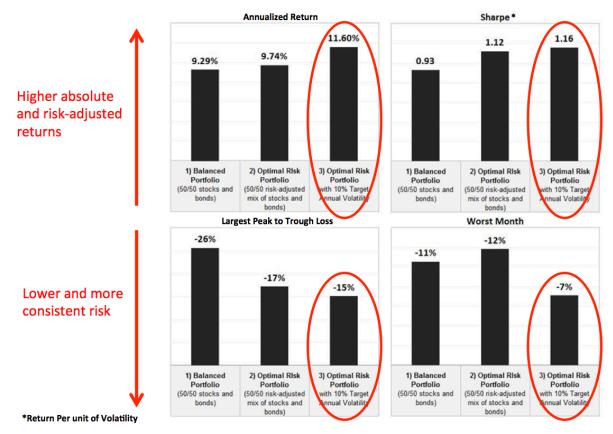
Source: Yahoo Finance

Notice how the traditional 50/50 portfolio (black line) experienced volatility in the range of 5% - 15%, and averaged 10% annualized over most of the period. 2008 – 2009 represented a notable outlier experience, with 60-day portfolio volatility peaking at 28%, or almost 300% of average. In contrast, the 50/50 risk-allocated portfolio (gray line) delivered a more consistent experience, with a much more manageable peak in 2008 – 2009 around 20%. Lastly, the 50/50 risk allocated portfolio with a portfolio risk target of 10% exhibited an extremely stable risk profile, hovering very close to the 10% target

throughout the period, and never straying more than 50% from the target even during the financial crisis.

Chart 8 is a montage of charts showing return and risk metrics for the three portfolio algorithms. Intuitively, one might presume that overall portfolio risk would be reduced by equally apportioning volatility, and even further by targeting a certain portfolio risk, and this is clearly the case per observed Sharpe, drawdown and worst month statistics. What may be less intuitive is that the absolute returns to the risk-managed portfolios are also improved substantially; by 25% in the case of the risk-targeted portfolio.

Chart 8. Chart montage of return and risk characteristics for traditional and risk-managed portfolios.

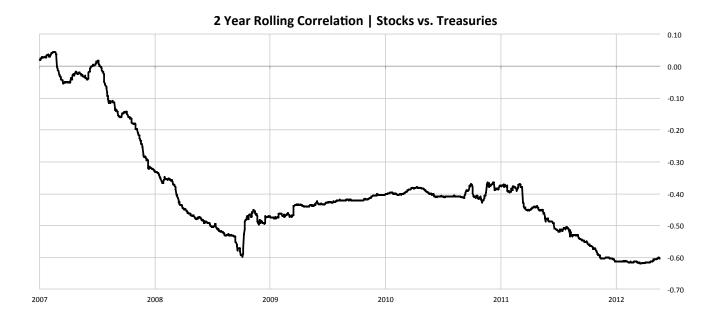


Source: Yahoo Finance

GIGO: Correlation

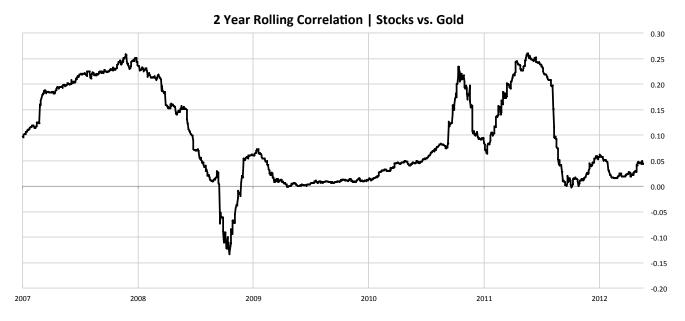
While the long-term correlation between major asset classes like U.S. stocks and Treasuries, and U.S. stocks and gold, are low or even negative over the long-term for structural reasons, the actual realized correlation between these assets oscillates between strong and weak over time.

Chart 9. 2-year rolling correlation between S&P 500 and U.S. 10-year Treasuries



Source: Yahoo Finance

Chart 10. 2-year rolling correlation between S&P 500 and gold.

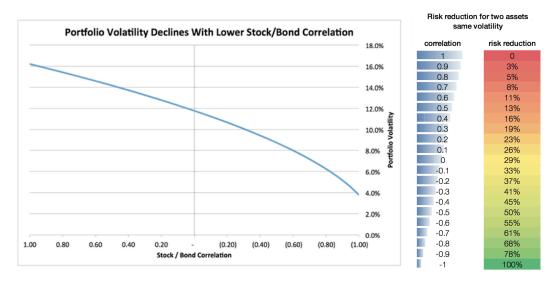


Source: Yahoo Finance

From the charts, notice that the long-term average 60-day rolling correlation between stocks and Treasuries over the 12-year period shown is -0.42, and the correlation between stocks and gold is +0.22.

However, the stock/Treasury correlation varies between -0.82 and +0.27 over the period, and the stock/gold correlation varies between -0.84 and +0.91. Importantly, Chart 11 illustrates the degree to which lower correlation between two assets with individual volatilities of 20% each results in exponentially lower portfolio level volatility.

Chart 11. Theoretical reduction in portfolio volatility as a function of the correlation between two portfolio assets.



Source: DarwinFunds.ca

In fact, from Chart 11 notice that the volatility of a 50/50 stock/bond portfolio decreases by 50% as correlation declines from +0.2 to -0.8, holding all else constant.

Return, volatility and diversification estimates vary widely from their long-term averages over the short and intermediate terms. Managers who do not monitor and adjust portfolios to these changes risk substantial deviation from stated portfolio objectives, and are almost certain to deliver a sub-optimal experience for investors.

In summary, one of the most important axioms in finance is that the best estimate of tomorrow's value is today's value. The examples above offer evidence for this axiom for return, volatility and correlation estimates, and illustrate how these better estimates lead to better performing portfolios.

This goes to the core of this paper: If it is possible to measure the value of these variables over the recent past, and they are better estimates over the near-term than long-term average values, why not use current observed values for portfolio optimization instead? Why hold a static asset allocation in portfolios when it is possible to adapt over time based on observed current conditions?

Adaptive Asset Allocation: Evolution

The objective of this section is to build a conceptual framework for an Adaptive Asset Allocation (AAA) approach from the ground up by starting from an equal weight basket of our investment universe, and building to a coherent and integrated AAA algorithm. Importantly, the purpose of this section is not to provide the exact mechanics of an AAA algorithm so that a practitioner can construct an AAA algorithm with step-by-step instructions. Rather, it is the vision of the authors of this paper that investors will come to see AAA as the most rational approach to asset allocation and invest time and energy in finding new and creative ways to approach this new challenge on their own.

A fundamental assumption of this research relates to the fact that markets are complex dynamical systems driven by psychology and structural factors in the short term, but dominated by emergent phenomena over the long term. With this context it is impossible to know where returns or risk will come from over the long term, and so a rational investor will entertain all potential sources of future return when making optimal portfolio decisions. For the purposes of this paper we have divided the world's major sources of return into the following 10 asset classes, which will represent out investment universe, with data from January 1st, 1995.

U.S. Stocks	International REITs
European Stocks	U.S. Intermediate Treasuries
Japanese Stocks	U.S. long-term Treasuries
Emerging Market Stocks	Commodities
U.S. REITs	Gold

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Finally, to get out ahead of the typical question of trading costs, which haunts any truly active investment approach, note that the asset classes listed above, can be accessed via mutual funds or Exchange Traded Funds representing some of the highest liquidity instruments available in markets. Trading costs for intelligent retail or institutional investors should be negligible, and the application of simple trading algorithms may actually introduce positive slippage.

Exhibit 1. Equal Weight

The equal weight basket will form the baseline for comparisons with other exhibits as we introduce concepts in a stepwise fashion to improve portfolio performance in pursuit of the final AAA framework. The implicit assumption of the regularly rebalanced equal weight basket is that there are no meaningful estimates for any of the three portfolio parameters. Going back to 1995, if we held this basket of assets in equal weight, and rebalanced monthly, we would have experienced the portfolio profile in Exhibit 1.¹

¹ Note that for all exhibits, CAGR stands for Compound Annualized Growth Rate, and for the purpose of this paper Sharpe represents the portfolio return/risk ratio without accounting for the cash yield. All data based on daily observations.

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Exhibit 1: 10 Assets, Equal Weight, Rebalanced Monthly

Curve		Trade		Time	
Total Return	303%	Trade Winning %	58%	% Winning Months	62%
CAGR	8.36%	Average Trade	0.72%	Average Winning Month	2.62%
Sharpe	0.66	Average Win	4.07%	Average Losing Month	-2.42%
DVR	0.58	Average Loss	-3.90%	Best Month	8.50%
MAR	0.19	Win/Loss Ratio	1.04	Worst Month	-18.21%
Max Daily Drawdown	-43.90%	Best Trade	32.5%	% Winning Years	83%
Average Drawdown	-1.63%	Worst Trade	-32.7%	Best Year	30.89%
Avg Drawdown Length	20.70	Avg Days in Trade	20.81	Worst Year	-25.38%
Avg Trades Per Year	120	Trades	2073	Positive 12 Month Periods	81%

Source: Yahoo finance

The GIGO: Volatility section dealt with how volatile assets like stocks and commodities tend to dominate the total risk of a typical portfolio, and the chart above provides further proof; note the steep drop in 2008-09 during the global financial crisis where risky assets overwhelmed safety havens throughout, dragging the portfolio down as much as 43.9% from peak-to-trough. Further, the portfolio struggled from 1995 until 2003 during a period where returns were isolated to a narrow group of developed market equities and the rest of the basket trended sideways or down.

Exhibit 2. Equal Volatility Weight, Rebalanced Monthly

The GIGO: Volatility section described a method of sizing asset allocations based on the observed volatility of each asset over the recent past for a portfolio of stocks and bonds. This concept can easily be extended to a universe of any size. Exhibit 2 below extends

the concept to our 10-asset basket by targeting the individual volatility of each asset. Specifically, the allocations are adjusted at each monthly rebalance period so that each asset contributes the same 1% daily volatility to the portfolio, to a maximum of 100% exposure.

The allocation to any asset is calculated as follows:

With n assets, the allocation equals:

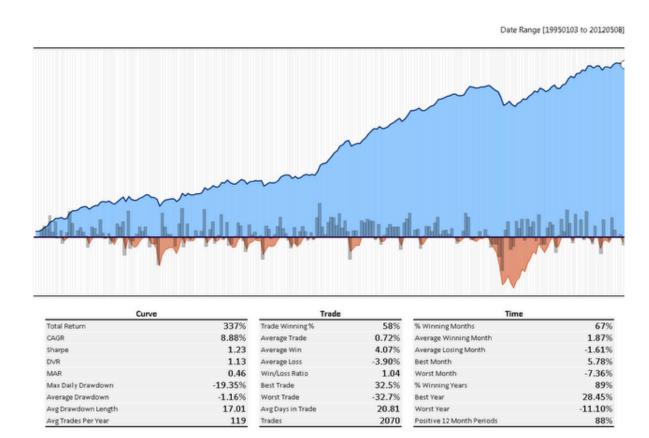
1/n * 1% / [observed volatility of the asset over the past 60 days], < 1 / n

Example: If there are 10 assets, and observed volatility of asset A is 0.8% then

allocation to asset A = 1/10 * 1% / 0.8% = 10% * 1.25 = 12.50% but

12.5% > 1 / 10 so allocation is truncated to 10%.

Exhibit 2: 10 Assets, Volatility Weighted Rebalanced Monthly



Source: Yahoo finance

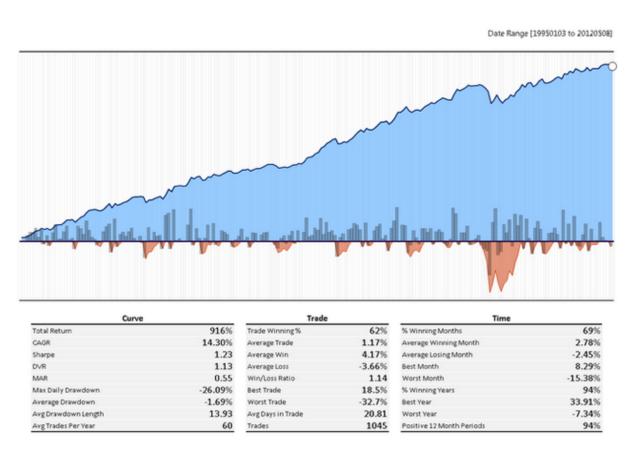
By simply sizing each asset in the portfolio so that it contributes the same 1% daily volatility based on observed volatility over the prior 60 days, the return delivered per unit of risk (Sharpe in the table) almost doubles from 0.66 to 1.23 versus the equal-weight portfolio. Further, the maximum drawdown is cut in half from 44% to under 20%. Not shown, the volatility of this portfolio is an extremely low 7.22% annualized.

This is a substantial reduction in risk without sacrificing returns. Note with this simple step we are introducing one new assumption: volatility can be estimated using recently observed data, and this information can be used to ensure the risk contribution from each asset in the portfolio is held constant through time. The portfolio level volatility is not managed explicitly at this stage.

Exhibit 3. Top Half Momentum Portfolio, Equal Weighted, Rebalanced Monthly

In this step momentum is introduced as a biased return estimate. Rather than holding all assets at all times, assets are screened for momentum based on 6-month returns, and portfolios are rebalanced each month to hold the top 5 assets only. No sizing mechanism is applied in this step, so each asset receives 20% of portfolio capital at each rebalance date.

Exhibit 3: 10 Assets, Top 5 Equal Weight By 6-Month Momentum, Rebalanced Monthly



Source: Yahoo finance

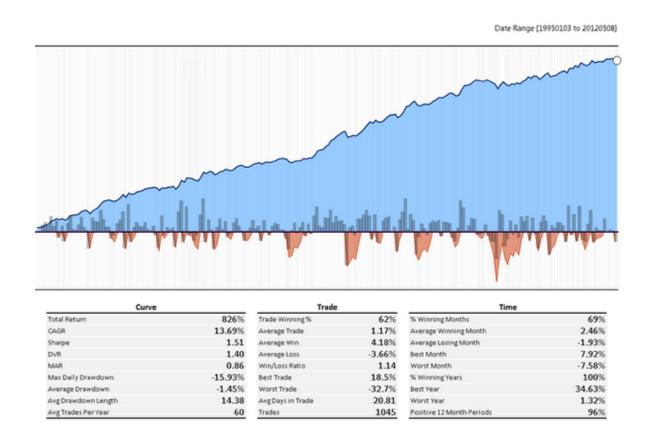
Importantly, Exhibit 3. isolates the effect of the return estimate only on portfolio performance. Holding the top 5 assets each month based exclusively on 6-month momentum nearly doubles the Sharpe ratio, but also substantially increases annualized

returns - from 8.88% for the volatility weighted portfolio to 14.30% for the momentum portfolio. The average volatility for the momentum portfolio is slightly lower than the equal weight portfolio at 11.6% versus 12.7% annualized, but 60% higher than the volatility weighted portfolio's 7.22%. The drawdown profile sits squarely between equal weight and risk weighted at 26% versus 49% and 19% respectively.

Exhibit 4. Top Half By Momentum, Volatility Weighted, Rebalanced Monthly

The next logical step is to combine estimates of return based on momentum with estimates of volatility based on recently observed volatility. Exhibit 4 shows the performance of an approach that assembles the top 5 assets by 6-month momentum, and then applies the same volatility-sizing overlay used in Exhibit 2 based on a 60-day observation period, so that each of the top 5 assets contributes the same 1% of daily risk to the portfolio, again to a maximum of 100% exposure.

Exhibit 4: 10 Assets, Top 5 By 6-Month Momentum, Volatility Weighted, Rebalanced Monthly



Source: Yahoo finance

This technique lowers returns slightly from 14.3% to 13.7%, but the Sharpe ratio increases from 1.23 to 1.51, and the maximum drawdown drops to 16% from 26%. Portfolio volatility declines measurably, from 11.6% to 9.1%. Intuitively, combining two of the three available parameter estimates delivers substantially better performance than either factor in isolation, improving absolute returns and risk adjusted returns, and significantly lowering drawdowns, even below the pure volatility sized portfolio.

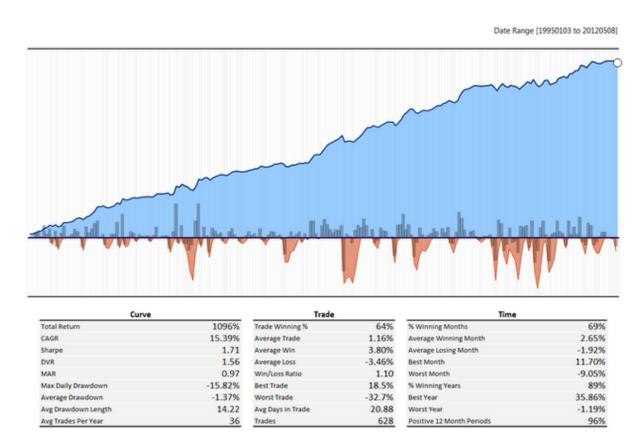
Exhibit 5. Top Half by Momentum, Minimum Variance, Rebalanced Monthly

The next and final step is to integrate momentum, volatility and correlation using better estimates based on observed near-term return (momentum), volatility and correlation measurements to achieve true **Adaptive Asset Allocation (AAA)**.

While far from the most elegant algorithm, a legitimate approach would be to create portfolios at each monthly rebalance based on the Top 5 assets by 6-month momentum, but allocate among the assets according to a minimum variance algorithm rather than by volatility sizing each asset individually.

The minimum variance algorithm takes into account the volatility and correlations between the Top 5 assets to create the momentum portfolio with the lowest expected portfolio level volatility. The better algorithms will include at least two assets, and more where other assets with low correlations will lower total portfolio volatility. Rebalancing the portfolio monthly with this approach achieves the following performance profile.

Exhibit 5: 10 Assets, Top 5 By 6-Month Momentum, Minimum Variance, Rebalanced Monthly



Source: Yahoo Finance

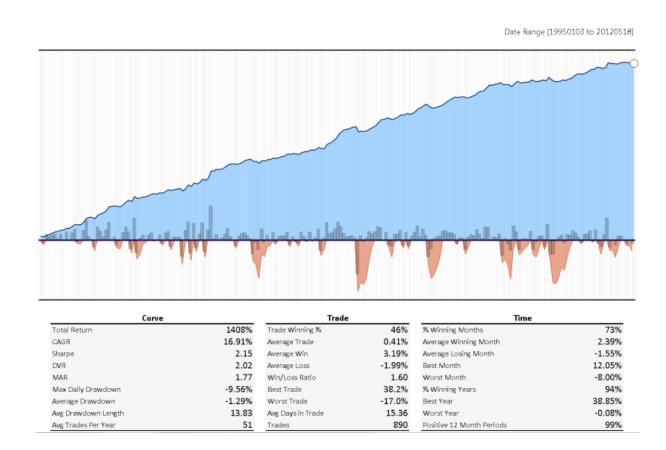
Notice that by integrating all three factors, this approach delivers a substantially higher Sharpe ratio of 1.71 versus 1.51. Maximum drawdown is maintained near 16%, and portfolio volatility is stable near 9%. The primary beneficiary of the minimum variance overlay is returns, which improve to 15.4% versus 13.7% for the momentum portfolio with individual volatility weighted allocations.

Adaptive Asset Allocation: Integration

While the authors in no way espouse Exhibit 5. as an optimal portfolio management approach, the stepwise improvement from Exhibit 1. through Exhibit 5 provides compelling evidence of the efficacy of an integrated Adaptive Asset Allocation framework. A true AAA framework would address issues around specific look-back periods for the generation of parameter estimates and assemble optimal portfolios without constraints on portfolio size. Further, volatility would be managed at the portfolio level to maintain a stable risk profile.

An algorithm that addresses these issues directly, along with some engineering improvements to improve the signal-to-noise ratio of parameter estimates, and more frequent rebalancing to better control risk might approximate the profile in Exhibit 6.

Exhibit 6. Adaptive Asset Allocation, Rebalanced Weekly, 8% Target Volatility



Source: Yahoo Finance

Return and risk statistics compare very favorably with all prior exhibits, with returns approaching 17% annualized and realized average volatility under 8%. Incredibly, drawdowns are less than 10% even with daily observations.

Aside from the traditional return and risk metrics discussed above, it is worthwhile addressing some of the other constructive features of a true AAA approach. For example, the return profile of the AAA portfolio is very close to a straight line, with a daily R-Squared of 0.94. The extreme level of stability delivers positive returns over 73% of individual months, and 99% of rolling 12-month periods. Further, the worst monthly loss is just 8%.

Adaptive Asset Allocation: Funding Implications

While the performance of the AAA portfolios is compelling on their own right, it is useful to examine how this approach impacts assumptions about sustainable cash-flows from typical retirement or endowment portfolios. After all, the vast majority of invested capital is managed with an objective of maximizing sustainable cash flows for lifestyle or funding priorities.

Moshe Milevsky's Quantitative Wealth Management Analytics Group at the Fields Institute in Toronto provides a comprehensive suite of algorithms for the purpose of optimizing cash flows for endowment, insurance and retirement portfolios. Perhaps the most critical measure of success for many institutions and retirees is the Sustainable Withdrawal Rate, which is simply the percentage of portfolio value that can be withdrawn each year for spending, adjusted for inflation, while maintaining an acceptable probability of impairment.

By subjecting the Exhibits above to QWeMA's algorithms, it is possible to solve for the Safe Withdrawal rate for almost any funding scenario. The table below summarizes the results of such an optimization based on the following assumptions for a typical retirement scenario, and using Statistics Canada mortality tables:

- Currently retired, age 65
- Married, spouse also 65
- Acceptable probability of impairment: 85%
- Objective of maximizing annual funding without regard to expected legacy
- No other sources of income
- All taxes, fees and costs are ignored for simplicity.

Table 1. Summary table of algorithms with associated safe withdrawal rates.

Algorithm	Return	Volatility	Drawdown	Safe Withdrawal Rate*
Equal Weight	8.36%	12.7%	43.9%	5.74%
Volatility Weight	8.88%	7.2%	19.4%	7.18%
Momentum	14.3%	11.6%	26.1%	10.2%
Momo Vol Weight	13.69%	9.1%	15.9%	10.4%
Momo MinVar	15.4%	9.0%	15.8%	11.8%
AAA Weekly	16.91%	7.9%	9.6%	13.4%

Source: QWeMA algorithms. For illustrative purposes only.

Clearly the stronger returns with lower risk result in much higher safe withdrawal rates for a typical retirement scenario, and the results for endowment and pension objectives are no less impressive.

The Next Generation of Portfolio Management

While there are better algorithms to integrate momentum, volatility and correlation, the Exhibits above show a clear evolution of techniques that demonstrate how to integrate the three primary variables used for portfolio construction under a true Adaptive Asset Allocation framework.

Portfolios assembled using classic Strategic Asset Allocation are vulnerable to the 'flaw of averages' where long-term average values hide enormous variability over time. Further, it improves over more contemporary isolated approaches like pure momentum, minimum variance and risk parity. It also benefits from a more robust theoretical basis than traditional Tactical Asset Allocation approaches, while also delivering higher absolute and risk-adjusted performance.

Adaptive Asset Allocation (AAA) is robust to changes in market character because proper application uses a variety of standard parameter look-backs for estimation. Further, volatility and correlation management, as well as more regular rebalance frequency, provides substantial tailwinds for portfolios. Lastly, AAA portfolios are always optimally diversified, which makes them robust to market shocks that often critically impair more concentrated tactical portfolios.

The portfolio management industry is undergoing a revolution analogous to the shift that occurred after Markowitz introduced his Modern Portfolio Theory in 1967. Managers who embrace the new methods will increasingly dominate traditional managers; those who fail to adapt will, inevitably, face extinction.