Asset Allocation Background

What is Asset Allocation?
Investment policy is made real by allocating assets among available investment categories or "asset classes." The number of asset classes considered is typically between 6 and 15. Ideally, each asset class's return could be tracked by some index return. Within each asset class, this index would explain a material percentage of return for individual investment opportunities within the class, but at the same time, have low correlation with indexes of other asset classes.

A primary list of asset classes would typically include: stocks, bonds, cash, real estate, private equity and "other" (e.g., venture capital and/or alternative investments/hedge funds). Many investors further subdivide stocks into domestic vs. foreign. In the domestic category one can differentiate large vs. small market capitalization stocks, growth stocks vs. value stocks. In the international (foreign) category one can divide developed country vs. emerging market stocks. In the bond category, one can sub-classify by maturity or by credit quality: e.g., high quality vs. low quality/ high yield bonds. "TIPS" or Treasury Inflation Protected Securities has become a separate asset class. While real estate, venture capital and private equity have long been part of most pension portfolios; hedge funds are a somewhat more recent addition. This new category of investments has sprung up in the last 10 years or so, and is sometimes called "alternative assets" or "absolute return funds" or simply "hedge funds." These too can be divided into sub-classes. The product of these various divisions takes the number of asset classes from 6 to 8, 12 or higher.

The final determination of asset class number involves a balancing of risk/return objectives and operational considerations. We must capture the distinct capital market alternatives not only in a policy statement but also in the real world. We must have enough asset classes represented to effectively mitigate risk if the plan is to maintain fully funded status. If there are too few asset classes and risks will be unacceptably high; too many classes and operational complexity becomes an issue. Fortunately, structural flexibility can help significantly to maximize the return potential and risk benefits of the investment managers hired to manage the portfolio assets entrusted to them.

An important distinction in defining asset allocation policy is to separate the long term or strategic policy from a shorter-term view or tactical asset allocation policy. The **strategic allocation policy** attempts to find an "optimal" asset mix that **blends** the **desire** for enhanced return **over the long run** with the pension sponsor's conflicting **need** to control risk. The strategic policy will be denoted by a set of target asset class percentages adding to 100%. A stated long-term expected return (a 5-10 year or longer expectation), a volatility measure or a reward-to-risk ratio to represent risk controls is also needed.

Importance: A number of empirical studies have been compiled for pensions and endowments to understand the impact or importance of the strategic asset allocation decision. Gary Brinson and colleagues completed a widely quoted study in 1986 and updated in 1991 for 80-90 large U.S pension funds over a 20-year period. In those studies, over 90% of the variation in average return earned across time was explained by the asset allocation policy weights. Other researchers have recalibrated the response variable to [a] variation of long term average return across funds or [b] proportion of the return level explained by asset allocation policy. Each of them confirms that asset allocation is a key determinant of performance, relative or absolute.

Tactical asset allocation ("TAA") is opportunistic in nature and shorter term in duration, e.g., 3-12 months.) TAA shifts asset class percentages away from their long-term policy targets in response to the changing patterns of reward available in the capital markets. These tend to be disciplined, analytic processes to capture excess return. They can be inherently contrarian, buying after a market decline, anticipating regression to the mean or mean reversion, or selling after a market rise.

A Framework for Strategic Asset Allocation Decisions

Modern Portfolio Theory was launched with Harry Markowitz' seminal work at the University of Chicago. The theory was embedded in his 1952 book and 1959 journal article. While Markowitz was not the first academic researcher to study investors' return expectations, aversion to risk, and need for diversification, he was the person who put it together in an analytical framework, and used mathematical programming tools to solve the "optimal portfolio." Practical implementation of Markowitz' ideas, however, did not take place immediately, but awaited faster, more powerful computers, efficient data gathering & management, and a perceived need from investment professionals for a better approach. [The latter came with the entry of a horde of MBA graduates who had learned the new tools in graduate school, combined with adverse volatility in the equity market in the early 1970s].

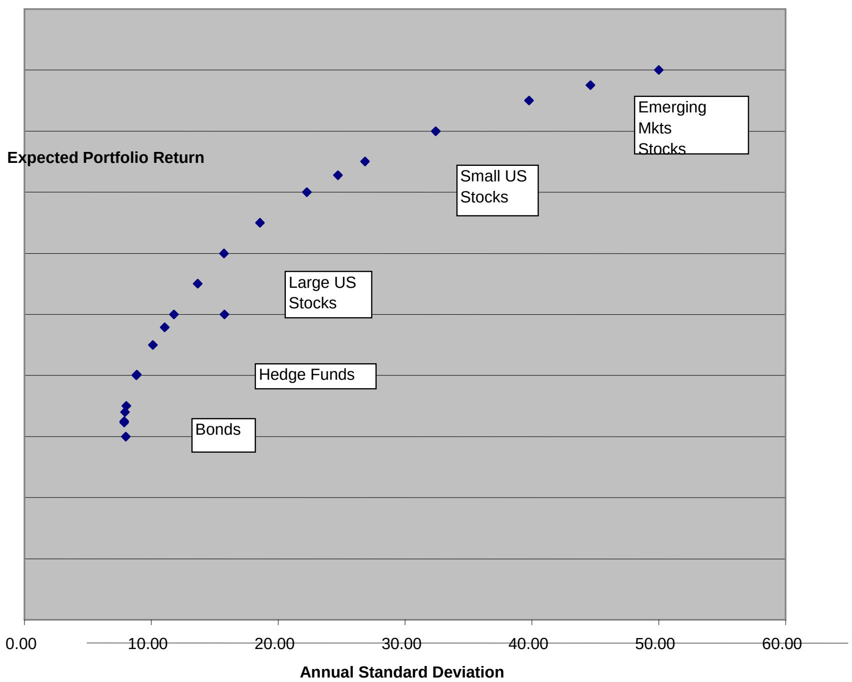
Mean-variance optimizers soon became quite common tools for portfolio analysis and portfolio building. The **required inputs** to an asset allocation model include:

1. Expected returns for each asset class
2. Predicted volatility (variance or standard deviation of returns) for each asset, and
3. Correlation of returns for each pair of asset classes

The **typical output** of the Optimization model would be:

1. A graph or mapping of combinations of various asset classes (portfolios) in a risk-return diagram. See the illustration below.
2. A boundary called the "efficient frontier" – the best tradeoff of risk and return that combinatorial mathematics could devise with the inputs provided.
3. A few candidate portfolios or perhaps a specific recommendation on the efficient frontier deemed most suitable for the pension client's fund.

One of Markowitz' key contributions was to demonstrate the role and importance of this third input factor, correlation. It changes dramatically how we view risk of an asset if we treat it in the proper context, i.e., a portfolio context. A specific asset may have large volatility and offer only mediocre return – so when viewed in isolation it plots well below the efficient frontier. One would not want to commit all one's funds to such an investment. However, its correlation with other asset classes may be low, perhaps near zero. Including such an asset as a candidate investment in combination with other asset classes actually improves the efficient frontier (moves it further "northwest" in the graph). Risk may be lowered or return improved by including, say 5-20%, of this seemingly high-risk asset class in the pension portfolio. The power of low-correlated assets is very strong indeed in mean-variance theory and practice. How the risks combine determines the outcome; such is the power of diversification.



Caveats. While the power and insights derived from this technique are great, there are some grave implementation concerns.

First, the results (recommend optimal portfolio weights) are extremely sensitive to small changes in the input parameters. **A small shift in relative return expectations may lead to a completely different portfolio mix than the one previously recommended.**

Second, the optimizers often locate a recommended portfolio that appears "extreme" to seasoned investors. The recommended portfolio(s) will often contain only 2-3 asset classes in the efficient frontier or optimal portfolio solution, even though the model was fed 10 or more asset class candidates. The optimizer will load up (portfolio weight) on a specific asset class like domestic equity, or emerging market debt. Users of these models have coped by adding constraints to the mathematical model – forcing greater diversification across several asset classes. At some point, however, the addition of such constraints defeats the usefulness of the process.

Data Quality. Defenders of the optimization tools will point out that the problem is with the quality of the data used as inputs rather than the optimizer itself. What is the source of the data used to develop the required inputs? Most analysts will start with historical data – perhaps running the optimizer based solely on history. Historical mean returns for asset classes will most certainly be replaced by forecasts, updating to current economic and capital market conditions or future economic scenarios. Volatility measures and correlations may be updated as well if trends can be determined. Still, knowing the <u>true</u> distributions of future asset class returns is impossible, but often, analysts' expectations are unreasonably "anchored" recent historical experience.

New Directions. Two approaches have been taken in the dozen years to mitigate the data quality issue. One involves the use of simulation, in particular Monte Carlo methods which draw from a distribution of input parameters, and then to re-compute the efficient frontier. This process, commonly known as **"resampling"** is replicated, perhaps several hundred times, rather than accept a single point estimate value. The efficient frontier graphical output now becomes a band (locus of points) rather than connecting one series of dots. The recommended portfolio will in effect be the <u>average</u> of several hundred trials of what's best by varying the input values of expected return, volatility and correlation.

A strong advocate of this approach is Dick Machaud, a long time Wall Street quantitative analyst, who refers to optimizers as "error maximizers" because they so easily glommed on to extreme (likely erroneous) solutions. The results of portfolio resampling tend to be less extreme (more asset classes included) and less sensitive to changing input values. However there are some pitfalls too. For example, there still is no guidance provided for the means of the returns distributions, and asset classes with more volatility tend to get more proportionate weight in the final solution, since the weights on the low end are bounded at zero.

A second direction and significant improvement has been made by the late Fisher Black (of Nobel Prize winning Black-Scholes option pricing model fame) and Bob Litterman – working at Goldman Sachs. Black and Litterman recognized that the asset class returns are the most difficult and critical estimates to identify in this modeling process, and they offer help to prepare reasonable estimates.

In effect they "reverse engineer" the classic optimization model to reflect the current market holdings of investors. That is, given the current holdings of investors in the aggregate, what return expectations are consistent with the asset allocation weights we observe? This engineering problem still requires volatility and correlation assumptions along with an overall risk tolerance, but it goes on long way to develop rational, base estimates for expected returns going forward.

Moreover, in the Black-Litterman model, based in equilibrium theory[1], the analyst can input his or her own views (views either more bullish or more bearish than the equilibrium base conditioned established by reverse engineering). The approach then blends the views together to compute a revised set of expected returns and optimal asset class weights.

An alternative way to think about the Black-Litterman approach is that it uses a Bayesian[2] perspective. The expected returns of the asset classes are not known but we can infer their probability distributions from empirical data. The inference begins with a prior belief, one based on capital asset pricing theory. Additional information is used along with the prior belief to develop the posterior probability distribution.

The Black-Litterman approach greatly improves the classic Markowitz mean-variance optimizer and helps it live up to its original expectations as a helpful investment tool. No model can be a perfect guide to the future, but Black-Litterman removes many of the issues encountered in the earlier implementations based on single parameter estimates, and is more robust and flexible than other solutions.

Risk is the fuel that drives return. In order to earn a certain actuarial rate fiduciaries must take on and manage risks. The questions they must answer are include: what risk, how much risk, how do we estimate risk and the return for taking risk and what is the best way to manage the risk? Vantage personnel work together with our clients to try to provide satisfactory answers to these important questions.

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1 In economics, equilibrium refers to a state of the world where supply equals demand.

2 Named for Thomas Bayes, an English clergyman and mathematician, Bayesian logic is a branch of logic applied to decision making and inferential statistics that deals with probability inference: using the knowledge of prior events to predict future events.