PORTFOLIO THEORY IS STILL ALIVE AND WELL

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In our article, “Portfolio Theory is Alive and Well” [1994], we argue that the mean-variance framework developed by Harry Markowitz in the 1950s is a valid and useful framework for many, not all, portfolio problems. Since Markowitz’s original work, several variations on mean-variance analysis have been developed. Each type of analysis has its own strengths and weaknesses.

Rom and Ferguson [1993] argue that the framework they prefer, mean-downside risk, where downside risk is measured with respect to an investor-specific minimum acceptable return, is superior to mean-variance analysis in all cases. In our article, we point out the weaknesses of Rom and Ferguson’s framework and the strengths of mean-variance analysis.

In particular, we argue that the type of behavior that an investor would have to exhibit in order to benefit from the Rom and Ferguson framework is generally inconsistent with investing exclusively in conventional asset classes. We also argue that variance (or standard deviation) is a good measure of risk of portfolios of conventional asset classes when it is understood and applied properly. Furthermore, we point out that mean-variance analysis does not rely on the distributions of asset or portfolio returns being normal.

Some of the arguments in “Portfolio Theory is Alive and Well” are made in the context of the theory of expected utility. Here we restate and expand some of our main arguments without the use of utility theory.

A DOWNSIDE RISK INVESTOR SHOULD NOT RUN AN OPTIMIZER

Investors with strong and specific downside risk concerns can do better than select a portfolio of conventional asset classes such as stocks, bonds, and cash. They need access to a richer field of assets, including those with asymmetric distributions. Such assets include options and option-based strategies.

For example, an investor desiring upside exposure with very limited downside risk can purchase a stock market index plus puts on the index (portfolio insurance). This position must be continuously traded to keep the puts at-the-money, so that the insurance is in force. A two-parameter optimizer, which specifies a static asset mix, is the wrong tool for allocating the assets of this investor; the approach should be dynamic, that is, to emphasize the specification of changes to the mix.

STANDARD DEVIATION AND DOWNSIDE RISK BOTH MEASURE RISK

Mean-downside risk optimization with a predetermined target is not wrong in principle. It can be properly motivated in a way that does not depend on the investor having a unique minimum acceptable return. Harlow [1991] says:

While the LPM$_n$ (downside) measure of risk has obvious intuitive appeal, it is important to consider the economic justification for its use and the general conditions under which it is
appropriate.... Within the LPM$_n$ (downside-risk) framework, distributions can be any one of a class characterized by a location and scale parameter (e.g., mean and standard deviation).

Harlow notes that these distributions include normal distributions, Student t-distributions with the same number of degrees of freedom, and stable distributions with the same skewness parameter. Bawa [1975] studied how risk-averse investors rank distributions that belong to the same location-scale family. He finds that distributions with the same mean are ranked by the scale parameter and that distributions with the same scale parameter are ranked by mean. A distribution's scale parameter measures the overall dispersion of returns, whether skewed or symmetric. Typically, it is proportional to standard deviation.

Bawa's findings lead to a mean-scale framework for analyzing portfolio choices. Because the economic justification and general conditions motivating the mean-downside risk framework and the mean-scale framework coincide, either downside risk or scale can be used to measure risk. The choice of a risk measure should be governed by whichever gives the investor more insight.

THE ROLE OF STANDARD DEVIATION AND OTHER STATISTICAL MEASURES

The purpose of any language, including a technical vocabulary, is communication. When choosing a statistical lexicon for talking about the properties of assets, one must care about the listeners. They are heterogeneous and appreciate simplicity. Investor-specific risk measures are not useful for communication between and among heterogeneous individuals. Simplicity dictates that the measures used be easy both to construct and to understand.

A useful vocabulary for describing the properties of assets consists of mean, standard deviation, skewness, kurtosis, serial correlation, and cross-correlation. These terms are sufficient to characterize and compare the members of a very large family of return distributions.

A few important assets (primarily options) are not well-characterized by these terms, and a different vocabulary is required. As we have shown, however, the statistical properties of options are not particularly germane to the problems of optimization (static asset allocation). The investor is well-served by using the conventional asset return statistics enumerated here, as well as by learning about new approaches to the measurement of risk.

ENDNOTES

1Markowitz [1991, pp. 188-201] proposes two mean-semivariance frameworks. In one, the semivariance of each distribution is computed relative to its own mean; in the other, semivariance is computed relative to a predetermined target. Bawa [1975] develops the general mean-scale framework, with mean-logarithmic variance as a special case for lognormal distributions (see also Bawa and Chakrin [1979]). Based on Bawa [1975, 1978], W.V. Harlow develops the mean lower partial moment framework. (See Harlow and Rao [1989] and Harlow [1991].) In that framework, downside risk of a given moment (first, second, or higher) is computed relative to a predetermined target, with second-moment downside risk being the same as Markowitz's below-target semivariance.

2Under the assumptions common to Harlow [1991] and Bawa [1975], the return on a portfolio can be expressed as $L + sZ$ where $L$ is the portfolio's location parameter, $s$ is its scale parameter, and $Z$ is a random variable with the same distribution for all portfolios under consideration. The portfolio's mean is $L + sE[Z]$, its standard deviation is $sE[Z]$, and its coefficient of skewness is the same as that of $Z$.

3This does not mean that they are the same thing, but that portfolios with the same expected return are identically ranked by the two measures.

Bawa and Mishra [1985] explored the relationship between the mean-downside risk frontier and the mean-scale efficient frontier in detail. Professor Bawa died while that research was under way, and the paper has never been published.

REFERENCES


