ECONOMIC FOUNDATIONS AND RISK ANALYSIS IN INVESTMENT MANAGEMENT

by

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Abstract

The risk management systems now used in investment analysis are based on Markowitz mean-variance optimization. Successful application depends on the accuracy with which market returns, risk, and correlation are predicted. Forecasting methods now commonly employed for this purpose rely on time-series approaches that generally ignore economic content. This article suggests that explicitly incorporating economic variables into the forecasting process can improve the ability of such systems to manage risk by providing a delineation between risk associated with changes in economic activity and that attributable to other shocks and discontinuities.

ECONOMIC FOUNDATIONS AND RISK ANALYSIS

IN INVESTMENT MANAGEMENT

Introduction

Over the last decade, investment management evolved from infancy into one of the fastest growing segments of the new service economy. This is evident in the tremendous growth of assets held in mutual funds, self-directed retirement programs, hedge funds, and in derivative instruments, as well as by the continued rise in assets held in pension funds and endowments.

While some of this growth is attributable to structural changes in the financial system, such as the transition from defined benefit to self-directed retirement schemes, a more important factor is the significant decline in global market risk. Some of the specific developments that facilitated systematic risk reduction included: more responsible monetary policy, which brought down inflation over the last two decades; the end of the Cold War; less capricious market intervention by governments; and the introduction of the euro.

A major consequence of lower risk is that it has allowed investment managers to increase allocations to equities, thereby increasing portfolio returns. That said, shocks still occur and significant market risks remain. This was made clear with the Asian currency crisis in 1997, and the Russian debt default and bailout of Long Term Capital Management in 1998. Thus, risk control remains a critical aspect of the investment management process.

In this paper, I analyze the role of risk in investment management, focusing particularly on the critical importance of economics to the process. My frame of reference is the classic Markowitz portfolio problem, which requires return, risk, and correlation prediction for successful implementation. I first briefly review the nature of Markowitz mean-variance risk management, emphasizing its advantages and shortcomings. I then discuss typical methods for forecasting risk and the other inputs used in the approach. I then illustrate how augmenting standard time series techniques with economic content improves results. Finally, I compare mean-variance risk management to the VAR approach now in vogue.

Key Elements of Portfolio Optimization and Investment Risk Management

Early influential studies by Brinson, Hood, and Beebower (1986), Brinson, Singer, and Beebower (1991), and a more recent update by Ibbotson and Kaplan (1999), show that the asset allocation decision is the key determinant of portfolio returns. These studies also conclude that individual security selection is of limited importance. For this reason, asset allocation decisions represent the key intellectual challenge for investment managers.

Most portfolio allocation decisions made by professional managers today rely on Markowitz (1959) mean-variance optimization or variants of the method. This approach explicitly forces comprehensive risk management on the user by formulating portfolio construction in a probabilistic framework. The results of mean-variance analysis are often presented in the context of the efficient frontier, which shows expected portfolio return as a strict function of risk (figure 1). The approach relies on three quantitative inputs—asset returns, measurable asset risk, and correlation between different assets. Key steps in the process include (1) specifying the investment alternatives to be considered; (2) performing the optimization; and (3) choosing the appropriate implementation vehicles. Resulting portfolios have the maximum expected return at minimum risk.

Mean-variance optimization has several important shortcomings that limit its effectiveness. First, model solutions are often sensitive to changes in the inputs. For example, a small increase in expected stock market risk can sometimes produce an unreasonably large shift into bonds. Second, the number of assets that can be included in the analysis is generally limited. Otherwise collinearity problems result. Third and most important, optimum asset allocations are only as good as the forecasts of prospective returns, risk, and correlation that go into the model. The first two limitations can be addressed through skillful model specification. The latter requires that one have superior forecasting skills.

There are few acceptable alternatives to mean-variance analysis and it is commonly used throughout the investment management business by brokerage firms, mutual funds, financial managers, and professionals responsible for institutional asset management. The technique remains a primary tool for making investment decisions and managing portfolios.

Naively Extrapolating the Past

Many users of mean-variance optimization obtain poor results largely because of errors in forecasting asset returns or risk. Often this is due to the common practice of naively extrapolating historical returns, risk, and correlation into the future and producing portfolios that are optimal, based on past data. Empirical studies show that setting investment allocations this way produces poor future performance. This is a chronic problem for all risk management systems--those that presume tomorrow will be exactly the same as today usually fail miserably.

As an example of the fallacy of simply extrapolating history into the future, consider portfolio performance in the 1990s compared with the 1980s. An efficient portfolio constructed in 1990 based on 1980's history would have resulted in large allocations to international equities, particularly Japanese stocks. This is largely because Japan experienced the best equity returns in the world up to 1989. Yet in the 1990s, Japanese equities fell by more than 50% from their 1989 peak and the best asset allocation would have been a 100% commitment to US equities and bonds (table 1).

Forecasting

Serious efforts to obtain superior asset allocations and good risk management thus concentrate on accurately predicting future returns, risk, and correlation. As with forecasting in general, this is no trivial task and is one of the major challenges normally assigned to the economics profession. Of course, forward-looking views may be subjective or quantitative. A subjective or purely judgmental approach allows one the luxury of considering any number of factors that can impact returns or risk. The disadvantage of purely judgmental approaches often used by economists is that they are sometimes instinctual, inconsistent, or overly conditioned on expected policy actions.

This has led most users of risk management systems to rely strictly on quantitative models to predict returns, risk, and correlation. In this regard, time-series methods are most often used and have received a great amount of attention in the finance literature. Beckers (1995) provides a good review of such approaches for forecasting returns, while Alexander (1995) surveys risk and correlation forecasting. Lummer, Riepe, and Siegle (1994) present an extrapolative judgmental approach as a basis for long-term risk management.

The problem with the financial modelers' time-series forecasts of returns, risk, and correlation, is that their views are largely atheoretic. While their models are often incredibly sophisticated mathematically, they are void of intellectual connection to real world events. For this reason, time series modelers inevitably experience difficulty in explaining their conclusions. This is because their model structures are not behavioral and do not lend themselves easily to pedantic interpretation.

As a result, there is often conflict between financial modelers and investment managers who must articulate the reasons for their decisions. The managers rely on economic logic and normally describe events in terms of causal relationships so that investors understand why actions are taken. For the financial modelers, such issues are peripheral and emphasis is placed on the adequacy of the mechanics contained in their "black boxes."

There has been some effort made to integrate economics more fully into the time series approaches used for risk management. For example, Connor (1995) and others explored macroeconomic factor models to explain equity returns and risk. However, such alternatives are generally overlooked in pure time series forecasting and, in the vast majority of cases, economic content in financial models is generally neglected in favor of complex lag and error structures.

The Role of Economics

To contrast typical time-series methods used in portfolio risk management with those that include economic content, I begin with one version of a standard financial model that produces forecasts for the Markowitz optimization process. This Garch bivariate model predicts returns, risk and correlation for the two standard asset classes--US stock and bonds--and assumes that the return-generating process for each is simply autoregressive. I then augment this model by adding economic factors to enhance the forecast of asset returns.

The bivariate Garch model is specified as:

(1) $r_{1t} = \varphi_{11} + \varphi_{12}r_{1,t-1} + \varepsilon_{1t}$

$r_{2t} = \varphi_{21} + \varphi_{22}r_{2,t-1} + \varepsilon_{2t}$

$\sigma_{1t}^2 = \alpha_{10} + \alpha_{11}\varepsilon_{1,t-1}^2 + \beta_{11}\sigma_{1,t-1}^2$

$\sigma_{2t}^2 = \alpha_{20} + \alpha_{21}\varepsilon_{2,t-1}^2 + \beta_{21}\sigma_{2,t-1}^2$

$\sigma_{12t} = \alpha_{30} + \alpha_{31}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \beta_{31}\sigma_{12,t-1}$

where the r_{it} are the returns on equities and bonds, respectively, the σ_{it}^2 are the corresponding variances, the ε_{it} are residuals, and σ_{12t} is the covariance between stocks and bonds. The first two equations are the return-predicting equations while the second two forecast the associated risk. The correlation between stocks and bonds in any period t is simply $\rho = \sigma_{12t}/\sigma_{1t}\sigma_{2t}$. which is derived from the last three equations of the model. The model entries without time subscripts are the parameters to be estimated.

To arrive at an augmented model with economic content, I simply add the same set of exogenous variables to each return-generating equation:

(2) $r_{1t} = \varphi_{11} + \varphi_{12}r_{1,t-1} + \Sigma\Upsilon_{1j}x_{jt} + \varepsilon_{1t}$

$r_{2t} = \varphi_{21} + \varphi_{22}r_{2,t-1} + \Sigma\Upsilon_{1j}x_{jt} + \varepsilon_{2t}$

where the x_{jt} are economic variables. I use monthly data for the analysis because adequate risk management requires frequent review and updating—investment managers often make numerous portfolio allocation decisions through the year. In this regard, although monthly prediction is notoriously difficult, it remains something that practitioners cannot escape. My sample covers the period from January 1986 through May 1999. The economic variables I include are corporate earnings for the S&P 500, the 10-year Treasury bond rate, the Consumer Price Index (CPI), and industrial production (IP).

To simplify the analysis and provide more straightforward descriptive statistics, I use least squares for estimation purposes. Obviously, maximum likelihood estimators or seemingly unrelated regression is more efficient, but in trial analyses these alternative approaches have little impact on my conclusions.

Results

Estimation results are presented in table 2. Figures 2 through 4 show the model fit using economic variables. Figure 5 compares correlation forecasts for the pure Garch model versus the augmented version with economic variables. The basic conclusions are that supplementing the purely time series approach with economic content produces significantly superior predictive power for the return-generating equations. The results show that for stocks, economic variables explain a third of the variation in returns. For bonds, economic variables explain a fifth of variation in returns.

In contrast, the autoregressive time-series models explain virtually none of the month-to-month returns for stocks and bonds. Thus, based on the time-series analysis, the conclusion is that monthly stock and bond returns are simply a random walk. This conclusion is perplexing to an investment manager who lives in a world where anecdotal evidence overwhelmingly indicates that stock and bond returns respond to changes in the economy. Yet these findings would be of little concern to time series analysts actually engaged in risk management.

For the risk and covariance equations, estimation results are more similar for the two approaches with the pure Garch bivariate model producing slightly more predictive power than the alternative model augmented with economic variables. Specifically, the augmented Garch model delivers R^2s of .94, .57, and .26 for stock variance, bond variance, and stock-bond covariance, respectively. For the Garch model augmented with economic variables, the corresponding statistics are .94, .55, and .22.

Note that what might appear to be somewhat low explanatory power for either model must be considered in the context of variable definition and time domain. Returns are measured as monthly percentage changes, not levels. First-order changes are much more difficult to explain. Regardless, it is reassuring that statistical improvement is obtained over the random walk Garch conclusion when economic content is added for returns prediction.

Implications and Caveats

The model estimates of the return-generating processes show that stochastic events beyond the information contained in economic variables can produce fairly large prediction errors. When such surprises occur, this pushes up subsequent risk and reduces correlation—exactly the pattern often observed in stock and bond markets. The advantage of augmenting pure Garch with economic content is that the approach allows one to distinguish business cycle changes versus unexplained ones that may be psychological or event driven. Pure time series allows no such delineation. Clearly, it is important to know when higher risk is attributable to changing economic conditions as opposed to unexplained factors. Critically, augmented Garch provides a more logical and systematic basis for reallocation decisions through the year as the economy evolves.

With respect to relative importance of different model forecasts, studies such as that by Chopra (1993) show that the most crucial decision for portfolio optimization is the return prediction. The addition of economic variables to the standard time-series approach as presented here obviously offers value to the extent that it improves such forecasts. If nothing else, it imposes a logical consistency absent in structures void of economic content.

The crude results I present are designed to be no more than illustrative. Certainly the augmentation variables I use are not the best. There are obviously superior candidates such as liquidity measures, tax rate changes, and Federal Reserve warnings of impending rate changes. In addition, the exogenous variables I use are contemporaneous and would have to be forecast. The obvious solution is to use lagged exogenous economic variables that further improve predictability.

Comparison of the Mean-Variance Approach with VAR

The value at risk (VAR) models used by institutions are fundamentally different from the Markowitz mean-variance models used in investment analysis in that they simply provide estimates of the maximum expected dollar loss on any given day with a specific degree of statistical confidence. In this regard, VAR models are rooted in time series analysis. A major problem with VAR systems is that they utilize limited history—often just the last three years. Furthermore, many VAR models use risk-forecasting techniques such as exponentially weighted moving averages that overly emphasize the importance of recent history.

This can lead to tragic mistakes and unexpected “five or six standard deviation events” that produce huge declines in portfolio value. Most economists would agree that reliance on a limited historical sample is extremely shortsighted. Business cycles are obviously longer than three years and one needs to examine a significantly longer history to fully understand inter-relationships between different markets.

The information provided by VAR is not of great value for investment managers. A dollar estimate of maximum potential one-day loss with 95% or some other chosen level of confidence has limited application. It does not reveal any information about optimum allocations, only the risk associated with the current allocation. VAR does provide an estimate of the amount of capital at risk. But it is only as good as the underlying forecasts that invariably ignore economic changes and are subject to larger errors.

The most obvious failings of VAR occurred last year when numerous investment banks posted large losses with the Russian debt default and the resulting hedge fund implosion as credit spreads widened sharply. As Lamm (1999) showed earlier this year, rapid widening of credit spreads is not unusual. The last such episode occurred in 1994. If VAR models used a more lengthy time series including data from 1993 onward, events in September of 1998 would not have been so surprising.

Even Long Term Capital Management, which must have possessed sophisticated VAR models, was not prepared because of what must have been a reliance on limited history. In fact, Long Term Capital Management did not exist in 1994 and obviously profited in subsequent years as credit spreads narrowed from their previous explosion during the Mexican peso crisis. A little attention to history would have revealed that 1994 was the worst performance year ever for hedge funds in what was a very similar environment.

Conclusion

My basic conclusion is that economic analysis appears to offer important information for making investment decisions and managing risk that is often ignored by the time series risk management models that now predominate. Augmenting standard approaches with economic content produces greater explanatory power and appears to improve forecasts of returns. Augmenting time series structures with economic variables also provides a logical connection to events in the economic system and a delineation of risk from other unexplainable discontinuities and shocks. This allows investment decisions to be made explicitly as a consequence of change in the economic environment in a more straightforward manner.

The current situation is similar to that which existed in the 1980s when the purveyors of large structural econometric models derided time series practitioners as agnostics incapable of understanding the forces of economic behavior. Now time has passed and the structuralists have faded, increasingly displaced by atheoretics who focus on risk forecasting. With the benefit of hindsight, it is now appropriate to ask: Why weren't the structuralists working on risk forecasting models with economic content?

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