MSCI

Research Insight

Is Your Risk Model Letting Your Optimized Portfolio Down?

Pitfalls in Portfolio Construction and MSCI Innovations for Overcoming Them

Jyh-Huei Lee, Oleg Ruban, Dan Stefek, Jay Yao

Jyh-Huei.Lee@msci.com

Oleg.Ruban@msci.com

Dan.Stefek@msci.com

Jay.Yao@msci.com

August 2012

Abstract:

This paper addresses the concern that some risk models used in optimization may not be forecasting risk accurately, or may be creating suboptimal portfolios. We review pitfalls in portfolio construction and explain how MSCI's best practices in model building are designed to overcome these challenges.

Introduction

Optimized portfolios aim to maximize expected return for a given level of risk, helping portfolio managers to best balance the trade-off between these competing objectives. While the optimization framework is elegant and sound, it presents practical challenges to those who implement it. Optimizers require a number of inputs, including a set of expected returns and a covariance matrix. Theory treats these inputs as exact, but in reality they are approximations that are estimated with some uncertainty.

Today, portfolio managers use multi-factor models of risk. These models are less sensitive to noise and produce covariance matrices that are particularly useful for optimization. Nevertheless, not all factor models are equally effective. Flaws in model construction can result in poor risk forecasts, and in optimized portfolios that are not efficient. While risk models are far from new, best practices in model building are being refined continually as more data become available and research innovations are made.

This paper addresses portfolio managers' concern that the risk model used in optimization may be falling short of the mark, by not forecasting an optimized portfolio's risk accurately or creating suboptimal portfolios. An inadequate model factor structure and deficient estimation methodology are two possible causes that affect all portfolios, not just those that are optimized. Optimized portfolios have a more complex connection to a covariance matrix. We discuss two special problems of optimized portfolios: (1) the tendency of risk models to under-forecast their risk, and (2) the prospect that the misalignment of risk and alpha factors may lead to unwanted bets and other problems. We highlight the main issues and explain recent MSCI innovations for overcoming them.

General Risk Model Problems

Poor risk model performance may arise from two broad underlying causes: factor structure and model estimation. The effects of these problems may be felt across both optimized and non-optimized portfolios.

Factor Structure – Missing Factors or Inaccurate Exposures

One source of risk forecasting inaccuracy may be the factor structure of the risk model itself. A risk model may be missing important risk factors, or may not accurately specify assets' exposures to the factors. This is sometimes known as *model error*. It may be the result of inadequate research or lack of comprehensive data coverage. When the set of common factors in a risk model is incomplete, systematic risk will be misrepresented , and this may well result in under-forecasting portfolio risk.

There are no shortcuts to addressing this problem. It is remedied by thorough research and access to comprehensive data that ensures the factor structure is adequate and well specified. Even this, however, may not safeguard against the emergence of transient commonalities or factors confined to a small group of stocks in the estimation universe. In our experience, given a well-constructed risk model, the resulting risk forecast bias is typically not of practical importance- and trying to correct it may create more problems than it solves. An exception to this is the case of optimized portfolios tilted towards the missing factor, which we discuss later in the paper (see the *Misalignment* section below).

Estimation—Inaccurate Volatility or Correlation Forecasts

Having the right factor structure is important, but it is not enough to guarantee accurate covariance matrices. To produce reliable risk forecasts, the factor covariance matrix and asset specific risks must be estimated properly as well. We briefly discuss two issues that may lead to inaccurate volatility or correlation estimates.

1. Non-Stationarity

Covariance matrices are estimated using historical data and provide conditional risk forecasts, based on the assumption that the past is useful in forecasting the future. The real world is non-stationary, and volatilities and correlations change over time. Since risk models use past data to make predictions about the future, they face the challenge of incorporating these changes in a timely fashion. Many risk models struggle not to under-predict risk in times of rising volatility and over-predict risk in times of falling volatility.

Factor models commonly address the issue of non-stationarity by placing greater weight on more recent returns in the estimation of factor volatilities and correlations.[1] Often this is accomplished through an exponential weighting scheme which decreases the weight each period, halving it as we go back a certain length of time into the past (i.e., the half-life). While reducing the half-life helps the model adapt to changing conditions, it also reduces the effective number of observations used in the estimation, leading to noisier covariance estimates (see the *Finite Return Histories and the Risk Forecast Bias of Optimized Portfolios* section below). One way to mitigate this effect is to use higher frequency data – to go from using monthly or weekly returns to using daily returns, for example. This increases the sample size[2] and makes the model more responsive to trends in the market. Daily updates of all components of the model allow new information to be reflected faster in portfolio risk forecasts.

A new technique—the volatility regime adjustment—increases the model responsiveness without sacrificing the number of effective observations (Menchero, Orr and Wang, 2011). This method uses cross-sectional information about model performance to identify periods of under- and over-forecasting. Once mis-forecasting is identified, an appropriate adjustment factor is calculated by comparing factor and asset returns to their risk forecasts. This method improves the forecast of both common factor and asset specific risks.

2. Finite Estimation Universes

Factor returns in fundamental models are estimated by regressing the returns of a universe of assets against the assets' factor exposures. Since the estimation universe contains a finite set of assets, both the factor returns and specific returns invariably contain some noise which we call *measurement error*. This noise may lead to the mis-estimation of the factor covariance matrix, including over-forecasting the factor volatility and, to some extent, the under-forecasting of asset specific risk.[3] This impact is most

---

[1] Other approaches could also be used. These include GARCH models (and their variants) and regime switching models. Exponential weighting is a special case of GARCH.

[2] Using higher frequency data does not necessarily increase the sample size as much as one might think at first glance. Daily factor returns exhibit some autocorrelation which reduces the effective number of independent observations. Risk modelers use autocorrelation adjustments to treat these effects.

[3] We run a regression of the form: $r = Xf + u$, where r is a vector of asset excess returns, X is a matrix of asset exposures, f is the vector of factor returns and u is the vector of specific returns. Let W be the matrix of regression weights. Then the estimated factor returns are: $\hat{f} = f + \left(X'WX\right)^{-1} X'Wu$, where the second term is measurement error. The estimated specific returns are $\hat{u} = u - X\left(X'WX\right)^{-1} X'Wu$. In expectation, the estimated factor covariance matrix is $F + \left(X'WX\right)^{-1} X'W\Delta WX\left(X'WX\right)^{-1}$ which differs from the true factor covariance matrix F. It's easy to show the specific variance estimates are biased as well.

relevant when the model estimation universe is small and tends to diminish as the universe grows in size.

Special Issues with Optimized Portfolios

The performance of optimized portfolios may suffer from two further problems. First, the risk of an optimized portfolio tends to be under-forecast even when the factor structure of the risk model is complete and the estimation process is sound. Second, a mismatch between a manager's alphas and the risk model factors may lead to unwanted portfolio bets. In this section, we explain these issues and describe ways of mitigating them.

Finite Return Histories and the Risk Forecast Bias of Optimized Portfolios

There is a pervasive form of error—*sampling error*—that afflicts all risk models because covariance matrices are based on a limited history of returns. Covariance matrices are built using a time series of returns. As the number of periods used to build the covariance matrix decreases, so does the precision of the covariance estimates. While this does not create a bias in the risk forecast of a randomly selected portfolio, it leads to underestimation of the risks of optimized portfolios (see Lee et al (2011) for a discussion). In the extreme case, it would result in the optimizer finding portfolios with no apparent risk.

The first step in addressing this problem is to impose structure on asset correlations through a factor model. Factor models provide significant protection against estimation error that is lacking in historical asset covariance matrices (Bender, et al 2009). A concise set of factors and uncorrelated specific risk matrix prevent the optimizer from trying to exploit spurious correlations.

While factor models reduce the risk forecast bias of optimized portfolios, they do not eliminate it—there is still a degree of bias that comes from the noise in the factor covariances. A natural way to improve the risk forecasts is to adjust the factor covariance matrix. In 2011, MSCI proposed a method (Menchero, Wang and Orr, 2011) that identifies a special set of portfolios that are relevant to the factor covariance matrix and whose risks are predictably under-forecast due to sampling error. A key insight is that portfolios with the lowest forecast risk are those whose risk is underestimated the most. By adjusting the covariance matrix to correctly reflect the volatilities of these portfolios, we can reduce the bias in forecasts of a broad set of optimized portfolios, while leaving the forecasts of other portfolios barely changed.

Lee, et al (2011) show a number of examples of this adjustment in the context of the Barra US Equity Model (USE3). The adjustment mitigates the bias in risk forecasts and has become an important part of MSCI's new methodology for constructing risk models.

Misalignment

Misalignment arises from discrepancies between risk and alpha factors. Portfolio managers' alphas are often based on asset characteristics that are similar but not identical to those used to form risk factors. Lee and Stefek (2008) showed that an optimizer will tend to emphasize the part of the alpha that is not shared by the risk factors- the *residual alpha*- because the risk model believes that part has no systematic risk. This may create bets in the portfolio that the manager did not intend to take.

To better understand the issue, consider a situation in which price momentum is defined differently by a risk model and an alpha model. The alpha model measures the momentum of a stock as the sum of its returns over the last 13 months, while the risk model only uses the last 12 months return. In that case, the optimizer will tend to emphasize the difference – the residual alpha.[4] It will take a disproportionately large bet on stocks that did well 13 months ago, because that bet has alpha but bears no systematic risk. Yet this is not what the manager had in mind.

This problem of unintended bets is not limited to technical signals like momentum. One can imagine situations in which the risk and alpha models differ in the way they define fundamental characteristics such as earnings yield and book to price. Again, the optimizer may amplify these differences. What, if anything, should be done about this?

Lee and Stefek (2008) examine the case in which the risk and alpha model are capturing the same factor, but measure it a little differently. They show that aligning the risk factors and alpha factors may improve performance, especially when the discrepancy between factor definitions does not contain much useful information. The momentum example illustrates this well. The difference between the alpha and risk factor forms of momentum—the return in month 13—has little power to forecast future returns.

Misalignment and Missing Risk

A somewhat separate concern is that the manager's residual alpha may also represent a source of risk that is not captured by the risk model[5]. This problem is more likely to happen if a risk model is poorly constructed. Unchecked, it may result in inefficient portfolios and the under-forecasting of the risk of optimized portfolios. In this case, we should assign the residual alpha its proper risk when building the portfolio. Bender, Lee and Stefek (2009a and 2009b) show how to modify the portfolio optimization to accomplish this by penalizing the residual alpha. While this method provides a handy solution to the problem, it requires the manager to estimate the missing volatility, and it assumes that the returns to the residual alpha and the risk model factors are uncorrelated.

Another approach to this problem is to incorporate the manager's alpha into the risk model as a risk factor. This is sometimes known as building as "custom risk model." It has the advantage of capturing any correlations that may exist between a missing factor in the alpha and the model risk factors. There is more than one way of adding the alpha to the risk model – one might add just the residual alpha, or one might add all components of the manager's alpha to the risk model (to give some polar opposite cases). This is an active area of research that we will report on in future papers.

It is important to understand that there are other ways of customizing a risk model, such as refining the estimation universe or restricting the model to stocks with a certain sector, each of which may affect portfolio construction. In general, the term *custom model* refers to onetailored to an investment process. In this paper, we use the term in the narrow sense of adding the alpha to the risk model.

In our empirical research, we find that both penalty and custom factor methods tend to improve the risk forecasts for optimized portfolios. The impact on information ratios, however, is mixed—in our

---

[4] In practice, portfolio managers usually drop the most recent month from the calculation because of a tendency for stock returns to reverse over that period. We ignore that here for simplicity of presentation.

[5]The reader may notice that this is an example of an incomplete factor structure, an issue that we discussed earlier. We revisit this issue here as because it often arises in discussions of misalignment, as managers wonder whether their residual alpha – the misaligned part of the alpha – has any risk. We note that misalignment is a broader issue, and it can be a problem whether or not the residual alpha is a source of risk.

preliminary work, we find both improvements and degradations in information ratios (Stefek, Lee and Yao, 2012).

This does not mean that a portfolio manager *always* needs to take remedial action to deal with residual alphas. Manager's alphas may represent ideas that do not conflict with the risk model and are not missing risk factors. In fact, there is a danger in always treating the residual alpha that way. While penalizing the residual alpha will increase the forecast risk, it may not improve the risk forecast (Stefek, Lee and Yao, 2012). More generally, our research makes us highly skeptical (with reason) of broad claims that any direction outside the risk factors should always be regarded as source of systematic risk that needs to be penalized.

Conclusion

This paper reviews ways in which a risk model can fall short in portfolio construction. There are several different causes, each requiring its own solution. Understanding these issues will help managers better evaluate the adequacy of their risk models. In future papers, we will address best practices in risk model construction, provide further insights into risk and alpha factor misalignment, and discuss the practical issues of building custom factor models.

References

Bender, J., Lee, J.-H., and Stefek, D. (2009a). Refining Portfolio Construction When Alphas and Risk Factors are Misaligned. MSCI Research Insight.

Bender, J., Lee, J.-H., and Stefek, D. (2009b). Refining Portfolio Construction by Penalizing Residual Alpha: Empirical Examples. MSCI Research Insight.

Bender, J., Lee, J.-H., Stefek, D. and Yao J. (2009).Forecast Risk Bias in Optimized Portfolios. MSCI Research Insight.

Lee, J.-H. and Stefek D. (2008) Do Risk Factors Eat Alphas? The Journal of Portfolio Management. Vol.34, No.4 (Summer 2008), pp. 12-24.

Lee, J.-H., Stefek, D., Xu, R., and Yao, J. (2011). Mitigating Risk Forecast Biases of Optimized Portfolios. MSCI Research Insight.

Menchero, J., Wang, J., and Orr, D.J. (2011). Optimization Bias Adjustment: Improving Risk Forecasts Using Eigen-Adjusted Covariance Matrices. MSCI Quantitative Insight.

Menchero, J., Orr, D.J., and Wang, J. (2011). The Barra US Equity Model (USE4). MSCI Model Insight.

Stefek, D., Lee, J.-H., and Yao, J. (2012). Getting the Most out of Optimization:
Risk Factor and Alpha Alignment– Issues and Answers. MSCI Client Summit, New York, US.

Client Service Information is Available 24 Hours a Day

clientservice@msci.com

Americas

Americas	1.888.588.4567 (toll free)
Atlanta	+ 1.404.551.3212
Boston	+ 1.617.532.0920
Chicago	+ 1.312.675.0545
Montreal	+ 1.514.847.7506
Monterrey	+ 52.81.1253.4020
New York	+ 1.212.804.3901
San Francisco	+ 1.415.836.8800
Sao Paulo	+ 55.11.3706.1360
Stamford	+1.203.325.5630
Toronto	+ 1.416.628.1007

Europe, Middle East & Africa

Cape Town	+ 27.21.673.0100
Frankfurt	+ 49.69.133.859.00
Geneva	+ 41.22.817.9777
London	+ 44.20.7618.2222
Milan	+ 39.02.5849.0415
Paris	0800.91.59.17 (toll free)

Asia Pacific

China North	10800.852.1032 (toll free)
China South	10800.152.1032 (toll free)
Hong Kong	+ 852.2844.9333
Seoul	798.8521.3392 (toll free)
Singapore	800.852.3749 (toll free)
Sydney	+ 61.2.9033.9333
Tokyo	+ 81.3.5226.8222

Notice and Disclaimer

About MSCI

MSCI Inc. is a leading provider of investment decision support tools to investors globally, including asset managers, banks, hedge funds and pension funds. MSCI products and services include indices, portfolio risk and performance analytics, and governance tools.

The company's flagship product offerings are: the MSCI indices with approximately USD 7 trillion estimated to be benchmarked to them on a worldwide basis[1]; Barra multi-asset class factor models, portfolio risk and performance analytics; RiskMetrics multi-asset class market and credit risk analytics; MSCI ESG (environmental, social and governance) Research screening, analysis and ratings; ISS governance research and outsourced proxy voting and reporting services; FEA valuation models and risk management software for the energy and commodities markets; and CFRA forensic accounting risk research, legal/regulatory risk assessment, and due-diligence. MSCI is headquartered in New York, with research and commercial offices around the world.

[1] *As of June 30, 2011, based on eVestment, Lipper and Bloomberg data.*