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Enhancing mean–variance portfolio selection by modeling distributional asymmetries

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ABSTRACT

Why do mean–variance (MV) models perform so poorly? In searching for an answer to this question, we estimate expected returns by sampling from a multivariate probability model that explicitly incorporates distributional asymmetries. Specifically, our empirical analysis shows that an application of copulas using marginal models that incorporate dynamic features such as autoregression, volatility clustering, and skewness to reduce estimation error in comparison to historical sampling windows. Using these copula-based models, we find that several MV-based rules exhibit statistically significant and superior performance improvements even after accounting for transaction costs. However, we find that outperforming the naïve equally-weighted ($1/N$) strategy after accounting for transactions costs still remains an elusive task.

1. Introduction

Mean–variance (MV) optimization (Markowitz, 1952), either assumes that portfolio returns are normally distributed or that investors exhibit quadratic utility preferences. As such, the theory is unable to account for the presence of higher moments beyond the mean and variance in both the portfolio returns distributions or investor preferences (Cremers, Kritzman, & Page, 2005). Thus, MV optimization is often criticized for having little practical use as it maximizes estimation error, produces

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unintuitive portfolio distributions, and extreme portfolio weights (Michaud, 1989). More recently, the empirical performance of MV optimization has been subject to intense scrutiny due to the findings of DeMiguel, Garlappi, and Uppal (2009) who show that the naïve equally-weighted ($1/N$) portfolio is able to outperform several advanced MV models over the long-term, in out-of-sample analyses across a broad range of data sets. But, can MV models perform better?

Our strategy for answering this question is to focus on the idea that optimal portfolio diversification is dependent upon the quality of the sample inputs into the MV model. Of particular interest are the asymmetries within the joint distribution of stock returns widely reported in the financial literature. These asymmetries manifest in the form of asymmetric volatility clustering (Glosten, Jagannathan, & Runkle, 1993), skewness within the distribution of individual stock returns (Aït-Sahalia & Brandt, 2001) or as asymmetric dependence (Ang & Chen, 2002; Longin & Solnik, 2001; Patton, 2004). Asymmetric dependence describes the scenario in which asset returns exhibit stronger correlations during market downturns than during market upturns. Practitioners also describe this effect as asymmetric correlations and are concerned about it because it reduces the benefits of diversification when they are needed the most (Chua, Kritzman, & Page, 2009).

Our paper makes three key contributions to the literature. First, we document evidence that MV optimization is improved in relation to use of historical samples by managing asymmetries within the marginals and reducing estimation errors in the variance–covariance (VCV) matrix. Second, we are the first paper to apply copulas to several sophisticated extensions of the MV optimization rule that allows the identification of models that might be robust to higher moment risk. Third, by including the combination portfolio rules of Tu and Zhou (2011), we assess how beneficial the application of model-based estimates are for an applied finance investigation in portfolio management.

Empirical studies typically use historical sampling returns or simulations that, to their detriment, do not explicitly account for such asymmetries within the returns distribution when testing MV optimization models (DeMiguel, Garlappi, & Uppal, 2009; MacKinlay & Pastor, 2000; Tu & Zhou, 2011). An inferior choice of the assumed data-generating process for samples used in the MV optimization process can lead to poor performance. Therefore, in this article, we simply ask: can we achieve performance improvements in MV optimization by enhancing the sample input models to capture asymmetries in the marginal distributions of returns? There are some encouraging signs from the recent literature in this regard. Thorp and Milunovich (2007) use predictions from asymmetric VCV forecasting models to calculate optimal weights for international equity portfolios. They find that investors who exhibit moderate levels of risk-aversion with longer re-balancing horizons benefit from using asymmetric forecasts. Their study is limited towards constructing three-asset MV portfolios comprising of two equity market returns (e.g., US, Japan, UK, and Australia) and the risk-free asset. DeMiguel, Plyakha, Uppal, and Vilkov (2013) finds that using option-implied volatility and skewness to adjust expected returns leads to an improvement in the Sharpe Ratio for MV optimization. Indeed, Markowitz (1952) explicitly recommends the use of a probability model to generate the inputs required by the MV model.

Portfolios generated by MV optimization use a sample VCV matrix as the Maximum Likelihood Estimator (MLE) due to the assumption of normally distributed returns. However, if the data deviates (even slightly) from normality, MLEs (e.g., VCV matrix) that are based on normality assumptions are not necessarily the most efficient (Huber & Ronchetti, 2009, Example 1.1). Fantazzini (2009) models returns data that exhibit asymmetries such as skewness with an elliptical copula (e.g., Gaussian and Student t) with intentionally misspecified symmetric marginals. He finds that the misspecification of the marginals can lead to severe negative biases (as much as 70% of the true values) in the correlation estimates when positive correlations are considered.[1] Such issues regarding efficiency and negative bias are of critical importance in portfolio selection where extensive evidence shows that the empirical distribution of returns usually deviates from normality (DeMiguel & Nogales, 2009).

Using historical returns samples to calculate the expected return and the VCV matrix increases the likelihood of estimation error. Therefore, we seek to understand if sampling from a joint distribution via a copula that links asymmetric marginals is able to reduce estimation error and negative bias in

[1] As compared to positive correlations, Fantazzini (2009) find that the bias almost doubles for negative correlations.