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The economic value of controlling for large losses in portfolio selection

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ABSTRACT

Research on asset pricing has shown that investor preferences include asymmetry and tail heaviness which affects the composition of optimal portfolios. This article investigates the out-of-sample economic value of introducing the risk of very large losses in portfolio selection. We combine mean–variance analysis with conditional Value-at-Risk using the subadditivity property of conditional Value-at-Risk, and we introduce a two stage method that preserves diversification while controlling for large losses. We find that strategies that account both for variance and the probability of large losses outperform efficient mean–variance portfolios, during and after the global financial crisis.

1. Introduction

Large losses in financial markets are more frequent and larger than expected under the classical Markowitz (1952) framework. This is due to the non-normality of asset returns and has been recognized since Mandelbrot (1963). Portfolios composed using the classical "normal" mean–variance portfolio optimization are subject to potential large losses originated by the fat-tailedness of asset returns. Hence the need to incorporate the risk of large losses happening in portfolio selection.

It has been shown that investor preferences include asymmetry and tail heaviness; see Harvey and Siddique (2000), Dittmar (2002), Smith (2007), Guidolin and Timmermann (2008), Kozhan et al. (2013). Hence, introducing higher order moments in portfolio optimization affects the composition of optimal portfolios; see Guidolin and Timmermann (2008), Jondeau and Rockinger (2006, 2012).

In the existing literature one stream of research investigates the effect of including higher moments in portfolio selection. This requires the estimation of possibly many high-order cross-moments; see Martellini and Ziemann (2010). Another stream focuses on constraining the portfolio downside risk via Value-at-Risk (VaR), conditional Value-at-Risk (CVaR) or spectral risk measures; see Rockafellar and Uryasev (2000, 2002), Alexander and Baptista (2002), Adam et al. (2008), Brandtner (2013). This literature focuses mostly on probabilistic properties and estimation methods rather than on the economic significance of considering the possibility of large losses in the criteria for portfolio selection. Our contribution is to evaluate the economic value of two portfolio selection strategies that we propose combining mean–variance with the risk of large losses happening.

The concept of limiting downside risk goes back to Roy (1952) who introduced into portfolio selection the principle of safety-first. Roy used the two first moments of the asset returns distribution to limit the probability of a disastrous loss. The study of portfolio selection for safety-first investors was then based on the assumption of normally distributed asset returns. Later Arzac and Bawa (1977) introduced an essentially distribution free approach and used Value-at-Risk (VaR) as a downside risk measure. Another paper on portfolio allocation with safety-first without the normality assumption is Gourieroux et al. (2000) who use a non-parametric estimate of the full distribution of the asset returns. Jansen et al. (2000) concentrate on estimating the portfolio fat-tail distribution using the safety-first principle combined with extreme value theory to limit downside risk. More recently Jondeau and Rockinger (2006) introduce higher moments in portfolio selection and Adam et al. (2008), Brandtner (2013) concentrate on using spectral measures of risk. Through time portfolio selection has departed from the assumption of normality.

Criteria for portfolio selection based on the tail properties of the asset returns distribution often choose a corner solution, meaning that most weight goes to the asset with the thinnest tail. This has

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been observed by, for instance, Jansen et al. (2000), Hartmann et al. (2004), Poon et al. (2003), Adam et al. (2008) and Brandtner (2013). The theoretical explanation for this is linked with a result from Geluk and de Haan (1987). They show that the tail-heaviness of the convolution of heavy-tailed variables is determined mainly by the variable with the heaviest tail. This means that the tail of a portfolio is mostly determined by the tail of the asset with the heaviest tail. As a consequence a portfolio strategy that minimizes tail risk leads to corner solutions by rejecting heavy tailed assets and allocating most weight to the asset with the lighter tail. Corner solutions are a serious drawback in the use of tail risk in portfolio selection because it discourages diversification. Recent work has been done exploring theoretical and empirical aspects of using tail risk measures such as spectral risk measures, a class which includes CVaR. Adam et al. (2008) find that risk measures that account primarily for worst case scenarios tend to overweight assets with thinner tails reducing diversification. Brandtner (2013) shows theoretically that portfolio selection using spectral risk measures tend to produce corner solutions. Brandtner and Kürsten (2014) show in the setting of optimal reinsurance that in particular using CVaR to find the optimal deductible also leads to corner solutions. For the case of optimal reinsurance Brandtner and Kürsten (2014) find that power spectral risk measures can overcome the corner solution problem. Hyung and de (2007) also attempt to overcome the corner solution problem by using a second order expansion at infinity of the asymptotically Pareto tail probability. In our empirical study we take a simpler route. In our first approach we make use of the subadditivity property of the CVaR and obtain optimal mean–variance-CVaR portfolios. Our second approach consists of choosing the portfolio with the lowest CVaR among the set of all possible efficient mean–variance portfolios. With this two stage criterion, on the one hand we do not lose the diversification effect of mean–variance portfolios, and on the other hand we keep the probability of large losses under control essential during the non-normal "heavy-tailed" market times. With the second approach in the first stage we use mean–variance which ensures diversification and avoids corner solutions. In the second stage we keep the risk of large losses under control by selecting the efficient portfolio with the lowest tail risk.

In order to evaluate the economic value of the proposed strategies we consider an investor who takes into account the risk of large losses. Our investor likes mean and positive skewness, and dislikes variance and kurtosis; see Scott and Horvath (1980). Using a concept in the spirit of the certainty equivalent we estimate the fee that an investor would be willing to pay to move from a mean–variance strategy to each of the proposed alternative strategies. A positive fee means that the proposed strategy has a higher economic value for the investor than the mean–variance strategy.

The data used in our analysis consist of stock returns on ten industries covering the U.S. equity market. We choose to analyze a period of time before the global financial crisis, the period during the crisis, and the post-crisis. We compare our benchmark strategy, mean–variance, with the strategies involving CVaR, and we also include an equally weighted portfolio.

Our results indicate that the strategies that control for variance and CVaR outperform mean–variance, a mean-CVaR strategy and the equally weighted portfolio. The performance is measured by the economic value given by a mean–variance equivalent. We include the Sharpe ratio, and the Sortino ratio in the results for comparison. The results are most striking during the global financial crisis and after the crisis.

The organization of this paper is as follows. In Section 2 we describe the methodology used in our study. In Section 3 we present the empirical study and the results obtained. Section 4 concludes the paper.

2. Methodology

We implement the proposed strategies on the U.S. equity market using daily data available from the Kenneth R. French data library.[1] We choose to use the data where equities are grouped into ten industry portfolios spanning from January 1999 to December 2014. The industry portfolios are equally weighted portfolios. In the following we refer to industry portfolios or to assets interchangeably.

The benchmark strategy is the classical mean–variance Merton (1972) approach where the investor minimizes the variance of the portfolio for a given level of return. In our alternative strategies the investor prefers a high mean and a low variance, as in the mean–variance approach, and dislikes the risk of incurring large losses in the portfolio. We use as a measure of risk of incurring large losses the CVaR, also known as expected shortfall. Denoting by R_t a random variable with a continuous distribution function representing the period t return on an asset or industry portfolio, the CVaR at probability level α for period t is given by the expected value of the losses larger than the $100\alpha\%$ VaR,

$$\mathrm{CVaR}_t = -E(R_t|R_t \leqslant -100\alpha\%\mathrm{VaR}_t), \tag{1}$$

The VaR of probability level α is the quantile

$$\mathrm{VaR}_t = -\inf\{r \in \mathbb{R} : P(R_t \leqslant r|\mathcal{F}_{t-1}) \geqslant 1-\alpha\},$$

where $\mathcal{F}_t$ represents the information available at time t. The probability level α typically takes values between 90% and 99%.

In line with related work, as Adam et al. (2008), Fleming et al. (2001) and Jondeau and Rockinger (2006), we assume that short selling is not allowed in all the strategies in our study. This restriction makes our results more relevant for unsophisticated private investors or institutional investors who cannot use short selling, as for instance pension funds. Our goal here is to evaluate the effect of considering large losses on the performance of a portfolio of risky assets. Hence, we follow Jondeau and Rockinger (2006) and assume that the investor does not hold neither bonds nor cash in the portfolio.

The calculation of the portfolio weights for each strategy depends on the estimation of asset expected returns and CVaR based on historical data. For the estimation of tail risk measures (for instance in the area of risk measurement) 1000 observations strike a balance between a sufficiently large number of observations for statistical estimation and a small enough time window for the estimates to be sensitive to changes in the market conditions. The Basel Committee (2013) favors the argument that the historical data used should reflect time varying market conditions and recommends to use one or two years of historical data but at the cost of larger errors. Hence, to increase the quality of the estimates we use 1000 observations corresponding to four years of data. We use the window of the first 1000 days of data to determine the portfolio weights for each strategy. The weights of the portfolio are then kept constant for one week and after one week we recalculate the portfolio weights according to the different strategies using the previous 1000 days of data. We continue with this procedure for the different strategies until December 2014, obtaining 605 out-of-sample weekly returns for each strategy. We follow Jondeau and Rockinger (2006) in using a weekly portfolio optimization in our study. We do not use higher frequency for rebalancing the portfolio because in that case the gains from a better portfolio strategy might tend to disappear due to transaction costs.

[1] Data downloaded from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.