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Applied mean-ETL optimization in using earnings forecasts

Barret Pengyuan Shao [a,*], Svetlozar T. Rachev [b], Yu Mu [c]

[a] Crabel Capital Management LLC, Charlottesville, VA, 22902, United States
[b] College of Business, Department of Applied Mathematics and Statistics, Stony Brook University, Stony Brook, NY, 11790, United States
[c] Department of Applied Mathematics and Statistics, Stony Brook University, Stony Brook, NY, 11790, United States

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ABSTRACT

In this article, we apply the mean-expected tail loss (ETL) portfolio optimization to the consensus temporary earnings forecasting (CTEF) data from global equities. The time series model with multivariate normal tempered stable (MNTS) innovations is used to generate the out-of-sample scenarios for the portfolio optimization. We find that (1) the CTEF variable continues to be of value in portfolio construction, (2) the mean-ETL portfolio optimization produces statistically significant active returns, and (3) the active returns generated in the mean-ETL portfolio with CTEF indicate a statistically significant stock selection.

1. Introduction

Fundamental data on stocks have been being used for selecting stock for a long time. For example, Guerard, Rachev, and Shao (2013) construct a stock selection model, the United States Expected Returns (USER) model, based on fundamental data. Jegadeesh and Titman (1993) show that buying stocks that performed well in the past and selling stocks that performed poorly the past can generate statistically significant positive returns over both 3-month and 12-month holding periods. The number of equities globally is much larger than that in the US, and the use of both can diversify the portfolio, as was noted by Solnik (1974). Guerard et al. (2013) show that global markets generate greater returns relative to risk than the US domestic market.

Markowitz (1959) uses a mean–variance portfolio optimization model to maximize the portfolio return for a given level of risk, which is represented by the portfolio variance. Based on global equities data, Guerard et al. (2013) show that both mean–variance and mean-expected tail loss (ETL) portfolio optimizations generate excess returns above transaction costs and statistically significant asset allocations during the period 1997–2011. Tsuchida, Zhou, and Rachev (2012) show the efficiency of mean-ETL portfolio construction in the US equity market based on different scenario-generated models. In this paper, we apply mean-ETL portfolio optimization to the consensus temporary earnings forecasting (CTEF) data from global equities. The scenarios for portfolio optimization are generated through the ARMA-GARCH-MNTS model, which will be discussed in Section 3.

In this paper, Section 2 discusses the importance of the consensus temporary earnings forecasting (CTEF) variable, which is used in this paper for further portfolio optimization. Section 3 presents the ARMA-GARCH model with MNTS innovations and shows how it can be used to generate scenarios based on CTEF data. Section 4 discusses the mean-ETL portfolio optimization with turnover and maximum weight constraints. The mean-ETL portfolio optimization is implemented in the CTEF scenarios, which are generated based on the method in the previous section. Section 5 presents the simulation results from empirical data and the corresponding risk analysis based on mean-ETL portfolio construction with CTEF data. Section 6 provides conclusions and a summary.

* Corresponding author.
E-mail addresses: barretshao@gmail.com (B.P. Shao), rachev@qf.ams.sunysb.edu (S.T. Rachev).

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2. Consensus temporary earnings forecasting

Analysts' earnings expectations and price momentum are often used for stock selection. Graham, Dodd, and Cottle (1934) select stocks based on fundamental valuation techniques, and show that stocks that are more stable in their earning power, or those with higher earnings-per-share (EPS), outperform the less stable ones. In 1975, Lynch, Jones and Ryan collected and published consensus statistics for EPS forecasting, forming the beginning of what is now known as the Institutional Brokerage Estimation Service (I/B/E/S) database (Brown, 1999). Elton, Gruber, and Gultekin (1981) show that the stock share price is affected by expectations about the earnings per share. Arnott (1985) shows that trends in consensus earnings have a strong tendency to persist, making it a highly consistent security timing indicator. Guerard, Gultekin, and Stone (1997) study the efficiency of consensus temporary earnings forecasting (CTEF), which is composed of forecasted earnings yield (FEP) from I/B/E/S, earnings revisions (EREV) and earnings breadth (EB), as created by Guerard et al. (1997). Guerard, Blin, and Bender (1998) find that a value-based model with CTEF variables produces statistically significant models for stock selection in the United States and Japan. In the global expected return model (see Guerard et al., 2013), CTEF and price momentum (PM) variables account for the majority of the forecast performance.

The importance of CTEF in portfolio construction has also been illustrated in the recent literature. Tsuchida et al. (2012) show an information ratio of 0.60 with mean-ETL optimization on the United States expected return (USER) data. Guerard, Markowitz, and Xu (2015) show that mean–variance portfolio optimizations produce excess returns that are greater than the transaction costs, based on global expected return (GLER) data. Shao and Rachev (2013) show that mean-ETL portfolio optimization based on GLER data can generate statistically significant active returns. In both the USER and GLER models, the CTEF variable contributes to the predictions significantly. The reader is referred to the studies by Guerard et al. (1997) for a more detailed analysis of the USER model and its relationship with CTEF, and Guerard et al. (2013) for the GLER model.

In this paper, we construct mean-ETL portfolios based solely on the CTEF variables of the global stocks that are included in the FactSet dataset from January 1997 to December 2011.

3. Scenario generation method

In this section, we introduce a scenario generation method for mean-ETL portfolio optimization with the CTEF variable. In this method, we choose the time series model autoregressive moving average (ARMA) generalized autoregressive conditional heteroskedastic (GARCH) with the multivariate normal tempered stable (MNTS) innovations as our scenarios generator. By using the ARMA-GARCH-MNTS scenario generator, some stylized facts in asset returns, such as joint volatility clustering, fat-tails, and asymmetric dependence structure, can be captured well. As was discussed by Fama (1963) and Mandelbrot (1963a,b), asset returns usually exhibit fat tails and an asymmetric dependence structure, which is hard to capture using a normal distribution under the assumptions of the mean–variance framework. In order to capture skewness and fat tails in the asset returns better, the α-stable distribution has been proposed as an alternative to the normal distribution (readers are referred to Rachev & Mittnik, 2000, for more details). However, due to the polynomial decay of the density function, the α-stable distribution usually does not have a finite variance, which renders it unsuitable for certain financial applications. Rosiński (2007) introduces a class of tempered stable processes which combine α-stable and Gaussian trends. Kim, Giacometti, Rachev, Fabozzi, and Mignacca (2012) discuss the use of MNTS as the multivariate market model for measuring risk. Before modeling the CTEF data using ARMA-GARCH-MNTS, we review the MNTS and its properties here briefly.

3.1. Multivariate normal tempered stable distribution

The definition of the univariate normal tempered stable distribution (NTS) is given in the subordination scheme. The subordinator used for constructing the NTS distribution is the *classical tempered stable (CTS) subordinator* T, which is defined by its characteristic function as follows:

$$\phi_T(t) = \exp\left(-\frac{2\theta^{1-\alpha/2}}{\alpha}\left((\theta - it)^{\alpha/2} - \theta^{\alpha/2}\right)\right), \quad (1)$$

where (α, θ) are the parameters of this distribution, with constraints $\alpha \in (0, 2)$ and $\theta > 0$. The univariate normal tempered stable (NTS) distribution is then defined as the distribution of the random variable X that satisfies the following subordination scheme:

$$X = \mu + \beta(T - 1) + \gamma\sqrt{T}\varepsilon, \quad (2)$$

where $\mu \in \mathbb{R}$, $\beta \in \mathbb{R}$, $\gamma > 0$, $\varepsilon \sim N(0, 1)$, T is the CTS subordinator independent with ε, and we denote X by $X \sim NTS(\alpha, \theta, \beta, \gamma, \mu)$. The characteristic function of X can be written as follows:

$$\phi_X(t) = \exp\left((\mu - \beta)ti - \frac{2\theta^{1-\alpha/2}}{\alpha} \times \left(\left(\theta - i\beta t + \frac{\gamma^2 t^2}{2}\right)^{\alpha/2} - \theta^{\alpha/2}\right)\right), \quad (3)$$

where the parameter μ represents the mean of X, and the variance of X is equal to $\mathrm{VaR}(X) = \gamma^2 + \beta^2\left(\frac{2-\alpha}{2\theta}\right)$.

The multivariate normal tempered stable distribution (MNTS) is defined in a similar way. We say that the multivariate random variable X follows the multivariate normal tempered stable (MNTS) distribution $X \sim MNTS(\alpha, \theta, \beta, \gamma, \mu, \rho)$ if

$$X = \mu + \beta(T - 1) + \gamma\sqrt{T}\varepsilon, \quad (4)$$

where $\mu \in \mathbb{R}^N$, $\beta \in \mathbb{R}^N$, $\gamma \in \mathbb{R}_+^N$ with $\mathbb{R}_+ = [0, \infty)$, and $\varepsilon = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_N)^T$ is an N-dimensional multivariate standard normal distribution with covariance matrix ρ,