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Incorporating asset growth potential and bear market safety switches in international portfolio decisions

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ABSTRACT

In the paper the impact of the growth potential index (*GPI*) of risky assets and bear market safety switches in portfolio decisions is discussed. A recursive formulation based on out-of-sample time series predictions of the underlying assets is applied in the empirical testing. It is demonstrated that the multiple representations framework provides useful forecasts for portfolio management. A number of alternative forecasting methods are included. The best forecast for each individual asset serves as input to the portfolio optimization module. The recursive time series estimation-optimization system is embedded in the genetic hybrid algorithm to improve the prediction accuracy. In contrast to single-period equilibrium models, the mathematical program recognizes cardinality constraints required in institutional banking, the opportunity cost, fixed and variable transactions costs, liquidity, the risk profile of the investor and the entry/exit time for risky investments. The database consists of the daily market indexes of 12 global stock exchanges in local and *Euro* converted currencies based on the daily European interbank exchange rates. Time series regressions indicate that *GPI*-constrained recursions outperform the buy-and-hold strategy. The downside risk of the portfolio is effectively controlled by crisp or fuzzy distress indicators to switch between cash or low-risk interest bearing instruments and risky assets.

1. Introduction

Portfolio selection models have attracted a wide research interest since the path-breaking mean-variance theory of efficient portfolios put forward by Markowitz [1]. The seminal work of Markowitz also intensified the research of asset pricing models, leading to important contributions such as the capital asset pricing model (CAPM) and the arbitrage pricing theory (APT). However, the observed non-normality of the financial market suggests asymmetric investment psychology, where the downside risk is considered differently from the upward return potential (cf. [45]).

A key problem with the Markowitz theory is the intractability of the covariance matrix when increasing the number of assets. The Markowitz theory is static by nature, providing the techniques needed for deriving the efficient risk-return frontier of financial assets in economic equilibrium (cf. [51]). However, for the investor operating under economic friction, a mean variance equilibrium model gives insufficient decision support [2]. The questions when to enter vs. exit from a risky investment and how to optimally respond to changing market conditions by rebalancing the portfolio under fixed and variable transactions costs remain unanswered in the Markowitz world (cf. [3]). Selecting an unfavorable entry point for risky investments can usually not be compensated by active governance within a reasonable investment period, irrespectively of how sophisticated the decision model is [48]. According to the mutual-fund separation theorem, more risk averse investors should hold more of their assets in the riskless asset, whereas the composition of the risky assets should be identical for all investors. Canner et al. [4] observed that public advisors recommend more complicated strategies than implied by the theorem (cf. [39,5]). They also recommend a lower ratio of bonds to stocks for aggressive investors than for conservative investors.

Konno and Yamazaki [6] proposed the MAD portfolio optimization model measuring risk by the (mean) absolute deviation instead of variance (cf. [7]). The model is computationally attractive as it results in (mixed integer) linear programming problems for discrete random variables. The model was extended by Michalowski and Ogryczak [46] to include the downside risk aversion of the investor in an m-MAD formulation (cf. Xidonas et al. [8]). This allows the investor to control and fine-tune the portfolio optimization process through m trade-off parameters λ_i, $i = 1,\ldots,m$ between risk and return. Vercher et al. [9] presented two fuzzy portfolio selection models for minimizing the downside risk at a given level of expected return. By considering the stock returns as fuzzy numbers, the multi-period problem formulation turns into an extension of single period fuzzy portfolio models. The extensions require elaborate specifications of fuzziness. The contrarian investment strategy [10] represents a completely

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different focus on risk management and investment activity. For example, the incentive to buy cheap (short sell expensive) assets emanates from the assumption that the majority of these assets are underpriced (overpriced). They are expected to provide better return opportunities than, for example, a MAD strategy minimizing the proportion of such holdings in the portfolio. The risk formulation presented below encompasses both traditional (diversity oriented) MAD and contrarian strategies for risk control.

Single period equilibrium models cannot fully cope with the decision needs encountered in portfolio decision making in practice [11]. Assuming an identical composition of the risky assets for all investors follows from the single-period equilibrium theory of financial decision making and not from the conditions under which all investors have to operate.

Multi-period portfolio theory combined with rigorous statistical time series algorithms and techniques anchored in artificial intelligence can cope with several intricacies in international trading (cf. [12]). The models imitate human expectations/beliefs and decisions through the interplay between forecasting and optimization. Multi-period formulations are robust with respect to, e.g., non-stationary returns or unknown return distributions. Artificial intelligence based techniques can cope with non-stationarity, regime shifts and related difficulties encountered in financial time series estimation. Contrary to single-period equilibrium models, multi-period models readily incorporate, for example budget limits, liquidity requirements, fixed/variable/minimum rebalancing costs [13], cardinality constraints, issues of additional cash input, time of entry and exit as well as downside risk control (cf. [43]). Since investment activity is periodic by nature, a recursive framework appropriately balancing forecasting and optimization is both intuitively appealing and focuses on the necessary practical issues directly to the point.

The main contribution of the paper is to demonstrate that the buy-and-hold benchmark portfolio can be outperformed by an integrated system recognizing the growth potential of individual assets and the downside risk through crisp or fuzzy bear market safety switches. Several key aspects of foreign investments and asymmetric returns are addressed. The empirical evidence is based on representative time series models providing out-of-sample input to a multi-period portfolio optimization framework (cf. [14]). The return potential of global asset portfolios is assessed subject to fixed and variable transactions costs, liquidity requirements, investor risk aversion, the growth potential of individual assets and bear market safety switches (cf. the safety layer in Maslowian portfolio theory [15]). Safety and downside risk control are central components of investor behavior (cf. [35,49]) and observed return asymmetries (cf. [44]). Market disagreement measured from individual-stock analyst forecast dispersions (cf. [16]) or evaluation of financial crisis [17] may serve as bear market indicators. The results imply that the downside risk of the portfolio is effectively reduced by using bear market safety switches and by explicitly recognizing the growth potential of individual stocks in the problem formulation. Competitive return opportunities are still preserved under liquidity requirements and fixed/variable transactions costs. The recursive system seems to provide valuable support to human intelligence in international trading.

The forecasting subsystem is summarized in the next section. The optimization subsystem is presented in Section 3, where the growth potential index and bear market safety switches are introduced in the optimization problem. In this section, the concept of fuzzy distress indicators is introduced. The return on assets and its connection to the stochastic discount factor are discussed in Section 4. The recursive system is tested in Section 5 with daily, weekly and monthly portfolio rebalancing. The return impact of the asset growth potential and bear market conditions is tested in bivariate regressions. The results are compared to the performance of the buy-and-hold benchmark. The results are summarized in Section 6.

2. The vector-valued time series support libraries of GHA

The recursive portfolio formulation is based on out-of-sample time series predictions of the underlying stock prices. A representative set of forecasting methods is employed, such that for each asset the best available forecast will serve as input to the optimization module. The time series algorithms are trimmed by the genetic hybrid algorithm Östermark [14]. The following vector-valued algorithms have been integrated as support libraries in GHA:

- SPMX, a vector-valued state space algorithm with exogenous inputs [18]
- VMX, a vector-valued VARMAX search algorithm [18]
- NET, an enhanced backpropagation three-layer neural net algorithm [19]
- KNN, a fuzzy VARMAX extension of the K nearest neighbor algorithm [20]
- MIX, a vector-valued mixture density algorithm for vector processes with GARCH-residuals [21]

GHA trims the algorithms by determining the optimal parameters for each algorithm (cf. Tseng [41], Tseng et al. [42]). The parametric search related to time series estimation can be accelerated through parallel processing. GHA contains facilities based on the message passing protocol (MPI) for parallel search on high performance parallel supercomputers [21,22].

> GHA is allowed to use all available cores on the massively parallel Cray XT supercomputer at the Center of Scientific Computing (CSC) in Helsinki. GHA is listed on the website of CSC as one of the few fully scalable parallel algorithms (http://www.csc.fi/english/research/Computing_services/computing/servers/louhi_scalability). Cray XT belongs to the group of the top 500 parallel supercomputers in the world (http://www.top500.org/, 11/2007). During 09-11/2011, the scalability of GHA was tested on the massively parallel supercomputer Jugene in Jülich (Germany) with up to 65536 parallel processors. At the time of the test, Jugene is the fastest massively parallel supercomputer in Europe. Some examples of the use of GHA in computational problems is provided in http://www.abo.fi/fak/esf/gha/research/geno_mathematics/presentation/download_gha_guide.php. The maximum number of processors is dependent on the computational problem and is not restricted by GHA.

An integrated system called SHAREX is tested in the empirical section on a set of 12 global stock market indexes covering the time period 12/1998-12/2008. Summary statistics are presented for KNN and VMX used as forecast generators in the below tests. The key parameters (e.g., the lag structure for the endogenous and exogenous vectors, the residual vector, etc.) are determined by GHA within given search intervals. The parameterization is based on maximizing the directional consistency of the predictions. Some statistics for the vector models and data are presented in Table 1 for the complete data set. Our results indicate that short term dynamics can be captured to a remarkable extent (Table 1; cf. [23]).

3. The recursive multi-period portfolio formulation

The intuition of the model is as follows: assume a rational investor operating in the financial market with a portfolio of an interest bearing cash deposit and a set of risky assets and a possibility to debt financing. The investor makes explicit or implicit assumptions of the expected price paths of the risky and riskless assets in his world of reference. The longer the time span, the more implicit the assumptions tend to get. In a long-term buy-and-hold