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Hedge fund return predictability; To combine forecasts or combine information?

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Abstract

While the majority of the predictability literature has been devoted to the predictability of traditional asset classes, the literature on the predictability of hedge fund returns is quite scanty. We focus on assessing the out-of-sample predictability of hedge fund strategies by employing an extensive list of predictors. Aiming at reducing uncertainty risk associated with a single predictor model, we first engage into combining the individual forecasts. We consider various combining methods ranging from simple averaging schemes to more sophisticated ones, such as discounting forecast errors, cluster combining and principal components combining. Our second approach combines information of the predictors and applies kitchen sink, bootstrap aggregating (bagging), lasso, ridge and elastic net specifications. Our statistical and economic evaluation findings point to the superiority of simple combination methods. We also provide evidence on the use of hedge fund return forecasts for hedge fund risk measurement and portfolio allocation. Dynamically constructing portfolios based on the combination forecasts of hedge funds returns leads to considerably improved portfolio performance.

JEL classification: G11; G12; C22; C53

Keywords: Forecast Combination; Combining Information; Prediction; Hedge Funds; Portfolio Construction.

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1 Introduction

Hedge funds have attracted a great deal of attention during the last fifteen years. High net-worth individuals or institutional investors seek premium returns in these alternative asset classes. The recent launch of investable hedge fund indices allowed a larger proportion of small- to medium-sized investors to gain access to this type of investment and boosted the interest in studying hedge fund investments. Following unconventional trading strategies, these funds have traditionally outperformed other investment strategies partly due to the weak correlation of their returns with those of other financial securities. However, the 2007-08 financial crisis revealed the interdependencies of these funds with the rest of the financial industry and caused a reduction in the number of hedge funds.

While the majority of the predictability literature has been devoted to the predictability of traditional asset classes, the literature on the predictability of hedge fund returns is quite scanty. Amenc et al. (2003) were the first to investigate return predictability in the hedge fund industry. The authors employ multi factor models based on a variety of economic variables and find significant evidence of hedge fund predictability. In a subsequent study, Hamza et al. (2006) consider both a broader set of risk factors and a longer time series and find evidence in favour of predictability. More recently, Wegener et al. (2010) address the issue of non-normality, heteroskedasticity and time-varying risk exposures in predicting excess returns of four hedge fund strategies. With the same aim, Bali et al. (2011) exploit the hedge funds' exposures to various financial and macroeconomic risk factors. Avramov et al. (2011) find that macroeconomic variables, specifically the default spread and the Chicago Board Options Exchange volatility index (VIX), substantially improve the predictive ability of the benchmark linear pricing models used in the hedge fund industry. Employing time-varying conditional stochastic dominance tests, Olmo and Sanso-Navarro (2012) forecast the relative performance of hedge fund investment styles one period ahead.

Given the long set of candidate predictors, suggested by the extant literature, we address the issue of constructing improved hedge fund returns forecasts by carefully integrating the information content in them. We proceed in two directions; combination of forecasts and combination of information. Combination of forecasts combines forecasts generated from simple models each incorporating a part of the whole information set, while combination of information brings the entire information set into one super model to generate an ultimate forecast (Huang and Lee, 2010). We employ a variety of combination of forecasts and information methodologies and evaluate their predictive ability in a pure out-of-sample framework for the period 2004-2011, which contains the 2007-2008 crisis that plagued the hedge fund industry. To anticipate our key results, our statistical evaluation findings suggest that simple combination of forecasts techniques work better than more sophisticated and computationally intensive combination of information ones. Evaluating the forecasts from an economic point of view points to the same direction. However, the utility gains a mean-variance investor would have can be large irrespective of the model employed. Our analysis revealed that hedge fund strategies like SB, EM and M are quite challenging for a researcher since they are very hard to predict. More importantly, we compare the performance of our forecasting approaches with respect to their ability to construct optimal hedge fund portfolios in a mean-Var and mean-CVaR framework. Overall, forecasting hedge fund returns leads to improved portfolio performance, while combination of forecasts proves to be the superior approach. Simple combining schemes can generate portfolios with high average returns and low risk.

The remainder of the paper is organized as follows. Section 2 describes the predictive models and the forecasting approaches we follow. Our dataset, the framework for forecast evaluation and our empirical findings are presented in Section 3. Section 4 discusses the approaches we employ to construct optimal hedge fund portfolios, presents the portfolio performance measures used in our empirical analysis and reports the results of our investment exercise. Section 5 summarizes and concludes.

2 Predictive Models and Forecast Construction

In this section, we describe the forecasting approaches we follow. To facilitate the exposition of our approaches, we first describe the design of our forecast experiment. Specifically, we generate out-of-sample forecasts of hedge fund returns using a recursive (expanding) window. We divide the total sample of T observations into an in-sample portion of the first K observations and an out-of-sample portion of $P = T - K$ observations used for forecasting. The estimation window is continuously updated following a recursive scheme, by adding one observation to the estimation sample at each step. As such, the coefficients in any predictive model employed are re-estimated after each step of the recursion. Proceeding in this way through the end of the out-of-sample period, we generate a series of P out-of-sample forecasts for the hedge fund indices returns. The first P_0 out-of-sample observations serve as an initial holdout period for the methods that require one. In this respect, we evaluate $T - (K + P_0) = P - P_0$ forecasts of the hedge fund returns $\{\hat{r}_{i,t+1}\}_{t=K+P_0}^{T-1}$ over the post-holdout out-of-sample period.

2.1 Univariate models

First we consider all possible conditional mean predictive regression models with a single predictor of the form

$$r_{t+1} = \beta_0 + \beta_i x_{it} + \beta_{N+1} r_t + \varepsilon_{t+1},\ i = 1, \ldots, N, \tag{1}$$

where r_{t+1} is the observed return on a hedge fund index at time $t + 1$, x_{it} are the N observed predictors at time t, and the error terms ε_{t+1} are assumed to be independent with mean zero and variance σ^2. Given the significant autocorrelation present in the majority of hedge fund returns, the set of potential predictors contains the lagged (one-month) return as well. Equation (1) is the standard prediction model, which links the forecast of one-period ahead hedge fund return to its current return and a candidate predictor variable. When no predictive variable is included in Equation (1), we get the benchmark AR(1) model which serves as a natural benchmark for the forecast evaluation.

2.2 Forecast Combination

Combining forecasts, introduced by Bates and Granger (1969), is often found to be a successful alternative to using just an individual forecasting method. Forecast combinations may be preferable to methods based on an ex-ante best individual forecasting model due to at least three reasons (see Timmerman, 2006, for a survey). First, combining individual models' forecasts can reduce uncertainty risk associated with a single predictive model (Hendry and Clements, 2004). Similarly to the simple portfolio diversification argument, combining models based on different information sets may prove more accurate than a single model that is aimed at incorporating all the information (Huang and Lee, 2010). Second, in the presence of unknown instabilities (structural breaks) that favour one model over another at different points in time, forecasts combinations are more robust to these instabilities, (Clark and McCracken, 2010 and Jore et al., 2010). Finally, in the event that models suffer from omitted variable bias, forecast combination may average out these unknown biases and guard against selecting a single bad model.

We consider various combining methods, ranging from simple averaging schemes to more advanced ones, based on the single predictor model specifications (Equation 1). Specifically, the combination forecasts of r_{t+1}, denoted by $\hat{r}_{t+1}^{(C)}$, are weighted averages of the N single predictor individual forecasts, $\hat{r}_{i,t+1}$, $i = 1, \ldots, N$, of the form

$$\hat{r}_{t+1}^{(C)} = \sum_{i=1}^{N} w_{i,t}^{(C)} \hat{r}_{i,t+1},$$

where $w_{i,t}^{(C)}, i = 1, ..., N$ are the *a priori* combining weights at time t.

The simplest combining scheme is the one that attaches equal weights to all individual models, i.e. $w_{i,t}^{(C)} = 1/N$, for $i = 1, ..., N$, called the mean combining scheme. The next schemes we employ are the trimmed mean and median ones. The trimmed mean combination forecast sets $w_{i,t}^{(C)} = 1/(N-2)$ and $w_{i,t}^{(C)} = 0$ for the smallest and largest forecasts, while the median combination scheme is the median of $\{\hat{r}_{i,t+1}\}_{i=1}^{N}$ forecasts.

The second class of combining methods we consider, proposed by Stock and Watson (2004), suggests forming weights based on the historical performance of the individual models over the holdout out-of-sample period. Specifically, their Discount Mean Square Forecast Error

(DMSFE) combining method suggests forming weights as follows

$$w_{i,t}^{(C)} = m_{i,t}^{-1} / \sum_{j=1}^{N} m_{j,t}^{-1}, \ m_{i,t} = \sum_{s=K}^{t-1} \psi^{t-1-s} (r_{s+1} - \widehat{r}_{i,s+1})^2, \ t = K + P_0, ..., T,$$

where ψ is a discount factor which attaches more weight on the recent forecasting accuracy of the individual models in the cases where $\psi < 1$. The values of ψ we consider are 0.9 and 0.5. When ψ equals one, there is no discounting and the combination scheme coincides with the optimal combination forecast of Bates and Granger (1969) in the case of uncorrelated forecasts.

The third class of combining methods, namely the cluster combining method, was introduced by Aiolfi and Timmermann (2006). In order to create the cluster combining forecasts, we form L clusters of forecasts of equal size based on the MSFE performance. Each combination forecast is the average of the individual model forecasts in the best performing cluster. This procedure begins over the initial holdout out-of-sample period and goes through the end of the available out-of-sample period using a rolling window. In our analysis, we consider $L = 2, 5$.

Next, the principal component combining methods of Chan, Stock and Watson (1999) and Stock and Watson (2004) are considered. In this case, a combination forecast is based on the fitted n principal components of the uncentered second moment matrix of the individual model forecasts, $\widehat{F}_{1,s+1}$, ..., $\widehat{F}_{n,s+1}$ for $s = K, ..., t-1$. The OLS estimates of $\varphi_1, ..., \varphi_n$ of the following regression

$$r_{s+1} = \varphi_1 \widehat{F}_{1,s+1} + ... + \varphi_n \widehat{F}_{n,s+1} + \nu_{s+1}$$

can be thought of as the individual combining weights of the principal components. In order to select the number n of principal components we employ the IC_{p3} information criterion developed by Bai and Ng (2002) and set the maximum number of factors to 5 and 7.

2.3 Combining Information

The second approach we consider is based on combining the information of all the available predictors in a single model.

The first model we consider is the following multiple predictive regression model

$$\hat{r}_{t+1} = x_t' \boldsymbol{\beta} + \varepsilon_{t+1} \tag{2}$$

where $x_t^{'}$ is a $(N+1) \times 1$ vector of predictors which contain the lagged (one-month) return, and $\boldsymbol{\beta} = (\beta_0, \beta_1, \beta_2, ..., \beta_N, \beta_{N+1})'$ is $(N+1) \times 1$ vector of parameters. This model includes all N predictive variables as separate regressors in addition to current values of hedge fund returns and is widely known as the Kitchen Sink (KS) model (see Goyal and Welch, 2008). As Rapach, Strauss and Zhou (2010) show the KS model performs no shrinkage, as opposed to the simple mean combination scheme that shrinks forecasts by a factor of $1/N$. To this end, we consider shrinking the estimated parameters of model (2) through bootstrap aggregating (bagging) along the lines proposed by Inoue and Kilian (2008). Bagging, introduced by Breiman (1996) is performed via a moving-block bootstrap. More specifically, a large number (B) of pseudosamples of size t for the left-hand-side and right-hand-side variables in (KS) are generated by randomly drawing blocks of size m (with replacement) from the observations of these variables available from the beginning of the sample through time t . For each pseudo-sample, we estimate (KS) using the pseudo-data, the model is reestimated using the pseudo-data, and a forecast of $\hat{r}_{t+1}$ is formed by plugging the actual included $\hat{r}_{t+1}$ values and r_t values into the reestimated version of the forecasting model (and again setting the error term equal to its expected value of zero). The bagging model forecast (Kitchen Sink BA) corresponds to the average of the B forecasts for the bootstrapped pseudosamples. Stock and Watson (2012) show that bagging reduces prediction variance and asymptotically can be represented in shrinkage form.

We also consider a pretesting procedure (Pretest) that decides on the set of candidate predictors to be included in (2). Specifically, we estimate (2) using data from the start of the available sample through each time t of the recursive out-of-sample window and compute the t-statistics corresponding to each of the potential predictors. The $x_{i,t}$ variables with t-statistics less than some critical value in absolute value are dropped from (2), and the model is reestimated. Moreover, we implement bagging for the pretesting procedure (Pretest BA) via a moving-block bootstrap as previously. The only difference is that for each pseudo-sample, the pretesting procedure determines the predictors to include in the forecasting model.

The next method we employ is the Ridge regression (Hoerl and Kennard, 1970), which minimizes the sum of squared residuals subject to an l_2 penalty term. Specifically, model (2) is estimated by minimizing the following objective function

$$\left[\sum_{t=1}^{T-1}(\hat{r}_{t+1} - x_t'\boldsymbol{\beta})^2 + \lambda_2 \sum_{i=0}^{N+1}\beta_i^2\right]. \tag{3}$$

The amount of shrinkage is controlled by the parameter, λ_2. As $\lambda_2 \to \infty$,the estimated parameters shrink towards zero, while as $\lambda_2 \to 0$, parameter estimates tend to their OLS counterparts.

Similar to ridge regression, the Least Absolute Shrinkage and Selection Operator (LASSO), introduced by Tibshirani (1996) minimizes the sum of squared residuals subject to a penalty term. Unlike ridge regression that shrinks parameter estimates based on an l_2 penalty, which precludes shrinkage to zero; the LASSO allows continuous shrinkage to zero—and thus variable selection—by employing an l_1 penalty function,

$$\left[\sum_{t=1}^{T-1}(\hat{r}_{t+1} - x_t'\boldsymbol{\beta})^2 + \lambda_1 \sum_{i=0}^{N+1}|\beta_i|\right]. \tag{4}$$

A drawback to the LASSO is that it tends to arbitrarily select a single predictor from a group of correlated predictors, making it less informative in settings with many correlated regressors.

The Elastic Net of Zou and Hastie (2005) avoids this problem by including both l_1 (LASSO) and l_2 (Ridge) terms in the penalty. This estimator is based on the following penalized sum of squared errors objective function:

$$\left[\sum_{t=1}^{T-1}(\hat{r}_{t+1} - x_t'\boldsymbol{\beta})^2 + \lambda_1\sum_{i=1}^{N+1}|\boldsymbol{\beta}_i| + \lambda_2\sum_{i=1}^{N+1}\boldsymbol{\beta}_i^2\right] \tag{5}$$

where λ_1 and λ_2 are regularization parameters corresponding to the l_1 and l_2 penalty functions. Apparently, setting $\lambda_2 = 0$ we get the LASSO estimator while for $\lambda_1 = 0$, we get the Ridge estimator.

We also employ the adaptive elastic net estimator (Zou and Zhang, 2009; Ghosh, 2011), which is a weighted version of the elastic net that achieves optimal large-sample performance in terms of variable selection and parameter estimation. The adaptive elastic net differs from the naive elastic net in the employment of weighting factors for the parameters $\boldsymbol{\beta}_i$ in the l_1 penalty. More in detail, the objective function of (5) is modified as follows:

$$\left[\sum_{t=1}^{T-1}(\hat{r}_{t+1} - x_t'\boldsymbol{\beta})^2 + \lambda_1\sum_{i=0}^{N+1}w_i\,|\boldsymbol{\beta}_i| + \lambda_2\sum_{i=0}^{N+1}\boldsymbol{\beta}_i^2\right] \tag{6}$$

where $w = (w_1, ..., w_N)$ is a $N \times 1$ vector of weighting factors for the $\boldsymbol{\beta}_i$ parameters in the l_1 penalty. Following Zou (2006), the weighting factor is given by $w_i = \left|\widehat{\boldsymbol{\beta}}_i\right|^{-\gamma}, \gamma > 0$,and $\widehat{\boldsymbol{\beta}}_i$ are the OLS estimates of $\boldsymbol{\beta}_i$ in (2). This moderates shrinkage in the l_1 penalty. For given values of λ_1, λ_2 and γ, we solve (6) using the Friedman, Hastie, and Tibshirani (2010) algorithm. Following Rapach, Strauss and Zhou (2012), we select λ_1, λ_2 and γ using five-fold cross-validation.

Instead of employing cross validation on the full sample which would suffer from in-sample overfitting as the KS model we draw from the combining forecast literature and employ the mean (EN_mean) and median (EN_median) of potential elastic net forecasts over a grid of parameter values for λ_1 and λ_2. Finally, we select the shrinkage parameters based on the historical performance of the elastic net models over the holdout out-of-sample period (EN_CV). In this way, we retrieve the specification with superior predictive ability and employ this specification to form next period's forecast.

3 Empirical findings

3.1 Data

We employ monthly data on fifteen hedge fund indices provided by Hedge Fund Research (HFR). The HFR indices are equally weighted average returns of hedge funds and are computed on a monthly basis. In our analysis, we use directional strategies that bet on the direction of the markets, as well as non-directional strategies whose bets are related to diversified arbitrage opportunities rather than to the movement of the markets. In particular, we consider the following fifteen HFR indices: Distressed/Restructuring (DR), Merger Arbitrage (MA), Equity Market Neutral (EMN), Quantitative Directional (QD), Short Bias (SB), Emerging Markets Total (EM), Equity Hedge (EH), Event-Driven (ED), Macro Total (M), Relative Value (RV), Fixed Income-Asset Backed (FIAB), Fixed Income-Convertible Arbitrage (FICA), Fixed Income-Corporate Index (FICI), Multi-Strategy (MS), Yield Alternatives (YA).[1]

Our sample covers the period January 1994 to December 2011 (216 observations). This period includes a number of crises and market events which affected hedge funds returns, and caused large variability in the return series. The initial estimation period is January 1990 to December 2003 (120 observations), while the out-of-sample forecast period is January 2004 to December 2011 (96 observations). Summary statistics for the hedge fund return series are reported in Table 1. Panel A reports descriptive statistics for the different hedge fund strategies for the full sample of 216 observations. Quite interestingly, hedge fund strategies exhibit quite diverse statistical characteristics. All strategies have a positive mean return ranging from 0.11% (SB) to.0.86% (QD). Some strategies display relatively higher volatility (QD, SB, EM), while the strategies with low volatility are MA, EMN, RV and FIAB. All strategies exhibit negative skewness with the exception of SB and M and excess kurtosis. The most leptokurtic ones are RV, FIAB, FICA, FICI and MS. As expected, the null hypothesis of normality is strongly rejected in all cases. Panel B reports pair-wise correlations between the hedge fund return series. The SB strategy is negatively correlated with all other strategies, but otherwise the correlations are all positive. The positive correlations range from 0.32 (between macro and relative value) to 0.92 (between EH and QD). Overall, the relatively moderate pair-wise correlations suggest that benefits may accrue from the construction of funds of hedge funds.

[TABLE 1 AROUND HERE]

We model the hedge fund returns by using an extensive list of information variables, pricing factors along the lines of Agarwal and Naik (2004), Fung and Hsieh (2001, 2004), Vrontos et al. (2008), Meligkotsidou et al (2009), Wegener et al. (2010), Olmo and Sanso-Navarro (2013) etc. Our first set of explanatory factors for describing the hedge fund returns consists of the Fung and Hsieh factors, which have been shown to achieve considerable explanatory power. These factors are five trend-following risk factors which are returns on portfolios of lookback straddle options on bonds (BTF), currencies (CTF) commodities (CMTF), short-term interest rates (STITF) and stock indices (SITF) constructed to replicate the maximum possible return on trend-following strategies in their respective underlying assets. Fung and Hsieh also

[1] We use the same ten HFR single strategy indices used by Harris and Mazibas (2013) and, in addition, the quantitative directional, the fixed income asset backed, the fixed income corporate index, the multi strategy and the yield alternatives indices. HFR construct investible indices (HFRX) as counterparts to these indices (HFRI). Details can be found on the HFR website: www.hfr.com.

consider two equity-oriented risk factors, namely the S&P 500 return index (SP500), the size spread factor (Russell 2000 minus S&P 500), the bond market factor (change in the 10-year bond yield), the credit spread factor (change in the difference between Moodys BAA yield and the 10-year bond yield), the MSCI emerging markets index (MEM), and the change in equity implied volatility index (VIX).[2] The next set of factors we consider are related to style investing and to investment policies that incorporate size and value mispricings. Specifically, the three Fama-French factors, namely HML (High minus Low), SMB (Small minus Big) and the risk free interest rate (RF). Accounting for the fact that hedge fund managers might deploy trend-following and mean-reversion investment strategies, we also employ the Momentum (MOM), the Long Term Reversal (LTR) and the Short Term Reversal (STR) factor.[3]

Following Wegener at al (2010) among others, we enhance our set of predictors with macro related / business indicators variables. Specifically, we employ the default spread (difference between BAA- and AAA-rated corporate bond yields), the term spread (10-year bond yield minus 3-month interest rate), the inflation rate (INF) along with its one-month change (D(INF)), the US industrial production growth rate (IP), the monthly percent change in US non farm payrolls (PYRL), the US trade weighted value of the US dollar against other currencies (USDTW) and the OECD composite leading indicator (OECD).[4] Finally, we also employ some additional market-oriented factors; namely the Goldman Sachs commodity index (GSCI), the Salomon Brothers world government and corporate bond index (SBGC), the Salomon Brothers world government bond index (SBWG) and the Lehman high yield index (LHY). Finally, we include two additional equity market oriented factors such as the Morgan Stanley Capital International (MSCI) world excluding the USA index (MXUS) and the Russell 3000 (RUS3000) equity index.[5]

3.2 Statistical Evaluation of Forecasts

In our application, the natural benchmark forecasting model is the AR(1) model, which coincides with the linear regression model (1) when only the lagged hedge fund return is included in the model. As a measure of forecast accuracy we employ *Theil's U*, which is defined as

$$\textit{Theil's } U = \frac{MSFE_i}{MSFE_{AR(1)}} \tag{7}$$

where $MSFE_i$ is the Mean Square Forecast Error (MSFE) defined as the average squared forecast error over the out-of-sample period of any of our competing models and specifications

[2] The trend following factors are available at David Hsieh's data library at http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls. Data sources for the remaining factors are available there too.

[3] For further details and data downloaad please consult the website of Professor Kenneth French at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

[4] The source of this set of factors is the FREDII database with the exception of the OECD leading indicator that was sourced from the OECD stats extracts.

[5] The source of this set of factors is DATASTREAM International.

and $MSFE_{AR(1)}$ is the respective value for the AR(1) model. Values less than 1 are associated with superior forecasting ability of our proposed model/specification and vice-versa.

3.2.1 Univariate models

We start our analysis with the univariate models (Equation 1) by which we assess the forecasting ability of each one of the factors for the hedge fund strategies at hand. Table 2 reports the related *Theil's U* values. As already mentioned values lower than 1 indicate superior predictive ability. Overall, we find considerable heterogeneity with respect to the predictive ability of the candidate factors and to the predictability of hedge fund strategies. Specifically, only two out of 31 factors do not improve forecasts over the benchmark for any of the hedge fund strategies under scrutiny. These are the long term reversal factor and the change in inflation. Quite interestingly, the most powerful predictor is the industrial production as it improves forecasts in 12 out of 15 hedge fund strategies followed by the momentum factor that improved predictability in 10 strategies. VIX and CMTF improve predictions in 9 strategies, while CTF is helpful at forecasting 8 strategies. The SP500, term spread, OECD, MXUS and RUS3000 rank fifth as they are associated with improved predictive ability in 7 strategies.

Considering the predictability of hedge fund strategies, the most easily predicted strategies are FIAB (15 factors) and YA (15 factors), EMN (14 factors), MA (11 factors), ED (11 factors), RV and FICI (10 factors). Nine factors improve forecasts of DR, EH and MS, while five factors improve forecasts for EM and FICA. More importantly, only 3 and 4 candidate predictors can improve forecasts of the EM and QD strategies, respectively.

[TABLE 2 AROUND HERE]

3.2.2 Combination of Forecasts

Table 3 (Panel A) reports our findings with respect to the predictive ability of the forecast combination schemes. Overall, our findings point to a quite robust picture as the majority of hedge fund strategies display MSFE ratios lower than 1 and thus improve on the ability of the AR(1) model to forecast each strategy. With the exception of the Median combining scheme and the Principal Components ones, the remaining combining schemes improve forecasts for 12 out of 15 strategies. Even the simple forecasting schemes, such as the mean and trimmed mean perform satisfactorily. The lowest MSFE ratios are associated with the Cluster(5) combining schemes which classifies the predictors in 5 clusters and forecasts on the basis of the best performing cluster. In the few cases (3 out of 15) that the PC methods display superior predictive ability over the AR(1) benchmark, their performance is associated with quite low MSFE ratios. For example, the MSFE ratios for the EMN strategy and the PC methods are as low as 0.81, while for the FIAB strategy and the PC(7) method the relative value is 0.895.

Turning to the Hedge fund strategies, we observe that two strategies, namely EMN and FIAB, are the ones for which all the combining methods appear superior to the benchmark. On the other hand, SB, EM and M are the ones for which no method can beat the benchmark. We now turn to the forecasting ability of the combining information approach.

[TABLE 3 AROUND HERE]

3.2.3 Combination of Information

Table 3 (Panel B) displays our findings for the combining information approach. Overall, we observe considerable heterogeneity with respect to the ability of the respective methods to improve forecasts over the AR(1) benchmark. Both the Kitchen Sink and the Kitchen Sink BA appear weak methodologies in our setting. Their forecasting ability is associated with three strategies, namely the RV, FICA and MS. Pretesting and Pretesting with bagging seems to work better, as these methods offer improved forecasts for 5 and 6 strategies, respectively. Lasso and Ridge improve forecasts in 8 strategies, while the mean Elastic Net specifications offer further improvement (9 strategies). Among the Elastic Net variants employed in this study the adaptive Elastic Net, despite its computational intensity, performs worse since it only displays superior ability for the EMN strategy. Five strategies, namely QD, SB, EM, EH and M appear hard to forecast, while FICA seems to be the one favoured by these methods. For the remaining strategies, forecast improvements depend on the choice of method. For example, DR, MA and EMN, broadly favour the Ridge, Lasso and Elastic Net specifications, while RV and MS favour the Kitchen sink, pretesting and bagging methods.

Overall, when comparing Panels A and B, the combination information methodologies seem inferior to the combination forecasts schemes at least from a statistical point of view. To this end, we assess whether the same picture pertains when the economic value of our forecasts is assessed.

3.3 Economic Evaluation

3.3.1 The framework for economic evaluation

As Campbell and Thompson (2008) and Rapach, Strauss and Zhou (2010) suggest, even small reductions in MSFEs can give an economically meaningful degree of return predictability that could result in increased portfolio returns for a mean-variance investor that maximizes expected utility. Within this stylized asset allocation framework, this utility-based approach, initiated by West, Edison and Cho (1993), has been extensively employed in the literature as a measure for ranking the performance of competing models in a way that captures the trade-off between risk and return (Fleming, Kirby and Ostdiek, 2001; Marquering and Verbeek, 2004; Della Corte, Sarno, and Tsiakas, 2009; Della Corte, Sarno and Valente, 2010; Wachter and Warusawitharana, 2009).

Consider a risk-averse investor who constructs a dynamically rebalanced portfolio consisting of the risk-free asset and one risky asset. Her portfolio choice problem is how to allocate wealth between the safe (risk-free Treasury Bill) and the risky asset (hedge fund strategy), while the only source of risk stems from the uncertainty over the future path of the respective hedge fund index. Since only one risky asset is involved, this approach could be thought of as a standard exercise of market timing in the hedge fund industry. In a mean-variance framework, the solution to the maximization problem of the investor yields the following weight (w_t) on the risky asset

$$w_t = \frac{E_t(r_{t+1})}{\gamma Var_t(r_{t+1})} \tag{8}$$

where E_t and Var_t denote the conditional expectation and variance operators, r_{t+1} is the return on one of the hedge fund strategies considered and γ is the Relative Risk Aversion (RRA) coefficient that controls the investor's appetite for risk (Campbell and Viceira, 2002; Campbell and Thompson, 2008; Rapach, Strauss and Zhou, 2010). The conditional variance of the portfolio is approximated by the historical variance of hedge fund returns and is estimated using a 5-year rolling window of monthly returns.[6] In this way, the optimal weights vary only with the degree the conditional mean varies, i.e. the forecast each model/ specification gives. Under this setting the optimally constructed portfolio gross return over the out-of-sample period, $R_{p,t+1}$, is equal to

$$R_{p,t+1} = w_t \cdot r_{t+1} + R_{f,t}$$

where $R_{f,t} = 1 + r_{f,t}$ denotes the gross return on the risk-free asset from period t to $t+1$.[7]

Assuming quadratic utility, over the forecast evaluation period the investor with initial wealth of W_0 realizes an average utility of

$$\overline{U} = \frac{W_0}{(P - P_0)} \sum_{t=0}^{P-P_0-1} (R_{p,t+1} - \frac{\gamma}{2(1+\gamma)} R^2_{p,t+1}) \tag{9}$$

where $R_{p,t+1}$ is the gross return on her portfolio at time $t+1$.[8] At any point in time, the investor prefers the model for conditional returns that yields the highest average realized utility. Given that a better model requires less wealth to attain a given level of $\overline{U}$ than an alternative model, a risk-averse investor will be willing to pay to have access to this superior model which would be subject to management fees as opposed to the simple HA (historical average) model. In the event that the superior model is one of our proposed i specifications, the investor would pay a performance fee to switch from the portfolio constructed based on the historical average to the i specification. This performance fee, denoted by Φ, is the fraction of the wealth which when

[6] See Campbell and Thomson (2008) and Rapach, Strauss and Zhou (2010).

[7] We constrain the portfolio weight on the risky asset to lie between 0% and 150% each month, i.e. $0 \leq w_t \leq 1.5$.

[8] One could instead employ other utility functions that belong to the constant relative risk aversion (CRAA) family such as power or log utility. However, quadratic utility allows for nonormality in the return distribution while remaining in the mean-variance framework.

subtracted from the i proposed portfolio returns equates the average utilities of the competing models. In our set-up the performance fee is calculated as the difference between the realized utilities as follows:

$$\frac{1}{(P-P_0)}\sum_{t=0}^{P-P_0-1}\left\{(R^i_{p,t+1}-\Phi)-\frac{\gamma}{2(1+\gamma)}(R^i_{p,t+1}-\Phi)^2\right\}= \\ \frac{1}{(P-P_0)}\sum_{t=0}^{P-P_0-1}\left\{R^{HA}_{p,t+1}-\frac{\gamma}{2(1+\gamma)}(R^{HA}_{p,t+1})^2\right\}. \tag{10}$$

If our proposed model does not contain any economic value, the performance fee is negative ($\Phi \leq 0$), while positive values of the performance fee suggest superior predictive ability against the HA benchmark. We standardize the investor problem by assuming $W_0 = 1$ and report Φ in annualized basis points.

3.3.2 Economic evaluation findings

We assume that the investor dynamically rebalances her portfolio (updates the weights) monthly over the out-of-sample period employing the forecasts given by our approaches. Similarly to the statistical evaluation section, the out-of-sample period of evaluation is 2004:1-2011:12 and the benchmark strategy against which we evaluate our forecasts is the naive historical average model. For every specification we calculate the performance fee from Equation (10) setting RRA (γ) equal to 3. Table 4 reports the respective findings.

[TABLE 4 AROUND HERE]

The first line (AR(1)) of Table 4 corresponds to the performance fee an investor would pay to have access to the simple AR(1) model. Given the significant autocorrelation of hedge fund returns, it is not surprising that Φ ranges from 0 bps (M strategy) to 1086 bps (FICA). Even with this simple model an investor can enjoy gains of up to 10.86%. While the majority of strategies point to gains greater than 100 bps, the MA, EMN, M and FIAB strategies generate lower, albeit positive, profits.

With respect to our proposed methodologies, the most striking feature of Table 4 is the generation of positive gains that exceed the ones generated by the AR(1) model for every strategy considered with the exception of RV. For this strategy, gains range from 103 bps (PC(7)) to 221 bps (AR(1)). However, consistent with our statistical evaluation findings, forecast combination methods seem to perform better than combination information methods, by a narrow margin though. For example, the Adaptive elastic net method that hardly generated improved forecasts statistically exceeds the performance of the AR(1) model in five strategies, among them the SB for which no other methodology succeeds in it. Similar improvements prevail for the Kitchen sink and BA methodologies that were found statistically inferior to forecast combination methods.

4 Dynamic Hedge Fund Portfolio Construction

In this section, we examine the benefits of introducing hedge fund return predictability in hedge fund portfolio construction and risk measurement. This is achieved through an investment exercise which compares the empirical out-of-sample performance of our forecasting approaches. Section 4.1 sets out the optimization framework and Section 4.2 the portfolio evaluation criteria. Section 4.3 reports our findings for various types of investors and portfolio optimization methods.

4.1 Optimization framework

Consider an investor who allocates her wealth among $n = 15$ hedge fund indices with portfolio weight vector $\mathbf{x} = (x_1, x_2, ..., x_n)'$. While several approaches to constructing optimal portfolios exist, the most common (standard) is the mean-variance model of Markowitz (1952), in which the risk measure is the portfolio variance. Given that our methodology is focused on the benefits of return predictability for asset allocation, the variance of the portfolio of hedge funds returns is approximated by the sample covariance matrix.

More in detail, in the mean-variance framework, portfolios are constructed through the following optimization scheme

$$\begin{aligned} &\min Var(r_p) \\ &\text{s.t. } x_L \leq x_i \leq x_U,\ i = 1, ..., n,\ \sum_{i=1}^{n} x_i = 1, \text{ and } E(r_p) \geqslant r_G, \end{aligned} \tag{11}$$

where r_p is the $n-$assets portfolio return, $\mathbf{x} = (x_1, x_2, ..., x_n)'$ is the vector containing the assets' weights in the portfolio, $E(r_p)$ and $Var(r_p) = \mathbf{x}'\mathbf{V}\mathbf{x}$ are the expected return and the variance of the portfolio, respectively, $\mathbf{V}$ is the $n \times n$ sample covariance matrix of the returns, and r_G is the target portfolio return. Given that currently short selling hedge fund indices does not represent an investment tactic, portfolio weights are constrained to be positive (i.e. the lower bound of weights, x_L, is set equal to 0). In order to facilitate diversification, we set the upper bound of portfolio weights equal to 0.50 ($x_U = 0.50$, see also Harris and Mazibas, 2013). This setup represents a conservative investor who is primarily concerned with the risk he undertakes.

The following more general framework can accommodate varying degrees of investor appetite for risk. Specifically, we also construct portfolios through the following optimization scheme

$$\begin{aligned} &\min\ \lambda Var(r_p) - (1-\lambda)E(r_p) \\ &\text{s.t. } x_L \leq x_i \leq x_U,\ i = 1, ..., n,\ \sum_{i=1}^{n} x_i = 1, \text{ and } E(r_p) \geqslant r_G, \end{aligned} \tag{12}$$

for various values of the risk appetite parameter $\lambda, \lambda \in [0, 1]$. For the case of $\lambda = 1$, we obtain the minimum variance optimization scheme (11). We set λ equal to 0.50, 0.25 and 0. The case of $\lambda = 0$ represents an aggressive investor that is primarily interested in maximizing returns, employing the following optimization scheme:

$$\begin{aligned} &\max \ E\left(r_p\right) \\ &\text{s.t. } x_L \leq x_i \leq x_U, \ i = 1, ..., n, \ \sum_{i=1}^{n} x_i = 1, \text{ and } Var\left(r_p\right) \leqslant \phi, \end{aligned} \tag{13}$$

where ϕ is the upper allowed level of portfolio variance.

Finally, we consider controlling for risk objectives such as the portfolio Conditional Value at Risk (CVaR) along the lines of Krokhmal et al. (2002). The CVaR is a risk measure defined as the expectation of the losses greater than or equal to the Value at Risk (VaR), which measures the risk in the tail of the loss distribution. The mean-CVaR optimization problem is expressed mathematically as follows

$$\begin{aligned} &\min CVaR(F_{r_p}, \alpha) \\ &\text{s.t. } x_L \leq x_i \leq x_U, \ i = 1, ..., n, \ \sum_{i=1}^{n} x_i = 1, \text{ and } E\left(r_p\right) \geqslant r_G, \end{aligned} \tag{14}$$

with

$$\text{CVaR}(F_{r_p}, \alpha) = -E(r_p | r_p \leq -\text{VaR}) = -\frac{\int_{-\infty}^{-\text{VaR}} z f_{r_p}(z) dz}{F_{r_p}(-\text{VaR})}, \tag{15}$$

where f_{r_p} and F_{r_p} denote the probability density and the cumulative density of r_p, respectively, α is a probability level, and $\text{VaR}(F_{r_p}, \alpha) = -F_{r_p}^{-1}(1 - \alpha)$. We employ Rockafellar and Uryasev's (2000) convex programming formulation. Rockafellar and Uryasev (2002) provide a thorough discussion of the properties of CVaR in risk measurement and portfolio optimization exercises.

4.2 Evaluation criteria

Similarly to the forecast evaluation (Section 2), the performance of the constructed portfolios is evaluated over the out-of-sample period using a variety of performance measures. Each portfolio is rebalanced monthly and the realized portfolio returns are calculated at the rebalancing date given the optimized weights.

First, we consider the realized returns of the constructed portfolios. Given the portfolio weights $\mathbf{x}_t = (x_1, x_2, ..., x_n)_t'$ at time t and the realized returns of the n assets in our sample at time $t+1$, $\mathbf{r}_{t+1} = (r_1, r_2, ..., r_n)_{t+1}'$, the realized return r_p of the portfolio at time $t+1$ is computed as

$$r_{p,t+1} = \mathbf{x}_t' \mathbf{r}_{t+1}.$$

We calculate the average return (AR) within the out-of-sample period and the cumulative return at the end of the period. We also calculate the end period value (EPV) of our portfolio at the end of the out-of-sample period for a portfolio with investment of 1 unit at the beginning of the out-of-sample period.

Next, we consider measures related to risk, i.e. we report and discuss the conditional volatility of the portfolio determined by each different mean/covariance model, which is computed as $\sqrt{Var(r_p)} = \sqrt{\mathbf{x}'\mathbf{V}\mathbf{x}}$. Due to the fact that portfolio optimization schemes generally arrive at a different minimum variance for each prediction model, the realized return is not comparable across models since it represents portfolios bearing different risks. Therefore, a more appropriate/realistic approach is to compare the return per unit of risk. In this sense, we use the Sharpe Ratio (SR) which standardizes the realized returns with the risk of the portfolio and is calculated through

$$SR_p = \frac{E(r_p) - E(r_f)}{\sqrt{Var(r_p)}},$$

where r_p is the average realized return of the portfolio over the out-of-sample period, and $Var(r_p)$ is the variance of the portfolio over the out-of-sample period.

A portfolio measure associated with the sustainability of the portfolio losses is the maximum drawdown (MDD) which broadly reflects the maximum cumulative loss from a peak to a following bottom. MDD is defined as the maximum sustained percentage decline (peak to trough), which has occurred in the portfolio within the period studied and is calculated from the following formula

$$MDD_p = \max_{T_0 \leq t \leq T-1} [\max_{T_0 \leq j \leq T-1} (PV_j) - PV_t],$$

where PV denotes the portfolio value and T_0, T denote the beginning and end of the evaluation period, respectively.

The next three measures we calculate, namely the Omega (OMG), Sortino (SOR) and Upside Potential (UP) ratios, treat portfolio losses and gains separately. In order to define these measures, we first define the n-th lower partial moment (LPM_n) of the portfolio return as follows (see Harlow, 1991; Harlow and Rao, 1989 and Sortino and van der Meer, 1991) :

$$LPM_n(r_b) = E[((r_b - r_p)_+)^n]$$

where r_b is the benchmark return and the Kappa function ($K_n(r_b)$) is defined as follows:

$$K_n(r_b) = \frac{E(r_p) - r_b}{\sqrt[n]{LPM_n(r_b)}}.$$

Then the respective measures are calculated as follows:

$$OMG(r_b) = K_1(r_b) + 1, SOR(r_b) = K_2(r_b), UP(r_b) = \frac{E[(r_p - r_b)^+]}{\sqrt{LMPM_2(r_b)}}$$

Next, we set out to incorporate transaction costs. Transaction costs associated with hedge funds, however, are not generally easy to compute given the variation in early redemption, management or other types of fees (Alexander and Dimitriu, 2004). Nevertheless, if the gain in the performance does not cover the extra transaction costs, less accurate, but less variable weighting strategies would be preferred. To study this issue we define portfolio turnover (PT) as (Greyserman et al., 2006):

$$PT_p = \sum_{t=T_0}^{T-1} \sum_{i=1}^{n} |x_{i,t+1} - x_{i,t}|$$

Finally, we investigate the capacity of the different prediction models to assess tail-risk. A CVaR of $\lambda\%$ at the $100(1\text{-}\alpha)\%$ confidence level means that the average portfolio loss measured over $100\alpha\%$ of worst cases is equal to $\lambda\%$ of the wealth managed by the portfolio manager. To compute CVaR, we use the empirical distribution of the portfolio realized returns. CVaR is calculated at the 90%, 95%, and 99% confidence levels.

4.3 Empirical Results

In this section, we report the out-of-sample performance of our optimization procedures and the proposed forecasting methodologies. The evaluation period is the same with the one employed for the statistical and economic evaluation of forecasts, i.e. January 2004 to December 2011. We construct portfolios in a recursive manner starting in January 2004 and employing the related mean forecasts. We calculate buy-and-hold returns on the portfolio for a holding period of one month and then rebalance the portfolio monthly until the end of the evaluation period. As aforementioned, the hedge fund portfolios are constructed based on two optimization techniques, the *mean-variance* and the *mean-CVaR.* We report the performance of the forecast combination and information combination approaches along with the naive (equally weighted) portfolio and the HFR fund of hedge funds index. We set an annual target return, $r_G = 14\%$, in the optimization schemes used and employ the US 3-month interest rate for the risk free rate and for the benchmark rate of return (r_b) necessary for the calculation of OMG, MDD and SOR.

For the mean-variance optimization framework, we consider four types of investor by varying the degree of risk appetite through the parameter λ. Using $\lambda = 1$ penalizes more the risk of the constructed portfolio and results in a *minimum variance* portfolio with a specific target return. Thus, inherent in the portfolio construction is an additional constraint that the mean portfolio return should be greater than or equal to the target value r_G. Using $\lambda = 0.50$ penalizes less the risk of the constructed portfolio and could be suitable for a medium risk averse fund manager. Furthermore, using $\lambda = 0.25$ describes the risk profile of a more aggressive fund manager while considering $\lambda = 0$ reduces to the optimization scheme of *maximizing expected return.* In this portfolio the upper allowed level for the portfolio variance is set at $\phi = 2.5\%$ monthly.

In the above portfolio optimization procedures we consider different restrictions on the weights of the constructed portfolios; at first, we restrict the weights to be greater than zero and smaller than 0.50, i.e. $0 \leq x_i \leq 0.50$, $i = 1, ..., n$, that is short selling is not allowed. We also examine the case that short selling is allowed, using $-0.5 \leq x_i \leq 0.5$ in our portfolio exercise. Thus, we examine the robustness/sensitivity of the constructed portfolio performance to different restrictions of portfolio weights. Allowing for short-selling enables us to benefit from the forecasting ability of the proposed methodologies in the case of negative future returns.

Second, we consider a *mean-CVaR* portfolio optimization approach, which involves constructing optimal portfolios by minimizing the Conditional Value at Risk (CVaR) employing the empirical distribution of asset returns based on the approach of Rockafellar and Uryasev (2002). In this optimization scheme, we also employ an additional constraint that the mean portfolio return should be greater than or equal to the target value r_G. The confidence level used is set at 95% and 99%.

Minimum variance ($\lambda = 1$)
Table 5 reports the results for the minimum variance investment strategy. The best performing forecasting methods, according to the majority of the performance measures are the Mean, the Trimmed mean and the DMSFE (0.9). These model portfolios have the largest average returns, ranging from 9.71% to 10.14%, as well as the highest Sharpe Ratios (0.450 to 0.496). They also have the highest Omega, Sortino and Upside values. It is worth mentioning that the naive strategy attains an average return of 5.03%, associated with high volatility resulting in a Sharpe ratio of 0.177. As expected, the performance of this strategy is associated with lower values of Omega, Sortino and Upside measures. Turning to the HFR fund of funds portfolio, we observe that its performance is inferior to the Naive strategy. It attains an average return of 2.68% and a Sharpe ratio of 0.037 due to increased volatility. While the combination of information methods appear superior to the Naive and HFR strategies, they lack in performance when compared to the combination of forecasts approaches with the exception of the PC methods. We have to note, though, that the majority of these portfolios have a low risk profile as depicted in the VaR, CVaR and maximum drawdown measures.

[TABLE 5 AROUND HERE]

Mean-variance ($\lambda = 0.50$)
Table 6 reports the results for the first formulation of the mean-variance investment strategy, which corresponds to a medium risk averse investor. Our findings are similar in spirit to the ones reported for the minimum variance investment strategy. Overall, the combination of forecasts methods (with the exception of the PC methods) rank first having an average return that exceeds 9.3%. These approaches have the highest Sharpe ratios, closely followed by the Kitchen Sink methods and the Pretest BA one. These approaches are associated with the lowest maximum drawdowns estimated at 5.61% to 7.32%. Furthermore, the least volatile methods are the

four variants of the Elastic Net approach along with the PC(7) method. Finally, we should note that portfolio turnover is quite similar across the forecasting approaches except for the Adaptive Elastic Net that displays a much lower portfolio turnover.

[TABLE 6 AROUND HERE]

Mean-variance ($\lambda = 0.25$)
The results associated with the more aggressive mean-variance formulation are reported in Table 7. As expected, our forecasting approaches generate higher returns compared to the investment strategies considered so far. Quite interestingly, these gains are not associated with significant increases in the portfolios' risk and as such we observe increases in the Sharpe, Omega, sortino and upside ratios. The maximum drawdown, VaR and CVaR measures improve (decrease) as well. The ranking of the methods remains broadly unchanged with the best performing method being the Mean combination method.

[TABLE 7 AROUND HERE]

Maximizing expected return ($\lambda = 0$)
Maximizing expected return is the investment strategy more related to the mean forecasting experiment we conduct. Our findings (reported in Table 8) suggest that the best performing methods are the forecast combination ones, although improved performance is attained for all the methods at hand. As such, average returns range from 8.41% (Pretesting model) to 12.48% (Median forecast combination). Since this strategy is riskier than the previous ones, Sharpe ratios are in general lower and the maximum one (0.427) is achieved for the Trimmed mean forecast combination scheme. Moreover, portfolio turnover is lower for the forecast combination methods than the combination of information ones.

[TABLE 8 AROUND HERE]

Minimum-variance ($\lambda = 1$)$-$ Shortselling allowed
Relaxing the short-selling restriction offers some interesting insights with respect to the risk return profile of the formed portfolios. Our findings with respect to the *minimum-variance* portfolio, reported in Table 9, point to non significant gains in terms of average returns compared to the long only portfolio (Table 5). However, the low risk profile of this strategy is enhanced leading to significant reductions in volatility. The standard deviation of the portfolios ranges from 2.37% to 2.83% as opposed to values ranging from 3.08% to 5.70% for the long-only case. As such, Sharpe ratios appear increased and reach the value of 0.808 for the Cluster 2 method, while the maximum drawdown hovers around 2.5%. Quite interestingly, the differences in the performance of the forecasting approaches appear to have phased out.

[TABLE 9 AROUND HERE]

Maximizing expected return ($\lambda = 0$)$-$ *Shortselling allowed*

We now turn to the performance of the *Maximizing expected return* strategy when shortselling is allowed. The respective evaluation criteria are reported in Table 10. The most striking feature of Table 10 is the impressive average return, which exceeds 22% for the forecast combination methods except for the PC ones. However, irrespective of the method considered, average returns are higher than 11.55% (Adaptive EN model), while the best performing method is the Cluster 5 combination scheme with an average return of 23.44%. The elevated volatility of these portfolios leads to lower Sharpe ratios compared to the previous formulation, which in general are quite high and exceed 0.5. Quite interestingly, the maximum drawdown associated with the best performing methods are quite low at values ranging from 4.8% to 5.8%. Naturally, relaxing short selling increases portfolio turnover.

[TABLE 10 AROUND HERE]

Min CVAR $\alpha = 5\%$, $\alpha = 1\%$

Finally, we report the performance of *Min-CVaR* optimal portfolios These results correspond to portfolios constructed through Equation (14) for a target return of 14% and for probability levels of 95% and 99%. Table 11 reports the results for the minimum CVAR optimization scheme at a 95% confidence level. The best performing forecasting methods, according to the majority of the performance measures are the Trimmed mean, the DMSFE (0.5), the DMSFE (0.9) and the Mean combining methods. These model portfolios have the largest average returns, ranging from 12.12% to 12.40%, as well as the highest Sharpe Ratios (0.363 to 0.371). They also have among the highest Omega, Sortino and Upside values.Table 12 reports the results for the minimum CVAR optimization scheme at a 99% confidence level. The results are similar to the results of the minimum CVAR optimization scheme at a 99% confidence level. The best performing forecasting methods, according to the majority of the performance measures are the Trimmed mean, the DMSFE (0.5), the DMSFE (0.9) and the Mean combining schemes. These model portfolios have the largest average returns, ranging from 12.00% to 12.45%, as well as the highest Sharpe Ratios (0.357 to 0.370). They also have among the highest Omega, Sortino and Upside values.

[TABLES 11& 12 AROUND HERE]

5 Conclusions

In this study we address the issue of hedge fund return predictability. Given the long set of candidate predictors, suggested by the extant literature, improved forecasts can be constructed by carefully integrating the information content in them. We proceed in two directions; combination of forecasts and combination of information. Combination of forecasts combines forecasts generated from simple models each incorporating a part of the whole information set, while combination of information brings the entire information set into one super model to generate an ultimate forecast.

We employ a variety of combination of forecasts and information methodologies and evaluate their predictive ability in a pure out-of-sample framework for the period 2004-2011, which contains the 2007-2008 crisis that plagued the hedge fund industry. Our statistical evaluation findings suggest that simple combination of forecasts techniques work better than more sophisticated and computationally intensive combination of informatio ones. Evaluating the forecasts form an economic point of view points to the same direction. However, the utility gains a mean-variance investor would have can be large irrespective of the model employed. Our analysis revealed that hedge fund strategies like SB, EM and M are quite challenging for a researcher since they are very hard to predict. More importantly, we compare the performance of our forecasting approaches with respect to their ability to construct optimal hedge fund portfolios in a mean-Var and mean-CVaR framework. Overall, forecasting hedge fund returns leads to improved portfolio performance, while combination of forecasts proves to be the superior approach. Simple combining schemes can generate portfolios with high average returns and low risk portfolios.

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Table 1. Summary Statistics and Correlations of Hedge Fund Indices

Panel A: Summary statisics of hedge fund strategy indices

	DR	MA	EMN	QD	SB	EM	EH	ED	M	RV	FIAB	FICA	FICI	MS	YA
Mean	0.77	0.67	0.47	0.86	0.11	0.76	0.85	0.84	0.70	0.68	0.74	0.65	0.51	0.55	0.66
Median	1.00	0.81	0.47	1.29	-0.19	1.40	1.05	1.20	0.59	0.80	0.84	0.88	0.75	0.72	0.73
Maximum	5.55	3.12	3.59	10.74	22.84	14.80	10.88	5.13	6.82	3.93	3.42	9.74	4.47	3.89	6.69
Minimum	-8.50	-5.69	-2.87	-13.34	-21.21	-21.02	-9.46	-8.90	-6.40	-8.03	-9.24	-16.01	-10.65	-8.40	-8.79
Std. Dev.	1.84	1.06	0.95	3.75	5.46	4.12	2.73	2.01	1.93	1.26	1.22	2.11	1.68	1.29	2.14
Skewness	-1.53	-1.60	-0.31	-0.44	0.31	-0.92	-0.21	-1.27	0.18	-2.86	-3.42	-2.82	-2.21	-2.54	-0.92
Kurtosis	8.48	8.96	4.75	3.71	5.52	6.92	4.93	6.95	3.94	18.58	25.25	26.74	13.53	16.95	6.11
Jarque-Bera	355.22	411.57	30.86	11.38	60.73	168.65	34.98	198.06	9.09	2479.52	4877.74	5356.57	1173.84	1984.94	117.41
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00

Panel B: Correlations between hedge fund strategy indices

	DR	MA	EMN	QD	SB	EM	EH	ED	M	RV	FIAB	FICA	FICI	MS	YA
DR	1.00														
MA	0.60	1.00													
EMN	0.43	0.47	1.00												
QD	0.68	0.64	0.34	1.00											
SB	-0.53	-0.43	-0.16	-0.87	1.00										
EM	0.74	0.55	0.29	0.77	-0.62	1.00									
EH	0.75	0.68	0.50	0.92	-0.79	0.77	1.00								
ED	0.88	0.77	0.47	0.84	-0.65	0.79	0.87	1.00							
M	0.42	0.34	0.34	0.54	-0.39	0.54	0.56	0.52	1.00						
RV	0.83	0.69	0.45	0.60	-0.43	0.66	0.72	0.82	0.32	1.00					
FIAB	0.43	0.13	0.18	0.17	-0.10	0.27	0.21	0.34	0.17	0.40	1.00				
FICA	0.71	0.53	0.34	0.45	-0.34	0.55	0.61	0.67	0.24	0.87	0.37	1.00			
FICI	0.86	0.56	0.35	0.59	-0.45	0.68	0.64	0.79	0.30	0.84	0.51	0.76	1.00		
MS	0.80	0.53	0.39	0.58	-0.43	0.68	0.69	0.78	0.40	0.85	0.62	0.83	0.86	1.00	
YA	0.62	0.51	0.40	0.50	-0.35	0.57	0.56	0.64	0.33	0.63	0.33	0.51	0.61	0.62	1.00

Notes:. The table (Panel A) reports summary statistics in percentages for the hedge fund strategy index series over the period of January 1994 to December 2011 (216 observations). Panel B reports the hedge fund index correlations.

Table 2. Statistical evaluation - Univariate Models

	DR	MA	EMN	QD	SB	EM	EH	ED	M	RV	FIAB	FICA	FICI	MS	YA
AR(1)	2.993	0.995	0.866	8.215	11.050	11.610	6.778	3.529	2.290	1.814	0.628	6.691	2.839	1.956	5.433
BTF	1.019	1.014	1.004	1.031	1.059	1.033	1.014	1.011	1.027	1.005	**0.981**	1.006	1.001	1.011	1.003
CTF	1.019	**0.994**	**0.996**	**0.985**	**0.991**	1.061	**0.988**	**0.979**	1.008	1.028	1.012	1.019	1.009	**0.993**	**0.974**
CMTF	1.001	**0.993**	**0.992**	1.036	1.053	1.024	**0.995**	1.009	**0.998**	**0.991**	**0.995**	**0.997**	1.025	**0.979**	**0.946**
STITF	1.017	1.038	1.004	1.026	1.026	1.051	1.009	1.025	1.106	1.019	**0.976**	1.012	1.045	1.017	**0.907**
SITF	**0.999**	1.002	1.011	1.022	1.047	1.004	1.012	1.005	1.012	1.009	**0.936**	1.005	1.000	1.001	1.005
SP500	**0.963**	1.043	**0.990**	1.006	1.049	1.008	1.004	**0.995**	**0.998**	1.005	**0.900**	1.008	**0.978**	1.005	**0.971**
Size	1.018	**0.954**	1.002	1.030	1.060	1.038	1.006	**0.998**	1.003	1.013	1.011	1.000	1.006	**0.999**	1.009
Bond	1.025	1.005	**0.997**	1.008	1.002	1.014	1.010	1.008	1.040	**0.999**	1.061	1.004	1.002	1.014	1.012
CreditSpr	1.006	1.019	1.003	1.009	1.006	1.018	1.008	1.001	1.087	1.014	**0.934**	**0.995**	1.011	1.029	**0.951**
MEM	**0.983**	1.000	1.013	1.012	1.010	1.009	1.004	1.006	1.012	1.006	**0.915**	1.006	**0.999**	1.006	**0.996**
VIX	**0.953**	1.008	1.014	1.004	**0.992**	1.011	1.003	**0.993**	1.010	**0.981**	**0.704**	**0.996**	**0.944**	**0.968**	**0.951**
HML	1.006	**0.999**	**0.982**	1.016	1.026	1.007	1.014	1.002	1.002	1.002	**0.980**	1.005	1.007	1.004	**0.999**
SMB	1.011	**0.956**	1.002	1.002	1.032	1.026	**0.996**	**0.980**	1.003	1.004	1.014	1.000	1.003	**0.994**	1.010
MOM	**0.944**	**0.994**	**0.952**	1.000	1.012	**0.980**	**0.983**	**0.978**	1.004	**0.997**	**0.988**	1.012	**0.979**	1.000	**0.965**
LTR	1.030	1.094	1.035	1.042	1.031	1.011	1.024	1.038	1.011	1.012	1.094	1.008	1.028	1.020	1.010
STR	**0.994**	1.002	**0.985**	1.012	1.010	1.004	1.007	1.004	1.021	1.004	**0.974**	1.006	1.008	1.004	1.007
RF	1.014	**0.977**	**0.894**	**0.994**	**0.988**	1.031	**0.987**	1.001	**0.976**	1.015	1.005	1.016	1.016	1.010	1.013
DefaultSpr	1.026	1.049	**0.936**	1.001	1.012	1.031	1.024	1.014	1.001	1.020	1.025	1.003	1.015	1.011	1.027
TermSpr	1.009	**0.979**	**0.955**	**0.993**	**0.996**	1.021	**0.994**	1.002	**0.979**	1.010	**0.978**	1.011	1.013	1.007	1.009
INF	1.016	1.006	1.039	1.035	1.076	1.015	1.013	1.021	1.028	**0.992**	1.053	1.000	1.009	1.001	1.045
d(INF)	1.011	1.018	1.018	1.017	1.017	1.023	1.016	1.023	1.021	1.024	1.030	1.027	1.015	1.032	1.017
IP	**0.973**	**0.878**	**0.950**	**0.925**	1.013	**0.943**	**0.935**	**0.934**	1.003	**0.919**	1.015	**0.951**	**0.983**	**0.961**	**0.974**
PYRL	1.025	1.038	**0.920**	1.003	1.018	1.026	1.022	1.011	1.014	1.022	1.028	1.014	1.031	1.021	1.022
USDTW	1.003	1.012	1.017	1.005	**0.994**	1.005	1.010	1.009	1.038	1.015	**0.970**	1.022	1.001	1.017	**0.993**
OECD	1.000	1.017	1.020	1.017	1.016	**0.983**	**0.999**	**0.998**	1.019	**0.996**	1.003	**0.974**	**0.996**	**0.983**	1.004
GSCI	1.013	**0.998**	1.012	1.013	1.012	1.014	**0.999**	1.016	1.010	1.019	1.092	**0.991**	1.011	**0.987**	1.014
SBGC	1.008	**0.985**	1.017	1.006	**0.981**	1.023	1.007	**0.994**	1.016	**0.983**	1.086	**0.982**	**0.999**	1.015	**0.978**
SBWG	1.002	1.018	1.005	1.016	1.013	1.012	1.019	1.006	1.008	**0.983**	1.062	1.000	**0.987**	1.001	**0.997**
LHY	1.010	1.015	**0.993**	1.009	1.011	1.009	1.008	1.008	1.026	1.015	1.163	**0.980**	1.013	1.023	1.021
MXUS	**0.965**	1.006	1.006	1.008	1.058	1.011	1.004	**0.992**	1.013	**0.991**	**0.798**	1.005	**0.966**	**0.998**	**0.961**
RUS3000	**0.957**	1.049	**0.992**	1.001	1.039	1.007	1.005	**0.999**	**0.997**	1.007	**0.901**	1.009	**0.979**	1.007	**0.973**

Notes: The table reports the *Theil's U* index for univariate models. The line named AR(1) displays the MSFE of the AR(1) benchmark model. A value lower than 1 (in bold) suggests superior predictive ability.

Table 3. Statistical Evaluation - Combination of forecasts and information

	DR	MA	EMN	QD	SB	EM	EH	ED	M	RV	FIAB	FICA	FICI	MS	YA
Panel A Combination of forecasts															
Mean	**0.990**	**0.978**	**0.962**	**0.996**	1.009	1.004	**0.992**	**0.991**	1.002	**0.994**	**0.959**	**0.996**	**0.991**	**0.997**	**0.980**
Median	**0.996**	**0.993**	**0.996**	1.001	1.004	1.005	**0.998**	**0.996**	1.001	1.001	**0.988**	1.001	**0.996**	1.000	**0.994**
Trimmed mean	**0.995**	**0.983**	**0.970**	**0.999**	1.009	1.011	**0.996**	**0.995**	**0.999**	1.000	**0.970**	**0.997**	**0.992**	1.000	**0.989**
DMSFE(0.9)	**0.990**	**0.975**	**0.958**	**0.994**	1.009	1.003	**0.991**	**0.990**	1.002	**0.994**	**0.953**	**0.996**	**0.991**	**0.997**	**0.979**
DMSFE(0.5)	**0.989**	**0.968**	**0.959**	**0.994**	1.010	1.001	**0.990**	**0.989**	1.003	**0.991**	**0.950**	**0.996**	**0.990**	**0.996**	**0.979**
Cluster(2)	**0.984**	**0.967**	**0.941**	**0.991**	1.006	**0.999**	**0.989**	**0.986**	1.011	**0.990**	**0.933**	1.000	**0.990**	**0.997**	**0.965**
Cluster(5)	**0.967**	**0.945**	**0.905**	**0.990**	1.010	1.000	**0.984**	**0.979**	1.029	**0.972**	**0.904**	**0.990**	**0.977**	**0.997**	**0.950**
PC(5)	1.030	1.066	**0.809**	1.037	1.121	1.069	1.111	1.089	**0.992**	1.319	**0.935**	1.648	1.074	1.071	1.069
PC(7)	1.041	**0.957**	**0.810**	1.096	1.169	1.063	1.063	1.190	1.054	1.216	**0.895**	1.326	1.161	1.327	1.078
Panel B Combination of information															
Kitchen sink	1.134	1.036	1.078	1.413	1.851	1.271	1.162	1.133	1.456	**0.938**	1.572	**0.901**	1.038	**0.996**	1.013
Kitchen sink BA	1.131	1.068	1.055	1.385	1.824	1.240	1.147	1.143	1.449	**0.938**	1.466	**0.859**	1.020	**0.967**	1.010
Pretesting	1.059	1.052	1.147	1.369	1.208	1.220	1.181	1.072	1.153	**0.958**	**0.995**	**0.963**	**0.981**	**0.979**	1.111
Pretesting BA	1.055	**0.982**	1.007	1.188	1.371	1.117	1.081	1.059	1.261	**0.916**	1.252	**0.861**	**0.979**	**0.978**	**0.934**
Ridge	**0.974**	**0.922**	**0.870**	1.151	1.478	1.133	1.017	**0.980**	1.171	**0.979**	1.041	**0.932**	**0.973**	1.010	**0.896**
Lasso	**0.963**	**0.922**	**0.817**	1.136	1.390	1.091	1.012	**0.983**	1.029	1.020	**0.943**	**0.931**	**0.970**	1.005	**0.914**
Elastic net	**0.987**	**0.917**	**0.875**	1.202	1.570	1.149	1.052	1.002	1.184	**0.948**	1.068	**0.910**	**0.975**	**0.999**	**0.916**
Adaptive EN	1.017	1.136	**0.888**	1.145	1.011	1.095	1.111	1.086	1.113	1.125	1.055	1.336	1.006	1.045	1.099
EN CV	1.059	**0.928**	**0.825**	1.119	1.024	1.250	1.106	1.114	1.013	1.028	**0.955**	**0.923**	1.025	1.086	**0.930**
EN Mean	**0.983**	**0.913**	**0.826**	1.101	1.335	1.068	**0.998**	**0.986**	1.042	1.008	**0.933**	**0.930**	**0.984**	1.014	**0.915**
EN Median	**0.961**	**0.923**	**0.838**	1.106	1.359	1.069	1.001	**0.980**	1.038	1.022	**0.940**	**0.941**	**0.979**	1.013	**0.909**

Notes: The table reports the *Theil's U* index for univariate models relative to the AR(1) benchmark model. A value lower than 1 (in bold) suggests superior predictive ability.

Table 4. Economic Evaluation - Combination of forecasts and information

Panel A Combination of forecasts	DR	MA	EMN	QD	SB	EM	EH	ED	M	RV	FIAB	FICA	FICI	MS	YA
AR(1)	406.27	57.70	22.07	291.96	371.95	753.22	282.72	296.13	0.00	220.92	96.40	1086.20	415.57	262.10	183.68
Mean	**407.28**	57.70	**30.70**	**328.57**	318.25	**753.54**	**294.31**	**302.25**	0.00	220.83	96.40	**1090.80**	**415.59**	250.47	**270.75**
Median	**409.60**	57.70	19.27	**295.24**	368.30	**753.22**	281.53	**297.55**	0.00	220.77	96.40	**1088.60**	**415.87**	260.09	**240.91**
Trimmed mean	**406.33**	55.81	14.20	**326.63**	301.62	748.19	**293.29**	**301.36**	**4.77**	218.98	86.39	**1090.60**	**415.54**	256.78	**223.44**
DMSFE(0.9)	**407.00**	57.70	**30.70**	**329.51**	309.26	**757.08**	**302.68**	**302.34**	0.00	219.43	**100.23**	**1090.70**	**415.62**	245.69	**263.13**
DMSFE(0.5)	**407.09**	57.70	**30.70**	**333.64**	308.32	**757.36**	**297.39**	**302.24**	0.00	220.69	**105.60**	**1091.00**	**415.66**	244.29	**265.04**
Cluster(2)	**406.33**	57.70	**30.98**	**333.78**	308.72	731.95	**315.71**	**325.85**	0.00	214.42	**105.80**	**1091.20**	411.63	243.09	**247.93**
Cluster(5)	**436.84**	46.04	**69.62**	273.50	238.98	740.90	**388.34**	**366.39**	-50.79	183.61	**117.06**	**1088.60**	427.23	**277.52**	**249.29**
PC(5)	**517.78**	36.67	**92.35**	-50.51	154.56	628.77	211.57	**316.73**	**12.22**	102.87	**108.28**	762.42	375.17	244.45	**216.26**
PC(7)	**444.41**	11.23	**76.85**	-237.49	166.94	502.79	164.20	**308.81**	**11.72**	130.29	**108.28**	709.61	340.02	152.65	**242.86**
Panel B Combination of information															
Kitchen sink	**411.05**	**84.46**	**217.89**	**521.30**	1.97	719.82	**504.40**	**459.22**	-125.47	171.80	17.39	**1096.00**	**446.53**	**274.62**	155.27
Kitchen sink BA	**413.94**	60.50	**186.78**	**422.25**	-57.49	643.06	**571.35**	**445.47**	-80.48	171.71	45.36	**1112.30**	**433.37**	240.69	**273.85**
Pretesting	349.51	**59.52**	**163.24**	126.58	51.64	352.34	224.64	228.94	**73.43**	126.01	89.78	1016.60	**482.82**	250.39	**279.66**
Pretesting BA	**443.88**	**62.76**	**179.54**	277.54	-55.86	823.11	**514.04**	**371.23**	-12.90	171.69	92.30	**1098.60**	**439.28**	**284.99**	145.31
Ridge	**490.50**	0.71	**143.43**	103.15	-84.63	378.25	256.37	**301.19**	-80.62	163.66	**119.45**	611.17	**507.64**	235.38	**290.72**
Lasso	**411.80**	42.90	18.23	25.22	-257.29	373.52	234.09	**319.27**	**101.01**	157.19	**105.97**	654.86	**441.72**	205.19	**267.49**
Elastic net	**517.82**	-30.32	**158.38**	121.84	-92.76	393.03	159.54	226.49	-18.37	162.26	**120.40**	663.90	**489.09**	253.96	**274.93**
Adaptive EN	345.00	-79.14	**166.15**	-51.18	**477.44**	260.54	**402.88**	252.54	-297.77	178.47	91.50	597.28	**515.76**	**478.23**	-62.29
EN CV	344.26	57.12	**140.85**	222.67	64.14	299.65	196.41	157.77	0.00	173.98	79.24	666.62	**441.08**	166.22	**245.17**
EN Mean	374.12	6.16	18.23	139.67	-121.95	330.12	280.33	**301.06**	**26.30**	186.50	82.61	629.21	399.47	217.36	**352.05**
EN Median	**416.06**	2.26	18.23	110.95	-249.06	362.62	270.76	**351.36**	**21.29**	200.14	**100.87**	609.84	**428.72**	213.50	**298.53**

Notes: The table reports the performance fee, Φ, (in annualized basis points) that an investor with mean-variance preferences and risk aversion coefficient of three would be willing to pay to employ our forecasting approaches relative to the historical average. Positive values denote superior performance of the forecasting approach while bold values indicate superior performance with respect to the AR(1) model, given on the 1st line of the Table.

Table 5. Out-of-sample performance of Minimum-Variance efficient portfolios ($\lambda = 1$)

	EPV	AR	SD	SR	VaR_{99}	VaR_{95}	VaR_{90}	CVaR_{99}	CVaR_{95}	CVaR_{90}	MDD	OMG	SOR	UP	PT
Naive	1.403	5.03	5.10	0.177	-19.75	-7.73	-4.21	-21.16	-13.19	-9.30	19.10	1.611	0.237	0.625	0.00
HFR	1.214	2.68	5.98	0.037	-22.14	-9.33	-7.45	-22.64	-14.65	-11.73	24.46	1.1031	0.047	0.502	0.00
Panel A Combination of forecasts															
	EPV	AR	SD	SR	VaR_{99}	VaR_{95}	VaR_{90}	CVaR_{99}	CVaR_{95}	CVaR_{90}	MDD	OMG	SOR	UP	PT
Mean	1.811	10.14	4.79	0.496	-12.95	-6.04	-1.78	-15.68	-9.48	-6.60	10.34	3.604	0.886	1.227	15.04
Median	1.749	9.36	4.62	0.465	-12.61	-5.95	-1.88	-15.44	-9.12	-6.55	9.38	3.213	0.809	1.175	14.91
Trimmed mean	1.777	9.71	4.97	0.453	-15.95	-6.33	-1.82	-15.96	-11.02	-7.36	12.41	3.262	0.741	1.069	15.29
DMSFE(0.9)	1.778	9.72	5.01	0.450	-15.82	-5.96	-1.79	-15.89	-11.08	-7.39	12.67	3.292	0.741	1.065	14.97
DMSFE(0.5)	1.758	9.47	5.11	0.427	-15.88	-6.52	-1.78	-15.94	-12.05	-7.85	12.28	3.104	0.682	1.007	15.04
Cluster(2)	1.748	9.35	5.01	0.429	-15.77	-7.48	-1.67	-16.03	-11.56	-7.60	13.96	3.098	0.693	1.023	15.09
Cluster(5)	1.700	8.75	4.78	0.413	-14.98	-5.23	-2.39	-15.90	-10.30	-7.20	12.42	2.954	0.673	1.018	15.15
PC(5)	1.538	6.72	4.73	0.293	-17.93	-6.42	-2.58	-20.23	-12.35	-8.37	10.86	2.275	0.407	0.727	14.82
PC(7)	1.473	5.91	4.75	0.243	-17.86	-7.67	-3.14	-18.80	-13.39	-9.09	15.06	1.963	0.322	0.656	15.08
Panel B Combination of information															
Kitchen sink	1.529	6.61	3.85	0.352	-11.98	-4.63	-2.19	-14.08	-8.08	-5.79	6.92	2.585	0.568	0.926	13.18
Kitchen sink BA	1.528	6.60	3.70	0.365	-11.49	-4.45	-3.10	-12.97	-7.92	-5.81	7.12	2.598	0.578	0.940	12.86
Pretesting	1.398	4.97	3.09	0.285	-8.55	-5.67	-2.07	-9.33	-7.17	-5.15	5.24	2.030	0.420	0.829	13.29
Pretesting BA	1.562	7.02	3.89	0.379	-11.37	-5.63	-2.69	-12.66	-8.05	-5.98	7.77	2.713	0.620	0.982	14.08
Ridge	1.543	6.79	4.03	0.349	-13.86	-5.66	-2.90	-15.80	-9.87	-6.90	8.07	2.515	0.506	0.840	13.58
Lasso	1.493	6.17	4.38	0.280	-17.57	-5.84	-2.62	-20.63	-11.54	-7.80	11.49	2.189	0.378	0.696	13.66
Elastic net	1.541	6.76	3.99	0.351	-13.81	-5.26	-2.84	-16.55	-9.92	-6.71	8.34	2.536	0.508	0.838	13.54
Adaptive EN	1.396	4.94	4.04	0.217	-19.22	-3.97	-2.53	-24.04	-9.99	-6.67	13.73	1.897	0.272	0.576	8.90
EN CV	1.582	7.28	5.70	0.272	-16.72	-9.30	-5.05	-17.47	-13.68	-10.46	13.43	2.088	0.400	0.767	14.18
EN Mean	1.475	5.94	5.07	0.229	-22.97	-6.45	-2.89	-30.51	-13.51	-8.75	13.71	1.980	0.290	0.586	14.04
EN Median	1.458	5.73	4.35	0.253	-16.82	-5.61	-2.67	-18.39	-11.19	-7.65	10.65	1.996	0.347	0.696	13.91

Notes: The table reports evaluation criteria for the out-of-sample monthly rebalancing portfolio. Benchmark models are HFR Fund of Funds Index and naive (equally-weighted) portfolios. Evaluation criteria include end of period portfolio value (EPV), annualized average return (AR), annualized standard deviation (SD), maximum drawdown (MDD), annualized value at risk (VaR) and annualized conditional value at risk (CVaR), Sharpe Ratio (SR), Omega Ratio (OMG), Sortino Ratio (SOR), Upside Potential (UP) and Portfolio Turnover (PT). CVaR and VaR are estimated at 99%, 95% and 90% confidence level. AR, SD, MDD, VaR and CVaR are in percentages.

Table 6. Out-of-sample performance of Mean-Variance efficient portfolios ($\lambda = 0.50$)

	EPV	AR	SD	SR	VaR_{99}	VaR_{95}	VaR_{90}	$CVaR_{99}$	$CVaR_{95}$	$CVaR_{90}$	MDD	OMG	SOR	UP	PT
Naive	1.403	5.03	5.10	0.177	-19.75	-7.73	-4.21	-21.16	-13.19	-9.30	19.10	1.611	0.237	0.625	0.00
HFR	1.214	2.68	5.98	0.037	-22.14	-9.33	-7.45	-22.64	-14.65	-11.73	24.46	1.1031	0.047	0.502	0.00
Panel A Combination of forecasts															
	EPV	AR	SD	SR	VaR_{99}	VaR_{95}	VaR_{90}	$CVaR_{99}$	$CVaR_{95}$	$CVaR_{90}$	MDD	OMG	SOR	UP	PT
Mean	1.861	10.77	5.02	0.509	-12.95	-6.04	-1.79	-15.68	-9.48	-6.60	10.35	3.800	0.953	1.294	15.11
Median	1.798	9.98	4.86	0.479	-12.61	-5.95	-1.88	-15.44	-9.12	-6.55	9.39	3.396	0.877	1.242	15.02
Trimmed mean	1.827	10.33	5.19	0.468	-15.95	-6.33	-1.82	-15.96	-11.02	-7.36	12.42	3.441	0.800	1.128	15.34
DMSFE(0.9)	1.828	10.35	5.23	0.465	-15.82	-5.96	-1.79	-15.89	-11.08	-7.39	12.68	3.474	0.801	1.124	15.01
DMSFE(0.5)	1.807	10.09	5.33	0.443	-15.88	-6.52	-1.79	-15.94	-12.05	-7.85	12.29	3.277	0.739	1.063	15.13
Cluster(2)	1.797	9.97	5.23	0.445	-15.77	-7.48	-1.67	-16.03	-11.56	-7.60	13.97	3.271	0.750	1.080	15.19
Cluster(5)	1.745	9.31	5.01	0.427	-14.98	-5.23	-2.39	-15.90	-10.30	-7.20	12.42	3.117	0.730	1.074	15.18
PC(5)	1.568	7.10	4.87	0.307	-17.93	-6.42	-2.58	-20.23	-12.35	-8.37	10.86	2.357	0.438	0.761	14.94
PC(7)	1.508	6.35	4.90	0.261	-17.86	-7.67	-3.14	-18.80	-13.39	-9.09	15.09	2.057	0.357	0.695	15.28
Panel B Combination of information															
Kitchen sink	1.623	7.78	4.22	0.402	-11.98	-4.68	-2.19	-14.08	-8.10	-5.82	7.45	2.877	0.703	1.078	15.32
Kitchen sink BA	1.627	7.83	4.06	0.421	-11.49	-4.49	-3.12	-12.97	-7.93	-5.84	7.32	2.932	0.724	1.099	15.01
Pretesting	1.518	6.48	3.59	0.367	-8.55	-5.58	-2.00	-9.33	-7.15	-5.23	5.61	2.513	0.622	1.034	14.90
Pretesting BA	1.652	8.15	4.23	0.426	-11.37	-5.63	-2.69	-12.66	-8.05	-5.98	7.78	3.029	0.755	1.128	15.24
Ridge	1.618	7.73	4.30	0.391	-13.86	-5.66	-2.90	-15.80	-9.87	-6.90	8.14	2.786	0.604	0.942	13.90
Lasso	1.558	6.98	4.72	0.310	-17.57	-5.84	-2.62	-20.63	-11.54	-7.80	11.49	2.399	0.449	0.770	13.62
Elastic net	1.630	7.88	4.31	0.399	-13.81	-5.26	-2.84	-16.55	-9.91	-6.71	8.40	2.862	0.624	0.959	13.97
Adaptive EN	1.521	6.51	4.72	0.281	-19.22	-4.11	-2.53	-24.04	-10.04	-6.70	13.79	2.321	0.411	0.722	9.02
EN CV	1.629	7.86	5.85	0.294	-16.72	-9.30	-5.05	-17.47	-13.68	-10.46	13.43	2.189	0.443	0.815	14.92
EN Mean	1.537	6.71	5.30	0.261	-22.97	-6.45	-2.89	-30.51	-13.51	-8.75	13.71	2.163	0.345	0.641	14.03
EN Median	1.514	6.42	4.62	0.281	-16.82	-5.61	-2.67	-18.39	-11.19	-7.65	10.65	2.166	0.410	0.761	13.90

Notes: The table reports evaluation criteria for the out-of-sample monthly rebalancing portfolio. Benchmark models are HFR Fund of Funds Index and naive (equally-weighted) portfolios. Evaluation criteria include end of period portfolio value (EPV), annualized average return (AR), annualized standard deviation (SD), maximum drawdown (MDD), annualized value at risk (VaR) and annualized conditional value at risk (CVaR), Sharpe Ratio (SR), Omega Ratio (OMG), Sortino Ratio (SOR), Upside Potential (UP) and Portfolio Turnover (PT). CVaR and VaR are estimated at 99%, 95% and 90% confidence level. AR, SD, MDD, VaR and CVaR are in percentages.

Table 7. Out-of-sample performance of Mean-Variance efficient portfolios ($\lambda = 0.25$)

	EPV	AR	SD	SR	VaR_{99}	VaR_{95}	VaR_{90}	$CVaR_{99}$	$CVaR_{95}$	$CVaR_{90}$	MDD	OMG	SOR	UP	PT
Naive	1.403	5.03	5.10	0.177	-19.75	-7.73	-4.21	-21.16	-13.19	-9.30	19.10	1.611	0.237	0.625	0.00
HFR	1.214	2.68	5.98	0.037	-22.14	-9.33	-7.45	-22.64	-14.65	-11.73	24.46	1.1031	0.047	0.502	0.00
Panel A Combination of forecasts															
	EPV	AR	SD	SR	VaR_{99}	VaR_{95}	VaR_{90}	$CVaR_{99}$	$CVaR_{95}$	$CVaR_{90}$	MDD	OMG	SOR	UP	PT
Mean	1.943	11.78	5.43	0.525	-12.95	-6.04	-2.46	-15.68	-9.48	-6.77	10.59	4.045	1.054	1.400	15.125
Median	1.880	11.00	5.31	0.494	-12.61	-5.95	-2.88	-15.44	-9.20	-6.70	9.75	3.620	0.974	1.345	15.135
Trimmed mean	1.908	11.36	5.60	0.486	-15.95	-6.33	-2.47	-15.96	-11.02	-7.52	12.66	3.674	0.891	1.224	15.326
DMSFE(0.9)	1.909	11.36	5.63	0.485	-15.82	-5.96	-2.46	-15.89	-11.08	-7.56	12.91	3.711	0.891	1.220	15.011
DMSFE(0.5)	1.890	11.13	5.73	0.464	-15.88	-6.52	-2.49	-15.94	-12.05	-8.02	12.52	3.504	0.827	1.157	15.092
Cluster(2)	1.878	10.97	5.63	0.464	-15.77	-7.48	-2.43	-16.03	-11.56	-7.78	14.18	3.495	0.838	1.174	15.364
Cluster(5)	1.827	10.34	5.43	0.448	-14.98	-5.23	-2.63	-15.90	-10.30	-7.23	12.64	3.356	0.825	1.175	15.234
PC(5)	1.607	7.59	5.05	0.324	-17.93	-6.42	-2.58	-20.23	-12.35	-8.37	10.96	2.464	0.478	0.804	15.873
PC(7)	1.582	7.28	5.32	0.291	-17.86	-7.67	-3.14	-18.80	-13.39	-9.09	15.04	2.262	0.430	0.771	15.934
Panel B Combination of information															
Kitchen sink	1.692	8.65	5.25	0.370	-12.11	-6.22	-4.20	-14.31	-8.60	-6.84	10.03	2.618	0.694	1.123	16.461
Kitchen sink BA	1.700	8.75	5.13	0.384	-11.86	-6.14	-4.21	-13.65	-8.53	-6.73	9.67	2.674	0.715	1.142	16.201
Pretesting	1.625	7.81	4.90	0.347	-9.26	-6.00	-4.11	-10.65	-7.69	-6.26	6.08	2.523	0.686	1.136	15.893
Pretesting BA	1.782	9.77	5.16	0.439	-11.37	-5.77	-3.93	-12.66	-8.08	-6.26	8.73	3.260	0.903	1.302	16.350
Ridge	1.697	8.72	4.91	0.400	-13.86	-5.66	-3.06	-15.80	-10.02	-7.06	8.71	2.859	0.684	1.052	15.556
Lasso	1.667	8.33	5.59	0.332	-17.57	-5.84	-3.32	-20.63	-11.42	-7.81	11.40	2.629	0.561	0.906	14.579
Elastic net	1.734	9.17	5.17	0.405	-13.81	-5.35	-3.56	-16.55	-9.93	-6.94	8.84	2.987	0.734	1.104	15.431
Adaptive EN	1.574	7.17	5.29	0.287	-19.98	-4.18	-3.41	-25.43	-10.92	-7.38	14.23	2.369	0.441	0.763	7.809
EN CV	1.707	8.84	6.19	0.323	-16.72	-9.30	-5.05	-17.47	-13.68	-10.46	13.55	2.364	0.514	0.890	15.821
EN Mean	1.639	7.99	5.98	0.294	-22.97	-6.39	-3.04	-30.51	-13.46	-8.77	13.71	2.384	0.434	0.747	14.835
EN Median	1.621	7.77	5.39	0.314	-16.82	-5.61	-3.13	-18.39	-11.05	-7.63	10.49	2.417	0.526	0.897	14.354

Notes: The table reports evaluation criteria for the out-of-sample monthly rebalancing portfolio. Benchmark models are HFR Fund of Funds Index and naive (equally-weighted) portfolios. Evaluation criteria include end of period portfolio value (EPV), annualized average return (AR), annualized standard deviation (SD), maximum drawdown (MDD), annualized value at risk (VaR) and annualized conditional value at risk (CVaR), Sharpe Ratio (SR), Omega Ratio (OMG), Sortino Ratio (SOR), Upside Potential (UP) and Portfolio Turnover (PT). CVaR and VaR are estimated at 99%, 95% and 90% confidence level. AR, SD, MDD, VaR and CVaR are in percentages.

Table 8. Out-of-sample performance of Maximimizing Expected Return efficient portfolios ($\lambda = 0$)

	EPV	AR	SD	SR	VaR_{99}	VaR_{95}	VaR_{90}	$CVaR_{99}$	$CVaR_{95}$	$CVaR_{90}$	MDD	OMG	SOR	UP	PT
Naive	1.403	5.03	5.10	0.177	-19.75	-7.73	-4.21	-21.16	-13.19	-9.30	19.10	1.611	0.237	0.625	0.00
HFR	1.214	2.68	5.98	0.037	-22.14	-9.33	-7.45	-22.64	-14.65	-11.73	24.46	1.1031	0.047	0.502	0.00
Panel A Combination of forecasts															
	EPV	AR	SD	SR	VaR_{99}	VaR_{95}	VaR_{90}	$CVaR_{99}$	$CVaR_{95}$	$CVaR_{90}$	MDD	OMG	SOR	UP	PT
Mean	1.986	12.32	7.16	0.419	-15.18	-8.75	-6.19	-15.88	-12.03	-9.64	14.14	2.877	0.806	1.236	14.86
Median	1.999	12.48	7.20	0.424	-15.18	-8.75	-6.19	-15.88	-11.92	-9.59	11.47	2.922	0.826	1.255	14.64
Trimmed mean	1.997	12.47	7.13	0.427	-15.18	-8.75	-6.19	-15.88	-11.98	-9.61	13.29	2.928	0.823	1.249	14.82
DMSFE(0.9)	1.994	12.42	7.17	0.423	-15.18	-8.75	-6.19	-15.88	-11.97	-9.61	14.14	2.899	0.816	1.246	14.92
DMSFE(0.5)	1.990	12.37	7.15	0.422	-15.18	-8.75	-6.19	-15.88	-12.05	-9.65	13.59	2.909	0.811	1.235	15.15
Cluster(2)	1.969	12.11	7.26	0.406	-15.18	-8.75	-6.43	-15.88	-11.49	-9.51	14.53	2.754	0.780	1.224	15.01
Cluster(5)	1.962	12.02	7.05	0.414	-15.18	-8.75	-5.71	-15.88	-11.49	-9.30	16.72	2.890	0.803	1.228	15.39
PC(5)	1.722	9.02	6.40	0.321	-18.23	-9.78	-5.36	-21.42	-14.05	-10.39	16.88	2.318	0.507	0.892	15.97
PC(7)	1.731	9.14	6.51	0.320	-18.74	-10.00	-5.25	-23.44	-13.96	-10.47	18.63	2.372	0.512	0.886	15.98
Panel B Combination of information															
Kitchen sink	1.755	9.44	5.89	0.369	-10.72	-5.71	-5.13	-11.32	-8.87	-7.12	9.60	2.518	0.730	1.211	16.62
Kitchen sink BA	1.755	9.43	5.97	0.363	-11.13	-6.38	-5.31	-11.46	-9.64	-7.56	9.33	2.473	0.693	1.163	16.07
Pretesting	1.673	8.41	6.80	0.276	-16.73	-9.13	-6.22	-21.05	-12.68	-10.10	8.59	2.067	0.472	0.915	16.69
Pretesting BA	1.767	9.59	6.16	0.360	-14.17	-8.20	-5.31	-16.22	-11.67	-8.55	11.50	2.537	0.649	1.071	16.53
Ridge	1.716	8.95	6.09	0.333	-16.62	-5.69	-5.32	-20.93	-11.67	-8.56	10.64	2.335	0.569	0.995	15.75
Lasso	1.708	8.85	6.54	0.307	-17.39	-6.64	-5.32	-21.81	-12.00	-8.79	11.87	2.293	0.544	0.965	16.17
Elastic net	1.687	8.59	6.48	0.297	-19.84	-6.79	-5.10	-26.98	-13.22	-9.34	14.06	2.206	0.480	0.878	15.92
Adaptive EN	1.714	8.92	6.30	0.321	-20.49	-7.31	-4.22	-25.43	-13.59	-9.47	17.75	2.515	0.518	0.860	9.37
EN CV	1.757	9.46	6.77	0.322	-17.34	-9.81	-6.86	-21.47	-13.53	-10.85	16.40	2.250	0.517	0.931	15.87
EN Mean	1.709	8.86	6.52	0.308	-16.69	-6.11	-5.10	-21.15	-11.79	-8.62	12.35	2.265	0.552	0.988	15.32
EN Median	1.699	8.74	6.40	0.308	-15.12	-5.87	-5.32	-17.86	-11.07	-8.31	11.12	2.269	0.572	1.022	15.53

Notes: The table reports evaluation criteria for the out-of-sample monthly rebalancing portfolio. Benchmark models are HFR Fund of Funds Index and naive (equally-weighted) portfolios. Evaluation criteria include end of period portfolio value (EPV), annualized average return (AR), annualized standard deviation (SD), maximum drawdown (MDD), annualized value at risk (VaR) and annualized conditional value at risk (CVaR), Sharpe Ratio (SR), Omega Ratio (OMG), Sortino Ratio (SOR), Upside Potential (UP) and Portfolio Turnover (PT). CVaR and VaR are estimated at 99%, 95% and 90% confidence level. AR, SD, MDD, VaR and CVaR are in percentages.

Table 9. Out-of-sample performance of Minimum-Variance efficient portfolios - Shortselling allowed ($\lambda = 1$)

	EPV	AR	SD	SR	VaR_{99}	VaR_{95}	VaR_{90}	$CVaR_{99}$	$CVaR_{95}$	$CVaR_{90}$	MDD	OMG	SOR	UP	PT
Naive	1.403	5.03	5.10	0.177	-19.75	-7.73	-4.21	-21.16	-13.19	-9.30	19.10	1.611	0.237	0.625	0.00
HFR	1.214	2.68	5.98	0.037	-22.14	-9.33	-7.45	-22.64	-14.65	-11.73	24.46	1.1031	0.047	0.502	0.00
Panel A Combination of forecasts															
	EPV	AR	SD	SR	VaR_{99}	VaR_{95}	VaR_{90}	$CVaR_{99}$	$CVaR_{95}$	$CVaR_{90}$	MDD	OMG	SOR	UP	PT
Mean	1.766	9.58	2.83	0.781	-7.95	-2.00	-0.18	-9.74	-4.86	-2.94	2.81	6.756	1.537	1.804	32.62
Median	1.767	9.59	2.79	0.794	-7.64	-2.10	-0.26	-9.43	-4.72	-2.90	2.72	6.828	1.583	1.855	32.39
Trimmed mean	1.767	9.58	2.81	0.788	-7.86	-2.03	-0.20	-9.71	-4.83	-2.94	2.80	6.801	1.547	1.814	32.21
DMSFE(0.9)	1.768	9.60	2.83	0.783	-7.93	-1.98	-0.21	-9.74	-4.86	-2.95	2.81	6.805	1.542	1.808	32.60
DMSFE(0.5)	1.763	9.53	2.84	0.773	-7.79	-2.12	-0.78	-9.49	-4.79	-3.10	2.74	6.451	1.524	1.804	32.73
Cluster(2)	1.778	9.73	2.79	0.808	-7.57	-1.75	-0.38	-9.30	-4.67	-2.89	2.68	7.100	1.618	1.884	31.88
Cluster(5)	1.743	9.29	2.70	0.790	-6.97	-1.67	-0.35	-8.50	-4.50	-2.72	2.45	6.888	1.610	1.883	31.58
PC(5)	1.562	7.02	2.63	0.561	-5.47	-3.10	-1.42	-5.55	-4.33	-3.15	2.42	3.808	1.092	1.481	24.49
PC(7)	1.491	6.13	2.67	0.457	-7.26	-3.99	-1.35	-8.46	-5.64	-3.85	3.61	3.099	0.749	1.106	20.74
Panel B Combination of information															
Kitchen sink	1.485	6.06	2.43	0.492	-4.80	-3.00	-1.53	-5.37	-3.93	-2.99	1.87	3.370	0.931	1.324	24.91
Kitchen sink BA	1.486	6.07	2.37	0.508	-4.10	-2.85	-1.82	-4.26	-3.55	-2.93	1.63	3.402	0.970	1.374	25.13
Pretesting	1.432	5.40	2.39	0.421	-7.51	-3.24	-1.46	-8.25	-5.16	-3.59	2.38	2.822	0.647	1.002	21.58
Pretesting BA	1.515	6.43	2.41	0.541	-4.14	-3.01	-1.87	-4.67	-3.59	-2.92	1.36	3.620	1.056	1.459	26.04
Ridge	1.536	6.69	2.75	0.502	-5.78	-4.18	-1.46	-6.07	-5.07	-3.66	2.20	3.261	0.903	1.302	25.39
Lasso	1.557	6.96	2.54	0.573	-6.49	-2.84	-1.19	-6.65	-4.97	-3.32	2.41	3.945	1.013	1.356	26.36
Elastic net	1.523	6.53	2.72	0.490	-6.82	-3.96	-1.64	-8.19	-5.49	-3.81	2.72	3.223	0.828	1.201	24.64
Adaptive EN	1.371	4.64	2.60	0.303	-10.48	-2.48	-1.39	-11.04	-6.14	-3.92	4.35	2.269	0.425	0.759	19.33
EN CV	1.607	7.58	2.57	0.636	-4.57	-2.28	-1.03	-5.35	-3.52	-2.53	1.54	4.846	1.453	1.830	26.84
EN Mean	1.602	7.53	2.64	0.613	-6.06	-3.36	-1.36	-6.36	-4.73	-3.39	1.84	4.048	1.122	1.491	27.88
EN Median	1.560	7.00	2.73	0.538	-7.05	-3.19	-1.44	-7.23	-5.58	-3.73	2.65	3.558	0.918	1.276	28.49

Notes: The table reports evaluation criteria for the out-of-sample monthly rebalancing portfolio. Benchmark models are HFR Fund of Funds Index and naive (equally-weighted) portfolios. Evaluation criteria include end of period portfolio value (EPV), annualized average return (AR), annualized standard deviation (SD), maximum drawdown (MDD), annualized value at risk (VaR) and annualized conditional value at risk (CVaR), Sharpe Ratio (SR), Omega Ratio (OMG), Sortino Ratio (SOR), Upside Potential (UP) and Portfolio Turnover (PT). CVaR and VaR are estimated at 99%, 95% and 90% confidence level. AR, SD, MDD, VaR and CVaR are in percentages.

Table 10. Out-of-sample performance of Maximimizing Expected Return efficient portfolios - Shortselling allowed ($\lambda = 0$)

	EPV	AR	SD	SR	VaR_{99}	VaR_{95}	VaR_{90}	$CVaR_{99}$	$CVaR_{95}$	$CVaR_{90}$	MDD	OMG	SOR	UP	PT
Naive	1.403	5.03	5.10	0.177	-19.75	-7.73	-4.21	-21.16	-13.19	-9.30	19.10	1.611	0.237	0.625	0.00
HFR	1.214	2.68	5.98	0.037	-22.14	-9.33	-7.45	-22.64	-14.65	-11.73	24.46	1.1031	0.047	0.502	0.00
Panel A Combination of forecasts															
	EPV	AR	SD	SR	VaR_{99}	VaR_{95}	VaR_{90}	$CVaR_{99}$	$CVaR_{95}$	$CVaR_{90}$	MDD	OMG	SOR	UP	PT
Mean	2.813	22.66	10.76	0.557	-15.44	-6.97	-4.51	-19.53	-10.48	-8.00	5.64	6.126	1.855	2.217	56.62
Median	2.791	22.39	10.79	0.548	-15.70	-6.72	-4.79	-20.07	-10.52	-8.20	5.79	5.888	1.785	2.151	57.77
Trimmed mean	2.797	22.46	10.80	0.549	-15.59	-6.90	-4.72	-19.79	-10.49	-8.03	5.71	6.014	1.825	2.189	56.31
DMSFE(0.9)	2.825	22.81	10.76	0.561	-15.39	-6.94	-4.58	-19.45	-10.45	-7.96	5.62	6.203	1.877	2.238	56.38
DMSFE(0.5)	2.843	23.04	10.74	0.568	-15.48	-6.80	-4.53	-19.66	-10.30	-7.90	5.68	6.338	1.906	2.263	56.40
Cluster(2)	2.870	23.37	10.72	0.578	-14.96	-6.84	-4.26	-18.67	-10.27	-7.72	5.39	6.581	2.000	2.358	54.87
Cluster(5)	2.875	23.44	10.42	0.596	-12.69	-5.59	-3.06	-14.26	-8.97	-6.64	4.82	7.698	2.365	2.718	52.81
PC(5)	2.335	16.69	8.26	0.516	-14.89	-8.17	-4.98	-17.32	-11.05	-8.84	11.92	3.925	1.212	1.626	55.91
PC(7)	2.183	14.79	7.56	0.492	-17.49	-8.16	-5.75	-20.66	-12.77	-9.89	11.54	3.447	0.971	1.367	55.36
Panel B Combination of information															
Kitchen sink	2.120	14.00	8.39	0.416	-12.70	-9.25	-5.87	-14.60	-10.73	-9.00	8.49	3.048	0.964	1.435	66.78
Kitchen sink BA	2.143	14.29	8.35	0.428	-11.96	-9.35	-7.64	-12.99	-10.79	-9.46	8.54	3.082	0.969	1.435	65.67
Pretesting	2.169	14.61	9.16	0.400	-18.42	-7.97	-4.15	-24.88	-12.83	-9.25	10.06	3.546	0.960	1.337	66.83
Pretesting BA	2.143	14.29	8.62	0.414	-14.63	-8.53	-6.34	-15.80	-11.86	-9.50	8.54	3.121	0.948	1.395	63.03
Ridge	2.167	14.58	9.88	0.370	-20.97	-12.17	-6.26	-25.33	-16.58	-12.51	17.96	2.894	0.759	1.159	62.51
Lasso	2.204	15.05	9.10	0.417	-15.88	-8.00	-4.14	-15.90	-12.57	-8.88	7.20	3.621	1.068	1.476	57.39
Elastic net	2.190	14.87	9.42	0.397	-20.15	-9.47	-5.94	-23.80	-15.04	-11.22	14.47	3.216	0.860	1.249	62.99
Adaptive EN	1.924	11.55	9.32	0.298	-26.49	-9.56	-5.88	-30.04	-16.96	-12.14	17.21	2.374	0.551	0.952	57.89
EN CV	2.334	16.67	7.91	0.538	-11.56	-5.86	-4.59	-13.24	-8.71	-6.81	4.74	4.547	1.536	1.970	51.84
EN Mean	2.268	15.85	8.62	0.467	-15.21	-7.89	-4.29	-16.02	-11.74	-8.76	4.97	4.143	1.185	1.563	58.79
EN Median	2.250	15.62	9.02	0.439	-16.04	-7.95	-3.82	-16.26	-12.82	-8.90	6.29	3.924	1.126	1.511	56.80

Notes: The table reports evaluation criteria for the out-of-sample monthly rebalancing portfolio. Benchmark models are HFR Fund of Funds Index and naive (equally-weighted) portfolios. Evaluation criteria include end of period portfolio value (EPV), annualized average return (AR), annualized standard deviation (SD), maximum drawdown (MDD), annualized value at risk (VaR) and annualized conditional value at risk (CVaR), Sharpe Ratio (SR), Omega Ratio (OMG), Sortino Ratio (SOR), Upside Potential (UP) and Portfolio Turnover (PT). CVaR and VaR are estimated at 99%, 95% and 90% confidence level. AR, SD, MDD, VaR and CVaR are in percentages.

Table 11. Out-of-sample performance of Mean-CVaR efficient portfolios ($\alpha = 95\%$)

	EPV	AR	SD	SR	VaR_{99}	VaR_{95}	VaR_{90}	$CVaR_{99}$	$CVaR_{95}$	$CVaR_{90}$	MDD	OMG	SOR	UP	PT
Naive	1.403	5.03	5.10	0.177	-19.75	-7.73	-4.21	-21.16	-13.19	-9.30	19.10	1.611	0.237	0.625	0.00
HFR	1.214	2.68	5.98	0.037	-22.14	-9.33	-7.45	-22.64	-14.65	-11.73	24.46	1.1031	0.047	0.502	0.00
Panel A Combination of forecasts															
	EPV	AR	SD	SR	VaR_{99}	VaR_{95}	VaR_{90}	$CVaR_{99}$	$CVaR_{95}$	$CVaR_{90}$	MDD	OMG	SOR	UP	PT
Mean	1.970	12.12	8.12	0.363	-25.61	-7.95	-4.77	-31.88	-17.15	-11.51	12.50	2.814	0.614	0.953	19.70
Median	1.935	11.69	7.85	0.360	-22.38	-8.08	-4.90	-25.60	-15.62	-10.63	11.04	2.733	0.644	1.015	19.24
Trimmed mean	1.992	12.40	8.16	0.371	-25.51	-8.05	-4.64	-31.63	-17.21	-11.52	12.49	2.885	0.632	0.967	20.27
DMSFE(0.9)	1.971	12.14	8.12	0.364	-25.55	-7.83	-4.77	-31.80	-17.11	-11.49	12.43	2.823	0.617	0.955	19.64
DMSFE(0.5)	1.975	12.19	8.00	0.371	-25.32	-7.46	-4.75	-31.50	-16.83	-11.30	11.31	2.896	0.628	0.959	19.88
Cluster(2)	1.827	10.34	8.29	0.293	-24.80	-13.58	-6.00	-30.69	-18.81	-13.65	16.57	2.292	0.464	0.823	20.34
Cluster(5)	1.817	10.21	7.94	0.302	-25.72	-10.97	-5.25	-29.21	-18.42	-12.97	17.45	2.376	0.473	0.817	20.98
PC(5)	1.624	7.79	5.86	0.290	-20.19	-8.95	-5.93	-21.77	-14.36	-10.63	12.97	2.237	0.422	0.763	19.85
PC(7)	1.602	7.53	5.45	0.297	-15.13	-6.38	-3.83	-15.57	-11.92	-8.46	10.35	2.345	0.492	0.858	19.95
Panel B Combination of information															
Kitchen sink	1.466	5.83	4.96	0.228	-18.10	-6.45	-3.75	-18.33	-12.04	-8.43	9.73	1.912	0.330	0.691	14.68
Kitchen sink BA	1.474	5.92	4.61	0.251	-15.60	-6.49	-3.48	-15.74	-11.20	-7.93	8.06	1.973	0.366	0.742	14.59
Pretesting	1.406	5.08	3.85	0.238	-9.90	-6.00	-3.59	-10.98	-8.06	-6.42	7.37	1.881	0.368	0.786	14.21
Pretesting BA	1.569	7.12	4.72	0.318	-15.52	-5.88	-3.06	-16.34	-10.17	-7.35	9.00	2.390	0.504	0.866	15.55
Ridge	1.613	7.66	5.47	0.303	-16.82	-7.16	-3.23	-17.82	-12.34	-8.78	9.43	2.310	0.480	0.847	15.31
Lasso	1.580	7.26	5.27	0.293	-17.62	-8.37	-3.16	-18.68	-13.30	-9.28	9.37	2.241	0.426	0.769	16.21
Elastic net	1.608	7.60	4.96	0.331	-15.02	-6.37	-3.21	-15.75	-10.93	-7.47	8.85	2.448	0.537	0.907	14.95
Adaptive EN	1.455	5.68	6.49	0.168	-23.60	-5.44	-3.22	-30.78	-14.78	-9.53	18.27	1.812	0.256	0.572	14.21
EN CV	1.465	5.81	5.88	0.191	-19.15	-10.62	-6.06	-19.89	-14.75	-11.14	13.25	1.669	0.265	0.660	18.12
EN Mean	1.549	6.86	6.48	0.220	-28.71	-7.77	-3.34	-37.22	-17.08	-10.96	15.43	1.952	0.288	0.591	16.35
EN Median	1.536	6.70	5.41	0.255	-17.91	-8.79	-3.29	-17.99	-13.62	-9.80	10.21	2.018	0.366	0.725	16.56

Notes: The table reports evaluation criteria for the out-of-sample monthly rebalancing portfolio. Benchmark models are HFR Fund of Funds Index and naive (equally-weighted) portfolios. Evaluation criteria include end of period portfolio value (EPV), annualized average return (AR), annualized standard deviation (SD), maximum drawdown (MDD), annualized value at risk (VaR) and annualized conditional value at risk (CVaR), Sharpe Ratio (SR), Omega Ratio (OMG), Sortino Ratio (SOR), Upside Potential (UP) and Portfolio Turnover (PT). CVaR and VaR are estimated at 99%, 95% and 90% confidence level. AR, SD, MDD, VaR and CVaR are in percentages.

Table 12. Out-of-sample performance of Mean-CVaR efficient portfolios ($\alpha = 99\%$)

	EPV	AR	SD	SR	VaR_{99}	VaR_{95}	VaR_{90}	$CVaR_{99}$	$CVaR_{95}$	$CVaR_{90}$	MDD	OMG	SOR	UP	PT
Naive	1.403	5.03	5.10	0.177	-19.75	-7.73	-4.21	-21.16	-13.19	-9.30	19.10	1.611	0.237	0.625	0.00
HFR	1.214	2.68	5.98	0.037	-22.14	-9.33	-7.45	-22.64	-14.65	-11.73	24.46	1.1031	0.047	0.502	0.00
Panel A Combination of forecasts															
	EPV	AR	SD	SR	VaR_{99}	VaR_{95}	VaR_{90}	$CVaR_{99}$	$CVaR_{95}$	$CVaR_{90}$	MDD	OMG	SOR	UP	PT
Mean	1.961	12.01	8.15	0.357	-25.59	-8.43	-4.16	-31.86	-17.26	-11.54	12.51	2.791	0.608	0.948	19.89
Median	1.933	11.66	7.88	0.357	-22.38	-8.50	-4.84	-25.60	-15.69	-10.80	11.20	2.693	0.639	1.017	19.49
Trimmed mean	1.996	12.45	8.22	0.370	-25.52	-8.48	-4.17	-31.65	-17.25	-11.57	12.51	2.887	0.635	0.972	20.40
DMSFE(0.9)	1.963	12.04	8.16	0.358	-25.53	-8.37	-4.14	-31.78	-17.24	-11.58	12.44	2.794	0.610	0.950	20.09
DMSFE(0.5)	1.960	12.00	8.06	0.361	-25.33	-8.13	-4.09	-31.51	-17.02	-11.42	11.44	2.829	0.614	0.950	20.27
Cluster(2)	1.798	9.98	8.28	0.281	-24.80	-13.17	-6.71	-30.70	-18.81	-13.64	16.12	2.221	0.446	0.811	20.62
Cluster(5)	1.804	10.05	7.96	0.295	-25.70	-11.41	-5.22	-29.20	-18.52	-13.10	17.88	2.310	0.461	0.814	21.34
PC(5)	1.640	7.99	5.88	0.299	-19.89	-8.93	-5.91	-21.77	-14.32	-10.58	12.94	2.280	0.438	0.781	19.85
PC(7)	1.590	7.38	5.62	0.281	-16.22	-7.50	-3.84	-17.99	-12.87	-8.96	10.83	2.253	0.453	0.814	20.09
Panel B Combination of information															
Kitchen sink	1.452	5.65	5.04	0.214	-17.69	-7.25	-4.14	-17.83	-12.12	-8.62	9.46	1.823	0.311	0.688	15.10
Kitchen sink BA	1.467	5.84	4.71	0.241	-15.32	-6.45	-3.84	-15.74	-10.91	-7.83	7.87	1.924	0.361	0.751	14.81
Pretesting	1.415	5.18	3.99	0.237	-10.32	-5.61	-3.74	-10.98	-8.33	-6.44	8.08	1.865	0.371	0.799	14.50
Pretesting BA	1.562	7.02	4.92	0.300	-15.51	-6.15	-3.50	-16.33	-10.23	-7.58	10.24	2.273	0.484	0.865	15.83
Ridge	1.628	7.85	5.74	0.299	-18.68	-6.22	-3.89	-19.41	-12.42	-8.76	9.68	2.295	0.479	0.849	15.25
Lasso	1.591	7.38	5.36	0.295	-17.55	-7.33	-4.02	-18.15	-12.94	-8.80	10.14	2.199	0.442	0.810	15.74
Elastic net	1.608	7.60	5.32	0.309	-17.09	-5.91	-3.91	-19.57	-11.51	-8.08	10.45	2.312	0.491	0.865	14.96
Adaptive EN	1.452	5.65	6.53	0.165	-23.49	-5.44	-3.00	-30.58	-14.69	-9.45	17.07	1.794	0.256	0.578	14.95
EN CV	1.451	5.64	6.06	0.178	-19.21	-10.39	-6.08	-19.88	-15.38	-11.46	14.35	1.614	0.245	0.645	18.02
EN Mean	1.490	6.12	6.65	0.183	-28.77	-8.82	-4.21	-37.32	-17.38	-11.71	17.01	1.714	0.238	0.570	16.09
EN Median	1.504	6.30	5.61	0.225	-17.52	-9.35	-4.31	-17.82	-13.77	-9.95	12.59	1.825	0.327	0.723	16.57

Notes: The table reports evaluation criteria for the out-of-sample monthly rebalancing portfolio. Benchmark models are HFR Fund of Funds Index and naive (equally-weighted) portfolios. Evaluation criteria include end of period portfolio value (EPV), annualized average return (AR), annualized standard deviation (SD), maximum drawdown (MDD), annualized value at risk (VaR) and annualized conditional value at risk (CVaR), Sharpe Ratio (SR), Omega Ratio (OMG), Sortino Ratio (SOR), Upside Potential (UP) and Portfolio Turnover (PT). CVaR and VaR are estimated at 99%, 95% and 90% confidence level. AR, SD, MDD, VaR and CVaR are in percentages.

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