Unveiling the Risk Profile of Fund of Funds

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Abstract

In this paper, we compare the risk-return profile of hedge funds and fund of funds in order to evaluate the added value of the fund of funds strategy in relation to the underlying hedge funds. We construct decide portfolios of hedge funds and fund of funds in order to create benchmarks for the risk return profile of both investment vehicles. In addition, we propose optimal fund of funds strategies in order to create a portfolio of hedge funds that minimizes downside risk. Our findings suggest that for low levels of risk, hedge funds are less risky than fund of funds while they provide better average returns. On the other hand, for high levels of risk, fund of funds provide a diversification effect at the cost of significantly reduced returns. More importantly, our proposed fund of funds strategy dominates the corresponding risk returns profile of funds of funds and individual hedge funds.

Keywords: Hegde funds; fund of funds; tail risk; optimal diversification strategies.

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1 Introduction

The risk-return relationship of hedge funds has received significant attention in the past two decades. Hedge funds can be described as investment vehicles that pursue abnormal returns and at the same time remain market neutral. Contrary to traditional asset classes, the hedge funds' industry is lightly regulated and reporting is voluntary. Their liquidity is limited compared to more traditional assets and they are not accessible to investors with limited capital.[1] An alternative investment vehicle of similar characteristics is the fund of funds or fund of hedge funds. Fund of funds are investment vehicles that invest directly on hedge funds. In contrast to hedge funds, they offer increased accessibility and more liquidity but charge a second layer of management fees.

As portfolio of hedge funds, fund of funds offer similar return characteristics and at the same time diversify the exposure to specific hedge fund strategies. Nonetheless, there is little, if any, information regarding the construction of portfolios of hedge funds. Typically, a fund of funds manager conducts the appropriate due diligence regarding the selection of hedge funds. Therefore, the questions that lie ahead is how fund of funds are constructed and if they provide significant gains in terms of the risk and/or return in comparison to hedge funds.[2] Given that there is no information regarding the fund of funds selection process, the evaluation of such properties can be performed by comparing the risk-return profile of fund of funds with their pool of hedge funds.

In pursue of abnormal returns and market neutrality, hedge funds implement option-like investment strategies that produce non-linear payoffs which in turn lead to asymmetric and platykurtic return distributions.[3] The asymmetry and kurtosis of returns make the interpretation of standard deviation as a risk measure problematic. Therefore, traditional portfolio theory may be inappropriate for deriving the risk-return profile of hedge funds and fund of funds. Instead, Bali *et al.* (2007) and Liang and Park (2007) evaluate the explanatory power of Value at Risk (VaR) and various risk measures on the returns of hedge funds. This is done by constructing portfolios of hedge funds through sorting the pool of funds according to their risk forecast. Using the same methodology, Bali *et al.* (2012) find a positive relationship between returns and systematic risk as described by the difference of the total variance calculated by a factor model and the corresponding residual risk. Similarly, Bali *et al.* (2014) evaluate the influence of macroeconomic risk and find a positive correlation with the returns of hedge funds.

With respect to the utility of fund of funds, Amin and Kat (2003a) suggest that both hedge funds and fund of funds are not efficient as a stand alone investment. Amin and Kat (2003b) evaluate the diversification effect of a portfolio of hedge funds, stocks and bonds and conclude

[1]See Agarwal *et al.* (2015), El-Kalak *et al.* (2016a), El-Kalak *et al.* (2016b), and Stafylas *et al.* (2016) for a more elaborate discussion of the characteristics of the hedge funds' asset class.

[2]Shawky *et al.* (2012) evaluate ex post the effect of diversification on the performance of fund of funds and conclude that investing across sectors has a positive impact to the performance of fund of funds. Cao *et al.* (2015) investigate whether hedge funds do hedge against bad times. Their findings suggest that there are gains in terms of performance during bad times.

[3]Liang (1999), Fung and Hsieh (2001), Patton (2009) provide evidence that the advertised market neutrality does not always hold.

that allocating 20% of the capital to hedge funds can provide gains in terms of returns and standard deviation.[4] Focusing on the implications of the return distribution, Amin and Kat (2003b) suggest that the inclusion of hedge funds in a mixed portfolio can improve the mean-variance frontier at the cost of decreased skewness. Within the mean-variance framework, Alexander and Dimitriu (2004) propose the minimum variance portfolio of performance-ranked funds as a portfolio formation strategy. In this way, the portfolio construction does not suffer from possible expected returns' estimation errors. Departing from the traditional mean-variance analysis, Krokhmal *et al.* (2002) compare the portfolios of hedge funds formed on the basis of Expected Shortfall (ES) and Conditional Drawdown at Risk minimization schemes with more traditional risk measures. They conclude that ES seems to provide better portfolio performance than competing risk measures. Vrontos *et al.* (2008) employ a bayesian model averaging approach in order to jointly account for model uncertainty and heteroscedasticity in hedge fund pricing. Creating alpha-ranked (and t-stat ranked) portfolios, the authors show that accounting for model uncertainty creates value to potential investors. Davies *et al.* (2009) utilize a polynomial goal programming technique in order to optimally allocate the weights in a portfolio of hedge funds. The proposed method is capable of treating all first four moments of the distribution according to the investor preferences.

Working with hedge fund strategies, Morton *et al.* (2006) construct portfolios of hedge funds subject to the minimization of utility functions that combine the expected regret and the relative performance from a benchmark. Giamouridis and Vrontos (2007) evaluate the impact of the time varying variance and covariance on the hedge funds' portfolio performance. In addition, they utilize ES in order to evaluate the performance in terms of risk. Harris and Mazibas (2010) extend the work of Giamouridis and Vrontos (2007) by utilizing multivariate conditional variance estimators, while Panopoulou and Vrontos (2015) utilize a mean variance, maximum utility, and mean-ES framework to construct portfolios of hedge fund strategies.

Regarding the selection of the individual hedge funds to enter the portfolio, we should note that there is no information about the due diligence procedure and the selection criteria of the manager. Given that hedge funds are advertised as market neutral investments that provide abnormal returns in all market conditions, it seems natural to select the funds with the highest alpha. Alpha maps the hedge fund manager's skill to provide returns in excess of those related to systematic risk. Kosowski *et al.* (2007) suggest that funds with high and statistically significant alpha are not just lucky. Fung *et al.* (2008) suggest that contrary to fund of funds, hedge funds produce a significant alpha. Alexander and Dimitriu (2004) argue that, although alpha varies with the specification of the factor models, considering the number of statistically significant positive alphas can serve as a reliable indicator of performance. Sun *et al.* (2016) suggest that the conditional performance of funds during bear markets is a more reliable indicator of the fund's overall performance. Specifically, the authors argue that good performance in turbulent market conditions is positively related with the performance of the funds during bad and good times. Commenting on the selection process effectiveness, Darolles and Vaissie (2012) suggest

[4] They use random sampling and equally weighted representative portfolios of hedge funds. These portfolios serve as a proxy of the fund selection process according to the due diligence of the investor.

that under a constant strategic allocation assumption, the fund selection process may have some added value on the funds returns. On the other hand, Aiken *et al.* (2014) fail to detect added value through the selection of hedge funds. However, they find evidence that fund of funds managers do drop hedge funds that consistently underperform.

This paper evaluates the risk-return trade-off of the fund of funds asset class by comparing them with the hedge funds. To the best of our knowledge, no other comparison exists in the literature between the risk-return profile of fund of funds and hedge funds. In order to proceed with such an analysis, we follow Bali *et al.* (2007) and Liang and Park (2007) and form equally weighted decile portfolios as proxies of the average risk-return profile of both hedge funds and fund of funds. The linkages between these decile portfolios provide a thorough understanding of the risk profile of fund of funds and their corresponding returns. In addition, we propose an optimal hedge fund portfolio selection process in pursue of a risk-return relationship that outperforms the ones offered by fund of funds. For the creation of such portfolios, we utilize the downside risk measures, VaR and ES, as they can potentially integrate the asymmetries and kurtosis of the hedge fund return distribution. Given that we focus on individual hedge fund returns and not on strategies/indices, the frequency of returns and the lack of sufficient history lead to the employment of unconditional risk estimation techniques. Specifically, we implement the non parametric Historical Simulation (HS), the Normal with the Cornish Fisher (CF) approximation and the Extreme Value Theory (EVT) methods.

Our key findings suggest that fund of funds are on average riskier than hedge funds only for the higher levels of risk. Furthermore, the average returns of fund of funds are significantly lower than the average returns of the low-risk hedge fund decile portfolio. In other words, there are small gains from investing in fund of funds in comparison to low risk hedge funds. There results are robust to the selection of the risk measure and the estimation method. More importantly, our findings suggest that for two of the risk estimation methods, the optimal portfolio outperforms both the fund of funds and hedge funds decile portfolios.

The rest of the paper is structured as follows. Section 2 describes the risk estimation and portfolio construction methodology. Section 3 describes the data and presents the empirical results on the hedge fund and fund of funds decile portfolios. In Section 4, we describe the results of our optimal portfolios and Section 5 concludes the paper.

2 Methodology

2.1 Risk Estimation

Measuring the risk of individual hedge funds and fund of funds is quite challenging. The asymmetry and kurtosis of hedge fund returns make the employment of standard deviation problematic. Commenting on the inability of standard deviation to cope with the skewness of returns, Estrada (2000) suggests that semideviation is a more appropriate measure in the presence of skewness. Therefore, utilizing measures that take into account the third and fourth moment improves significantly the approximation of the risk profiles of both fund of funds and hedge funds.

Gupta and Liang (2005) introduce VaR as a more appropriate risk measure for the evaluation of the capital adequacy of hedge funds. The authors conclude that VaR is superior to traditional risk measures in describing the risk of hedge funds. Furthermore, the findings of Agarwal and Naik (2004) and Liang and Park (2007) suggest that ES is more appropriate than the VaR measure. From a different perspective, Agarwal *et al.* (2017) utilize the ES measure to synthesize a systemic risk measure in order to explain the tail risk of hedge funds. This superiority of downside risk measures is also evident in forecasting hedge fund failure. Bali *et al.* (2007) suggests that the VaR of hedge funds increases before the fund stops reporting at the hedge funds database. In the same vein, Liang and Park (2010) utilizes a battery of risk measures and the Cox proportional hazard model in order to investigate accurately the explanatory power of related measures in predicting a failure.

Following the results of the aforementioned literature, we utilize the downside risk measures VaR and ES which are defined as:

$$VaR\,(q) = \inf\{x \in R : P(r \leq x) \geq q\} \tag{1}$$

$$ES\,(q) = \frac{1}{q}\int_0^q VaR\,(a)\,da \tag{2}$$

where q is the coverage level, r is the random variable describing the returns and $P(r \leq x)$ is the corresponding Cumulative Distribution Function (CDF). VaR is considered a frequency measure given that it is defined as the q quantile of the distribution of returns. The main advantages of VaR are its simplicity and ease of implementation as it can incorporate every relevant risk factor. However, VaR does not provide any information for losses that violate the corresponding quantile. In addition, it does not satisfy the subadditivity property for all return distributions. Hence, VaR is not always consistent with the notion of diversification (see Artzner *et al.* (1997)). On the other hand, ES as a severity measure quantifies the expected magnitude of losses when the corresponding VaR threshold is violated. Therefore, it combines the magnitude of losses and their frequencies in order to fully describe the tail of the distribution.

From Equations (1) and (2), it is obvious that VaR and ES measures require distributional assumptions in order to identify the corresponding tail characteristics. There is a vast literature on the conditional estimation of the density of returns (see Bollerslev (1986)). With respect to hedge funds returns, Giamouridis and Ntoula (2009) evaluate the VaR and ES measures of fund of funds and hedge funds through a conditional variance framework on daily data of hedge funds strategies. In our case, the low frequency (monthly) of hedge fund returns and their limited history hinder the implementation of such an approach. Therefore, we opt for an unconditional density estimation. Following Bali and Gokcan (2004), Bali *et al.* (2007) and Liang and Park (2007) we implement three methods for the estimation of the risk measures. First, we implement the non-parametric Historical Simulation (HS) method which uses the empirical distribution of returns to calculate the corresponding risk measures as:

$$VaR_{t,HS}\left(q\right) = F_q^{-1}(\{r_i\}_{i=1}^{t-1}) \tag{3}$$

$$ES_{t,HS}\left(q\right) = \frac{1}{N(\Delta)}\sum_{a\in\Delta} F_a^{-1}(\{r_i\}_{i=1}^{t-1}) \tag{4}$$

where F_a^{-1} denotes the a empirical quantile of the sample of returns, Δ is the partition of the tail and $N(\Delta)$ is the number of elements within the partition Δ. Contrary to the non-parametric HS, fitting a parametric distribution imposes a specific structure for the returns which is then fitted on the sample data. As with many applications in finance, the Normal distribution would have been the first choice for a benchmark model. However, the excessive kurtosis and asymmetry of hedge fund and fund of funds returns make the fit of a symmetric Normal distribution problematic. Instead, we use the Cornish Fisher (CF) approximation in order to account for the third and fourth moment of the return distributions. Under the CF approximation, the q quantile of the standardized returns $\left(\frac{r-\mu}{\sigma}\right)$, where μ is the sample mean and σ is the standard deviation, is given by the following equation:

$$\Omega\left(q\right) = Z^{-1}(q)+\frac{1}{6}((Z^{-1}(q))^2-1)S+\frac{1}{24}((Z^{-1}(q))^3-3Z^{-1}(q))K-\frac{1}{36}((2Z^{-1}(q))^3-5Z^{-1}(q))S^2$$

where $Z^{-1}(q)$ is the standardized normal inverse cumulative function, S is the sample skewness and K is the is the sample excess kurtosis. Therefore, VaR and ES under the CF Normal method are given as:

$$VaR_{t,CF}\left(q\right) = \mu + \Omega_q^{-1}(\{z_i\}_{i=1}^{t-1})\sigma \tag{5}$$

$$ES_{t,CF}\left(q\right) = \frac{1}{N(\Delta)}\sum_{a\in\Delta} VaR_{CF}\left(a\right) \tag{6}$$

where $\Omega_q^{-1}(\{z_i\}_{i=1}^{t-1})$ is the CF q quantile of the standardized returns sample $\{z_i\}_{i=1}^{t-1}$.

Finally, we implement the extreme value theory (EVT) in order to approximate the tail of the distribution. Specifically, we fit the Generalized Pareto Distribution (GPD) on the sample of standardized losses in order to get a better approximation of the left tail of the distribution. In such a case, the risk measures are calculated as:

$$VaR_{EVT}\left(q\right) = \mu + GPD_q^{-1}(\{z_i\}_{i=1}^{t-1})\sigma \tag{7}$$

$$ES_{EVT}\left(q\right) = \frac{1}{N(\Delta)}\sum_{a\in\Delta} VaR_{EVT}\left(a\right) \tag{8}$$

where $GPD_q^{-1}(\{z_i\}_{i=1}^{t-1})$ is the GPD q quantile of the standardized returns.

With respect to the in-sample length and the risk coverage level, Bali and Gokcan (2004), Bali *et al.* (2007) and Liang and Park (2007) require 60 observations and a 5% coverage level for both VaR and ES. Similarly, Gupta and Liang (2005) require a sample period of 60 observations while setting the coverage level at 1%. According to Gupta and Liang (2005), a minimum of 60 observations is enough for VaR to capture the cross section between the risk and return of hedge funds. The authors argue that this sample length might increase the variance of the risk estimate but will not induce bias. On the contrary, Breymann *et al.* (2016) argue that when considering risk measures as a selection criterion, a more precise measurement is needed. Given that we don't account for the conditional dynamics in the variance, selecting the optimal sample length does not increase the accuracy of our risk forecasts. On the contrary, an unconditional estimation process requires an adequate sample in order to approximate accurately the tail of the return distribution. Therefore, in our empirical analysis we require an eight year in-sample period (96 observations) and set the coverage level to 5% for both VaR and ES.[5] The 5% coverage level entails less estimation risk than more conservative coverage levels. Finally, the estimation of the risk measures is performed by rolling the estimation sample of 96 observations forward until the end of the out-of-sample period.

2.2 Portfolio Formation

Following Bali *et al.* (2007) and Liang and Park (2007) we construct equally weighted portfolios according to the risk profile of the individual funds. In more detail, at each point of the out-of-sample period we rank each individual fund according to its risk forecast. Then, we create 10 equally weighted portfolios which correspond to each decile of the pool of ranked funds. For example, if the ranked funds are 1000, then the first portfolio would be the equally weighted combination of the 100 least risky assets while the tenth portfolio would be the equally weighted portfolio of the 100 most risky assets. The returns for these portfolios are calculated as the next month's equally weighted returns of the individual funds included in the decile portfolio. As noted by Liang and Park (2007), this methodology is similar to the Fama and French (1992) one but with monthly rebalancing instead of yearly. Finally, we calculate the difference between the returns of the high- and low-risk portfolios and test the null hypothesis of equality between the respective means.[6,7]

The aforementioned portfolios are constructed for both hedge funds and funds of funds (alive and defunct). For the hedge funds, each decile portfolio represents an equally-weighted fund of funds strategy for different levels of risk. In addition, the hedge funds decile portfolios provide, through equally weighted proxies, an average picture of the risk-return range and characteristics. For the fund of funds case, the decile portfolios provide the average risk-return profile of the fund of funds strategy. Therefore, the fund of funds decile portfolios set a benchmark for the average risk-return characteristics of the fund of funds. To account for possible survivorship bias, we construct the decile portfolios for both alive and defunct funds and the group of all funds and compare the results.

With respect to risk-optimal portfolios, following Krokhmal *et al.* (2002) we construct hedge fund portfolios by selecting weights that would minimize the VaR and ES of the portfolio. Our intention is to examine whether we can construct an optimal portfolio of hedge funds (i.e. a

[5]For ES, we set the partition of the tail equal to $\Delta = \{0.005, 0.01, ..., 0.045, 0.05\}$.

[6]The test is a simple t-test with Newey-West heteroskedasticity and autocorrelation corrected standard errors (due to the overlap of the risk measures estimation windows).

[7]Similar approaches are followed by Liang and Park (2010), Bali *et al.* (2012) and Bali *et al.* (2014) in order to evaluate the cross- sectional dependecies between risk and returns.

fund of funds) that dominates the existing fund of funds in the terms of risk and return. Instead of ranking hedge funds according to their alpha (see Alexander and Dimitriu (2004)), we use the risk measure forecast as a reference. This is in accordance with the findings of Sun *et al.* (2016) who suggest that hedge funds that perform better in down market conditions would consistently outperform their competitors. More in detail, the authors define two conditional performance measures to relate the realized returns with good and bad periods of the aggregate hedge fund markets. Both measures are calculated as the conditional average of twelve monthly returns in good and bad conditions, over a 3-year period. Their findings suggest that good performance during bad times has significant explanatory power over the returns while good performance in good times does not.

As noted by Bali *et al.* (2007), the main difference between the alive and defunct funds is the outcome of risk taking. Risk taking for alive funds leads to gains while for defunct funds leads to losses. Therefore, instead of focusing on the returns, we focus on the aggregate risk of each individual fund as described by the respective downside risk measures. Given the excessive kurtosis of the hedge funds returns, low-risk funds would have a return distribution that places more mass of probability on the positive returns. This leads to lower but consistently positive returns. On the other hand, riskier funds have a wider range of returns at the cost of increased volatility. Hence, the probability of losses is significantly larger. This is in line with Sun *et al.* (2016) who suggest that large gains in good market conditions may also come from unskilled managers that increase their exposure to risks undervalued by the benchmarks.

We create our risk-optimal portfolios by focussing on the less risky, but probably more persistently well-performing, hedge funds. Specifically, at each point in the out-of-sample period, we rank hedge funds by the aforementioned risk measures (VaR and ES) and construct portfolios of hedge funds by assigning weights on the 50 least risky funds. Out of the pool of these 50 funds, we select at least 10 hedge funds to be in the optimal portfolio following Brown *et al.* (2012). The corresponding risk measures are calculated directly for portfolio returns and in this way, we avoid additional assumptions regarding the aggregation of risk. More in detail, our portfolios are constructed by means of the following optimization scheme:

$$\begin{gathered} \min VaR(r_p) \text{ or } ES(r_p) \\ \text{s.t. } x_L \leq x_i \leq x_U,\ i = 1, ..., n,\ \sum_{i=1}^{n} x_i = 1, \text{ and } E\left(r_p\right) \geqslant r_G, \end{gathered} \tag{9}$$

where r_p is the $n-$funds portfolio return, $\mathbf{x} = (x_1, x_2, ..., x_n)'$ is the vector containing the funds' weights in the portfolio, x_L, x_U are the weight constraints and r_G is the target annualized return with $r_G \in \{24\%, 23\%, ..., 1\%\}$. Given that currently short selling hedge funds 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 0.10 ($x_U = 0.10$). Finally, $VaR(r_p)$ and $ES(r_p)$ are calculated by the three aforementioned ways, namely HS, CF and EVT.

2.3 Evaluation criteria

In order to evaluate the performance of the portfolios of hedge funds and fund of funds, we implement a variety of performance measures calculated over the out-of- sample period. 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 funds 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) over the out-of-sample period and the cumulative return (CR) at the end of the out-of-sample period. Next, we consider measures related to portfolio risk. Specifically, we calculate the standard deviation (SD), the 1%, 5% and 10% VaR and the 1%, 5% and 10% ES. VaR and ES of the portfolios are calculated as described in Section 2.1 by equations (3) and (4).

Given that the decile and optimal portfolios do not entail the same risk profile, we also calculate risk adjusted performance measures that provide a uniform representation of the expected returns per unit of risk. Specifically, we use the Sharpe Ratio (SR) which is calculated as:

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

where $E(r_p)$ is the average return of the portfolio, $SD(r_p)$ is the standard deviation of the portfolio over the out-of-sample period and r_f is the risk free rate. Similarly, we calculate the Omega (OMG), Sortino (SOR) and Upside Potential (UP) ratios which, contrary to the SR, treat losses and gains of the portfolio separately. These measures are calculated as:

$$OMG(r_b) = \frac{E(r_p) - r_b}{E[(r_b - r_p)_+]} + 1$$

$$SOR(r_b) = \frac{E(r_p) - r_b}{\sqrt[2]{E[((r_b - r_p)_+)^2]}}.$$

$$UP(r_b) = \frac{E[(r_p - r_b)_+]}{\sqrt[2]{E[((r_b - r_p)_+)^2]}}$$

where r_b is the benchmark return (taken equal to the average risk free rate) and $(.)_+$ is the positive part function. Although these measures have similar intuition to the SR, they are more robust to possible skewness and excessive kurtosis.

Finally, we calculate the maximum drawdown (MDD), which uses the maximum cumulative losses in order to assess the risk profile of a fund/portfolio. Specifically, MDD is defined as the maximum loss incurred by the portfolio between the peaks and the following troughs over the out-of-sample period:

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

where PV denotes the portfolio value and T_0, T denote the beginning and end of the evaluation period, respectively. The aforementioned measures are calculated for all optimal and decile portfolios specifications. To save space, for the decile portfolios we report only the cumulative returns, average returns, standard deviation, SR and 5% HS-VaR. For the optimal and competing decile portfolios we report the full set of evaluation criteria.

3 Empirical Findings

3.1 Data

We employ monthly data provided by the BarclayHedge database, with a sample period spanning from January 1994 to December 2014. The initial dataset includes 6489 live funds and 16748 defunct funds. Following similar studies, we implement a variety of filters on the initial sample. First, we exclude funds that do not report returns on a monthly basis and funds that report returns on different than the US dollar currency. In order to reduce any size bias caused by small funds, we exclude the funds that have less than ten million of Assets Under Management (AUM). Finally, we exclude funds that have a history of returns less than eight years (96 observations). The requirement of at least eight years of historical returns leads to an out-of-sample period of thirteen years spanning from January 2002 to December 2014. The implementation of these filters results in a dataset of 2561 hedge funds and 908 fund of funds. In addition, the dataset is further divided to 1135 alive hedge funds and 359 alive fund of funds, with the rest comprising the defunct ones for both groups, respectively. We follow Joenvaara *et al.* (2016) strategy classification and regroup the filtered dataset to 13 groups based on the similarities of their strategies. Specifically, the 13 group of funds consist of the Relative Value (RV), Emerging Markets (EM), Event Driven (ED), Global Macro (GM), Long (L), Long/Short (LS), Multi Strategy (MS), Others (OT), Commodity Trade Advisors (CTA), Sector (SE), Short Bias (SB), Market Neutral (MN) and Fund of Funds (FoF).

Table 1 reports the cross-sectional average values of the descriptive statistics for both fund of funds and hedge funds along with the rejection rates of the Jarque Bera test for normality. We first present our results for the individual hedge funds. Overall, our findings confirm the presence of excessive kurtosis and negative skewness reported in the literature. When comparing alive and defunct hedge funds, both return profiles seem similar. However, the slightly larger average mean (10.30% vs. 10.17%) and median (10.25% vs. 9.54%) for the group of alive hedge funds suggests that the return distribution of alive funds is located at the right of the return distribution of the defunct funds. In other words, risk taking for the alive funds results in more positive returns. For the defunct funds, risk taking results in losses which eventually lead to the demise of the fund. Regarding the normality of returns, the rejection rates of the Jarque Bera test reveals that at least 84% of the hedge funds return series reject the normality hypothesis.

Turning to the fund of funds, the descriptive statistics reveal a less volatile profile which is accompanied by lower mean returns. Specifically, fund of funds returns have a smaller average dispersion in comparison to the hedge funds. These findings are attributed to the portfolio diversification effect of the fund of funds strategy. However, both the third and fourth moment of the fund of funds returns are higher than the ones of the group of all hedge funds. This is in line with the results of Amin and Kat (2003a) and Davies *et al.* (2009) who report a trade-off between the moments of the return distribution of portfolio of hedge funds. Specifically, the authors provide evidence that the minimization of variance can lead to increased kurtosis. The characteristics of the alive and defunct fund of funds are similar to the hedge fund case with the return distribution of the alive funds located at the right of the distribution of the defunct fund of funds.

[Table 1 around here]

Table 2 reports the cross-sectional averages for the returns of each hedge fund strategy. The majority of hedge fund strategies share similar mean return profiles attaining annualised returns of over 9%. However, MS, MN and FoFs have the lowest returns equal to 7.21%, 4.65% and 5.86% respectively. More importantly, there is significant variation among strategies in terms of risk. For instance, EM and MN have the most volatile returns, while MS and FoFs have the smallest average volatility. Moreover, the average kurtosis of each strategy exceeds 5, signaling increased probability of extreme returns. In addition, the average skewness and average absolute skewness suggest that the return distributions of the strategies are not symmetric. Comparing the fund of funds with the individual hedge fund strategies, we have to note that although the average standard deviation of the fund of funds is the smallest, the corresponding kurtosis is the third largest, signaling an increased risk of excessive losses. Furthermore, the returns of fund of funds seem to be more negatively skewed than the majority of the hedge fund individual strategies. In other words, although there are clear signs of the diversification effects embedded in FoFs, the risk stemming from the third and fourth moment of the fund of funds return distribution seems significantly high.

[Table 2 around here]

To gain a visual insight, we plot the distribution of the related mean returns in Figure 1. As shown, individual hedge fund returns have a wider distribution than fund of funds, with the latter located at the left of the former. When considering both alive and defunct funds, we observe that the related distributions have similar left tails, while the right tail of the fund of funds distribution is significantly thinner. Therefore, fund of funds do not avoid possible excessive negative returns while relinquishing possible excessive gains. For the alive group of funds, our findings suggest that the fund of funds do avoid excessive negative returns since the left tail of the mean returns has almost no mass over the negative part of the axis. However, almost 75% of the fund of funds mean returns are below the median of the hedge funds mean returns. Finally, for defunct funds, the left tails of the related distributions seem similar for both fund of funds and hedge funds.

[Figure 1 around here]

To gain a first impression of the risk entailed by the hedge funds and fund of funds, Figure 2 plots the distribution of the 5% empirical quantile (HS-VaR) for the fund of funds and hedge funds. Overall, the fund of funds risk distribution is more leptokurtic than the hedge funds distribution with almost 75% of the risk estimates located over the median of the corresponding VaR distribution of the hedge funds. This is probably due to the diversification effect of the fund of funds strategy. However, in all cases there is significant mass on the left tail of the distribution signalling possible extreme cases of risks.

[Figure 2 around here]

To sum up, the preliminary descriptive analysis suggests that the fund of funds strategy can provide significant gains in terms of variance reduction. However, these diversification effects come at the cost of significant return reduction. In addition, the third and fourth moment statistics suggest that the left tail risk profile of fund of funds may not be significantly different from that of hedge funds. This is partially backed up by both the return and VaR distributions for both hedge funds and fund of funds. Overall, the fund of funds strategy may provide marginal gains in terms of risk-return when compared to individual hedge funds.

3.2 Risk-Return Profile of Hedge Funds

In order to gain a deeper understanding of the risk-return profile of hedge funds, we calculate the risk decile portfolios of hedge funds for the out-of-sample period following the methodology outlined in Section 2.1. Tables 3 to 5 report the characteristics of the hedge fund decile portfolios for each estimation method and risk measure. Besides setting the benchmark for the average risk levels and returns, the hedge fund decile portfolios can be considered as a naive fund of funds strategy. However, such a strategy lacks practical relevance due to the number of funds included in it. For example, when our pool of hedge funds reaches 2000 funds, each decile portfolio would include 200 funds which is unrealistic due to management and transaction costs. In practice, portfolios of 10 funds would achieve a meaningful diversification effect (see Davies *et al.* (2009) and the references therein.).

Table 3 reports the risk-return profile for the hedge funds HS decile portfolios. For the VaR case (Table 3, Panel A) and the groups of all funds (both alive and defunct), our findings suggest a strictly decreasing risk pattern both in terms of standard deviation and empirical quantile (5% VaR). Average returns are also decreasing (from 11.13% to 5.69%) without however preserving a strictly monotonous profile. For instance, we observe that the returns of the mid- to low-risk decile portfolios are similar with the exception of the second decile portfolio that has marginally smaller average returns. SR broadly follows the fluctuations in risk and returns and increases from 0.61 to 1.72 for the high- and low-risk portfolios respectively. It is worth noting that the second and third low-risk portfolios just exceed 1.05 in SR.

Turning to the alive group of funds, our findings suggest that the risk levels (both for SD and VaR) are strictly decreasing. However, we observe a pronounced decreasing pattern in average returns. Specifically, average returns exceed 16% for the high-risk portfolio and are below 6.5% for the low-risk decile portfolio. Interestingly, there is a flat relationship between risk and return for the four less risky decile portfolios with returns around the level of 6.5%. Nevertheless, the difference between the high- and low-risk portfolio returns is statistically significant and reaches an annualised return of 10.38%. In other words, we expect to gain more than 10% if we invest in the high-risk portfolio as opposed to the low-risk one. Similar to the all funds group, the best risk-return profile is provided by the low-risk portfolio since it has the highest SR. For the defunct group of funds, a flat relationship between returns and risk exists, while the risk levels of the decile portfolios show broadly a decreasing pattern. Specifically, the corresponding average returns seem to fluctuate within the 3%-5% range and the difference between the high- and low-risk portfolio is only 1.35% and not significant. As with the previous case, the best risk-return profile is provided by the low-risk portfolio that has the highest SR of 1.03. However, this is very low when compared to the SR of 1.83 of alive funds.

Similar findings pertain for the ES case (Table 3, Panel B) as the risk levels show a decreasing pattern for each group of funds. Compared to portfolios calculated on VaR (HS), more cross-sectional variation is present in term of returns for the ES portfolios. As such, for the alive group of funds the difference between the high- and low-risk portfolio returns is statistically significant and equal to 12.12%, while for the defunct funds, this difference is 3.51%. Finally, for each group of funds the low-risk portfolio seems to at least double the average returns per unit of risk in comparison to the rest of the decile portfolios, reaching an impressive figure of 2.02 for the low-risk portfolio of the alive funds.

[Table 3 around here]

Table 4 reports the decile portfolio characteristics when portfolios are formed via the CF method. For both VaR and ES cases, our findings are similar to the HS ones, with the risk levels following a decreasing pattern for all groups under consideration, while the returns follow a more random gradually decreasing pattern. Nevertheless, in all cases, the low-risk decile portfolio provides the highest SR, reaching 1.90 for the alive funds and ES risk measure. For this group of funds, the differences in returns between the high- and low-risk portfolio are statistically significant and equal to 10.03% and 11.13% for the VaR and the ES measure, respectively. Finally, as in the HS method, the defunct group of fund of funds experiences significantly lower average returns that are more randomly distributed.

[Table 4 around here]

Finally, Table 5 reports the characteristics of the decile portfolios formed via the EVT method. Similar to all the cases considered so far, the findings for both the VaR and ES case suggest decreasing patterns for risk. In addition, for the EVT case the average returns reveal a more distinguishable decreasing profile with more than two broader levels of risk for the groups of all and alive funds. Again, the low-risk portfolios provide the best risk-return profile and the difference between the high- and low-risk portfolio returns of the group of alive funds is statistically significant (11.61% and 10.40% for the VaR and ES case, respectively). Finally, the average risk and return levels are similar to the aforementioned cases of decile portfolios, with the highest SRs attained by the alive funds and the low-risk portfolio.

[Table 5 around here]

To sum up, the hedge fund decile portfolios unveil a decreasing pattern of risk which is accompanied by a decrease in returns for the groups of all and alive funds. Focusing on the mid- to low-risk decile portfolios, our findings suggest that the low-risk portfolio offers average returns similar to portfolios that are closer to mid risk levels and in general dominates the risk-return profile as they produce the highest SR. In other words, moderate increases of risk do not affect significantly the average returns. This is in support of our argument that lower risk hedge funds may offer lower but more persistent positive returns than the riskier hedge funds. These results are robust to the choice of the implemented risk measure and estimation method.

3.3 Risk-Return Profile of Fund of Funds

In order to benchmark the average risk-return profile that fund of funds offer to investors, we calculate the decile portfolios of fund of funds for the out-of-sample period. Tables 6 to 8 report the characteristics of these benchmarks for each estimation method and risk measure. Table 6 reports the HS decile portfolios average risk-return profile. For the VaR case and each group of funds (Table 6, Panel A), the risk levels show a decreasing pattern with some breaking points at the fifth decile portfolio. On the other hand, the returns do not reveal a decreasing pattern but remain bounded within specific levels. Contrary to the hedge fund decile portfolios case, the difference between the high- and low-risk portfolio returns is not statistically significant while for the groups of all and defunct funds is negative, a finding that is rather counter-intuitive. Furthermore, the levels of SRs suggest that for the groups of alive and defunct funds, the best risk-return profile is provided by the low-risk portfolio while for the group of alive funds the third decile portfolio has the best SR. Similar results are reported for the ES risk measure (Table 6, Panel B).

[Table 6 around here]

Table 7 reports the risk-return profile of the fund of funds decile portfolios for the CF estimation method. The risk of the decile portfolios has a decreasing profile with some breaking points at the fifth decile portfolio for the ES case. On the other hand, the average returns are again bounded in a narrow range. This is true for every group of funds while the mean returns for the defunct funds are smaller. For the groups of all and alive fund of funds, the third portfolio provides the highest return per unit of risk while for the defunct funds the low-risk portfolio has the best SR.

[Table 7 around here]

Table 8 reports the risk-return profile of the fund of funds decile portfolios for the EVT risk method. As with the previous cases, the risk levels are decreasing while the average returns are similar for all risk portfolios. This is true for both VaR (Table 8, Panel A) and ES (Table 8, Panel B) risk measures. Similarly, SR suggests that for the group of all and defunct funds the low-risk portfolio provides the best risk-return profile. For the group of alive funds, the third decile portfolio has the highest SR but the difference with the low-risk portfolio is marginal.

[Table 8 around here]

Comparing the risk-return profile of the fund of funds with the hedge fund decile portfolios, we observe that the average risk levels reported for the fund of funds are a subset of the hedge funds average risk levels. Specifically, the risk levels of the fund of funds portfolios span over the mid range of the risk levels of the hedge fund decile portfolios. For high levels of risk, fund of funds seem to provide significant risk reduction since the high-risk decile portfolios have significantly less risk that the corresponding hedge fund high-risk decile portfolios. For the low-risk portfolios, fund of funds do not show any risk reduction. On the contrary, the low-risk hedge fund decile portfolios are less risky than the corresponding fund of funds decile portfolios. Turning to the returns, when we compare the average returns range for the group of all funds, the hedge funds outperform the fund of funds average returns for almost every level of risk. For instance, average returns of the low-risk HS-VaR decile portfolio of hedge funds are higher than almost all the average returns of the fund of funds decile portfolios. In addition, SR of the low-risk hedge fund decile portfolio is almost double the fund of funds one.

To sum up, the fund of funds decile portfolio characteristics suggest that the average risk levels are not related with the average returns. Specifically, the expected returns do not vary across the levels of risk while, on average, there is a clear distinction between the risk levels. In addition, selecting a riskier fund of funds would lead to less gains compared to the low-risk fund of funds. When we compare this set of results with the corresponding hedge fund decile portfolios, we find that the range of risk levels of hedge funds is wider than the corresponding fund of funds risk levels. However, the range of average returns for the hedge funds decile portfolios does not overlap with the fund of funds average returns. For almost every case under consideration, the average returns of the hedge fund decile portfolios surpass the corresponding returns of fund of funds. In other words, fund of funds seem to provide marginal gains to the investors since there are hedge funds that dominate, on average, the fund of funds both in terms of risk and returns. Finally, these results are robust to the estimation methods and the measures used to quantify the risk of individual funds.

4 Optimal Portfolios

The comparisons between the average risk-return profile of the hedge fund and fund of funds decile portfolios reveal that riskier fund of funds do not provide significant compensation for the additional risk. Fund of funds reduce significantly the risk for the higher levels of risk, while for the lower levels the hedge fund low-risk decile portfolio dominates the corresponding fund of funds portfolio. In addition, when we account for each decile portfolio average return the hedge fund low-risk portfolios outperform all the fund of funds decile portfolios. These results suggest that there might be added value in the optimal combination of low-risk hedge funds, subject to risk minimization. As described in Section 3.2, low-risk hedge fund decile portfolios seem to have persistent positive returns that do not differ significantly from the medium risk decile portfolios. In order to explore possible optimal combinations of lower risk persistent returns, we propose a portfolio formation strategy which focuses on minimizing the downside risk of a portfolio. For each month in the out-of-sample period, we rank individual hedge funds according to their downside risk measure forecast, RM$\in$ {VaR, ES}. Based on this ranking, we select the 50 less risky funds and assign weights that would minimize the portfolio's VaR or ES. In addition, we constrain the weights to a maximum of 10% of the total wealth invested in any individual fund. The target return for the portfolio is set to 24% annualized and if it is not achieved, we reduce it consecutively by 1%.

4.1 VaR-constructed optimal portfolios

Table 9 reports the characteristics of the VaR optimal portfolios calculated with each estimation method. In addition, we include the three low-risk hedge fund and fund of funds portfolios and the full set of evaluation criteria in order to proceed with a more detailed evaluation of the risk-return profile of the optimal portfolios. For the HS estimation method (Table 9, Panel A), the optimal portfolio is less risky than the low-risk fund of funds decile portfolio. According to the reported risk measures, the left tail of the optimal portfolio's return distribution is located at the right of the hedge funds decile portfolio. Taking into account the similar standard deviation, we expect the probability of positive returns to be higher for the optimal portfolio. Furthermore, the average returns of the optimal portfolio are twice the average returns of the low-risk fund of funds decile portfolio, reaching 8.19% and offering the investor a cumulative return (over the out-of-sample) period of almost 107%. Hence, the optimal portfolio dominates the low-risk fund of funds decile portfolios in both terms of risk and returns. This is also reflected on the other evaluation criteria such as the SR, OMG, SOR and UP, which have the double value than the corresponding figures for the fund or funds portfolios. In addition, MDD, which measures the maximum sustained percentage decline of the portfolio suggests that our risk-optimal portfolio offers persistently high returns given that the maximum observed drawdown is 8.79% as opposed to 16.75% for low-risk fund of funds portfolio. Comparing the optimal portfolio with the hedge fund decile portfolios, our findings suggest that the optimal portfolio is slightly riskier than the low-risk hedge fund decile portfolio as the left tails intersect. On the other hand, the high average returns of the optimal portfolio lead to a better risk-return profile according to the majority of the performance evaluation criteria. The only case where the optimal portfolio is inferior is the MDD measure with the difference being equal to 1.2%. However, this is expected given the larger standard deviation of the optimal portfolio than the low-risk hedge fund decile portfolio.

[Table 9 around here]

Turning to the CF estimation method (Table 9, Panel B), our findings suggest that the optimal portfolio's risk profile is inferior to the risk profile of the low-risk fund of funds portfolio. However, the returns are slightly larger than the HS case and therefore compensate for the increased risk. This is confirmed by all the evaluation criteria except for the MDD. In other words, the optimal portfolio offers a better risk-return profile than the fund of funds decile portfolios. When we compare the optimal portfolio with the hedge fund decile portfolios, our findings suggest that the optimal portfolio does not offer any added value. According to the risk measures, the hedge fund decile portfolios have a less pronounced risk profile especially deep in the tails of the return distribution. For example, the 1% ES of our portfolio and the low-risk fund of funds are -26% and -17%, respectively. In addition, the higher realised return of the optimal portfolio (8.42%) does not compensate for this elevated risk as the three hedge fund decile portfolios provide a better risk-return profile. These results are indicative of the inability of the Normal distribution to cope with hedge funds returns even when we account for the excessive kurtosis and skewness via the CF approximation.

Panel C (Table 9) reports the EVT optimal portfolio's characteristics. Similar to the HS case, the EVT optimal portfolio has a less risky return distribution than the fund of funds, with a return larger than -0.64% occurring with probability 90%. The respective returns for the low-risk fund of funds portfolios are around -3%. All the evaluation criteria suggest that the optimal portfolio provides a better risk-return profile than the fund of funds. Comparing the optimal portfolio with the hedge fund portfolios, our findings suggest that the optimal portfolio remains dominant in terms of the risk-return profile. These finding are confirmed by the higher SR, OMG, SOR, UP and lower MDD.

To gain a visual understanding of our findings, we plot the histogram of the average returns and 5% HS-VaR of the fund of funds and locate our VaR-optimal portfolios in these distributions. Specifically, Figure 3 describes the position of each optimal portfolio relative to the average returns of fund of funds. It is evident that the average returns of the optimal portfolios outperform the majority of the fund of funds in our sample. Specifically, the HS-optimal portfolio has larger average returns than the 91.6% of the fund of funds in the sample. For the CF-optimal portfolio this percentage is 92.5% while for the EVT optimal portfolio the percentage is 86.9%. Figure 4 describes the position of the 5% HS-VaR of each optimal portfolio in relation to the whole sample of fund of funds. The CF-optimal portfolio is not performing well since it is less risky than only 36.7% of the total sample of fund of funds. On the other hand, the HS-optimal portfolio is less risky than 57.2% of the sample of fund of funds. Finally, the EVT optimal portfolio is less risky than 76.6% of the fund of funds.

[Figures 3 and 4 around here]

4.2 ES-constructed optimal portfolios

We now turn to the characteristics of the ES-optimal portfolios, reported in Table 10 for the three estimation methods. For the HS method (Table 10, Panel A), the optimal portfolio outperforms the fund of funds decile portfolios in terms of both risk and returns. In addition, all the evaluation criteria suggest that the optimal portfolio has a better risk-return profile than the fund of funds decile portfolios. When we compare the optimal portfolios with the hedge fund decile portfolios, we find that the low-risk decile portfolio is less risky than the optimal portfolio. However, the economic evaluation criteria suggest that the higher returns of the optimal portfolio compensate adequately for the increased risk and therefore provide a better risk-return profile. For example, the optimal portfolio has the highest SR of 1.79 along with the highest OMG, SOR and UP. Turning to the CF-optimal portfolio case (Table 10, Panel B), our findings are slightly different than the VaR-optimal portfolios. For the ES case, the risk of the CF-optimal portfolio converges to the risk level of the low-risk fund of funds decile portfolio. Therefore, its superior returns provide a better risk-return profile. The corresponding comparisons of the optimal portfolio with the hedge fund decile portfolios suggest that the optimal portfolio ranks within the second place after the low-risk hedge fund decile portfolio. Finally, for the EVT-optimal portfolio (Table 10, Panel C), our findings suggest that the optimal portfolio dominates both fund of funds and hedge funds low-risk decile portfolios.

[Table 10 around here]

To gain a visual impression of the ES optimal portfolio position amongst the fund of funds, we plot (in Figure 5) the average returns and 5% HS-VaR of the ES based optimal portfolios and the histogram of the average returns and 5% HS-VaR of the fund of funds. Similar to the VaR case, the average returns of the optimal portfolios are significantly larger than the average returns of the fund of funds, with the HS, CF and EVT optimal portfolio surpassing the 91.4%, 95.3% and 89.9% of the fund of funds, respectively. Figure 6 describes the position of the 5% HS-VaR of each optimal portfolio in relation to the whole sample of fund of funds. In this case, it is evident that the ES optimal portfolios are performing better than the VaR ones. Specifically, the HS optimal portfolio is less risky than the 67.4% of the fund of funds, the CF portfolio is less risky than the 52% of the fund of funds and finally the EVT optimal portfolios is less risky than the 76.3% of the fund of funds.

[Figures 5 and 6 around here]

Finally, Figure 7 describes the evolution of the cumulative returns of the optimal portfolio and the three lower risk decile portfolios of the fund of funds for each estimation method. It is obvious that the HS and CF optimal portfolios value is growing at a faster pace from the start of the out-of-sample period. On the other hand, the EVT optimal portfolio's value is similar to the low-risk decile portfolios until 2007. Interestingly, at the crisis of 2007 the optimal portfolios lose a part of their value but the correction is smaller than the corresponding decile portfolios. The gap in cumulative returns continues to widen up to the end of the out-of-sample period (December 2014). Similar findings pertain with respect to Figure 8 that plots the cumulative returns of the ES optimal portfolios. Again the optimal portfolios are more robust to the subprime crisis with the value correction being smaller that the VaR ones. This is more pronounced for the EVT optimal portfolio that seems to experience a small, if any, correction on its value.

[Figures 7 and 8 around here]

To sum up, our findings on the HS and EVT optimal portfolios characteristics suggest that their risk-return profile dominates the corresponding profile of the fund of funds and hedge fund decile portfolios. This is not the case, however, for the CF optimal portfolios. In addition, there is evidence that the ES risk measure combined with the EVT estimation method is more appropriate for the construction of optimal portfolios. Finally, the optimal portfolios seem to be more robust to the turbulent times after 2007. Next, we shed light on the compositions of our optimal portfolios.

4.3 Composition of Risk-Optimal Portfolio

Table 11 reports the annual composition of the optimal portfolios as average percentages of each strategy included in each portfolio. For the HS-VaR optimal portfolios (Table 11, Panel A), the emerging markets, long short and sector specific strategies are dominant in the construction of the optimal portfolios. In more detail, the sector specific strategy seems to be the main contributor of funds as for each year in the out-of-sample period, the average percentage of the funds included in the optimal portfolio is over 20%. Similarly, the emerging markets strategy contributes constantly over 10% while the long short's contribution fluctuates from 6.35% to 33.95%. Interestingly, during 2007 the emerging market contribution drops to its lowest point while the long short's contribution peaks. This is an indicator that the long short strategy may provide a less risky profile during turbulent times.

The composition of the HS-ES optimal portfolio, is similar to the HS-VaR case with the emerging markets and sector specific strategies contributing on average over 9% and 25%, respectively. On the other hand, the long short strategy fluctuates more within the out-of-sample period, which leads to the lowest of 1.67% average contribution. Similar results are reported for the CF and EVT optimal portfolios case (Table 11, Panels B and C) with minor differences in the percentages of each strategy. To conclude, our findings regarding the composition of the optimal portfolios suggest that the emerging markets, long short and sector specific strategies are the main contributors of funds, regardless of the risk measure and estimation method. Finally, there is evidence that the long short strategy performs better in turbulent times since its contribution peaks in 2007.

[Table 11 around here]

5 Conclusions

In this paper, we compare the risk-return profile of hedge funds and fund of funds and propose an optimal portfolio strategy aiming to outperform the corresponding benchmarks. Using a large database of hedge funds and fund of funds, we construct decile portfolios as proxies of the average risk-return profile. Then we proceed to construct optimal portfolios of hedge funds by investing in the less risky hedge funds.

The preliminary descriptive statistics suggest that fund of funds indeed provide a reduction of variance of returns. However, this reduction comes at the cost of reduced returns and increased kurtosis and skewness. Therefore, the fund of funds strategy may not provide significant gains in terms of risk. Focusing on the decile portfolios, our findings suggest that hedge funds and fund of funds have distinct risk levels that decrease as the risk of individual funds decrease. On the other hand, while the hedge fund returns are smaller for low risk levels, the fund of funds seem to have similar average returns regardless of the risk levels of the decile portfolios. Interestingly, the decile portfolio results are robust to the estimation methods and the measures used to quantify the risk of individual funds.

Comparing the risk-return profile of both asset classes, the average risk levels of fund of funds consist of a subset of the hedge funds' risk levels. However, the range of hedge funds average returns does not overlap with the average returns of the fund of funds. Hence, the fund of funds reduce risk by bounding its levels to a more narrow range at the cost of significantly smaller returns. However, this reduction of risk does not provide significant gains to investors as there are less risky hedge fund decile portfolios that offer larger or equal average returns.

The aforementioned results suggest that possible optimal combinations of the least risky hedge funds may produce a significantly better risk-return profile. The results of the HS and EVT optimal portfolios suggest that their risk-return profile outperforms all fund of funds decile portfolios. More importantly, the optimal portfolios seem to perform significantly better in the turbulent times after 2007. Finally, with respect to the composition of the optimal portfolios, the sector specific, long short and emerging markets strategies are the main fund contributors.

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Table 1: Descriptive statistics of fund of funds and hedge fund returns and the test for normality

	All Funds		Alive		Defunct	
	Fund of Funds	Hedge Funds	Fund of Funds	Hedge Funds	Fund of Funds	Hedge Funds
Mean	5.86	10.23	5.79	10.30	5.91	10.17
Standard Deviation	25.16	51.46	23.48	50.79	26.27	52.00
Median	7.81	9.85	7.90	10.25	7.74	9.54
Kurtosis	9.25	8.50	9.08	8.46	9.36	8.53
Skewness	-1.02	-0.16	-1.02	-0.14	-1.02	-0.17
Absolute Skewness	1.30	0.93	1.29	0.89	1.31	0.96
Jarque Bera	0.95	0.84	0.96	0.84	0.95	0.84

Notes: This table shows the average values of the sample mean, median, standard deviation, skewness, absolute skewness and kurtosis of the returns of Hedge Funds and Fund of Funds (all, alive and defunct). The mean, median, and standard deviation values are reported in annualised percentages. It also reports the rejection rates of the Jarque-Bera (JB) test for normality. The data is from BarclayHedge database and cover the period from January 1994 to December 2014.

Table 2: Descriptive statistics per strategy

	RV	EM	ED	GM	L	LS	FoF
Mean	9.13	11.55	9.82	10.50	10.45	10.91	5.86
Median	6.98	12.81	10.47	8.64	14.29	10.86	7.81
Standard deviation	43.98	71.81	34.82	48.28	62.88	53.72	25.16
Kurtosis	6.27	9.75	8.88	7.08	5.21	6.76	9.25
Skewness	0.50	-0.49	-0.55	0.24	-0.38	0.07	-1.02
Absolute Skewness	0.76	0.98	0.96	0.74	0.54	0.71	1.30
Number of Funds	89	259	240	110	81	623	908
	MS	OT	CTA	SE	SB	MN	
Mean	7.21	9.34	9.76	9.32	10.45	4.65	
Median	6.79	9.21	8.91	9.60	8.29	-1.21	
Standard deviation	25.75	34.61	39.21	35.35	62.92	87.69	
Kurtosis	5.88	9.29	8.59	17.30	6.45	6.14	
Skewness	-0.02	-0.61	-0.01	-1.24	0.39	0.37	
Absolute Skewness	0.54	1.11	1.07	1.92	0.73	0.49	
Number of Funds	68	146	96	284	548	17	

Note: This table shows the average values of the sample mean, median, standard deviation, skewness, absolute skewness and kurtosis of the returns of Hedge Fund Strategies and Fund of Funds. The mean, median, and standard deviation values are reported in annualised percentages. It also reports the rejection rates of the Jarque-Bera (JB) test for normality. The data is from BarclayHedge database and cover the period from January 1994 to December 2014.

Table 3: Hedge funds decile portfolio characteristics-Historical Simulation

Panel A: Value at Risk

	All Funds					Alive					Defunct				
Decile	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$
High	144.68	11.13	15.86	0.61	-22.06	219.31	16.87	18.89	0.82	-26.44	70.72	5.44	14.46	0.28	-24.48
9	112.22	8.63	10.96	0.66	-15.14	152.67	11.74	12.00	0.86	-16.23	56.87	4.37	11.21	0.27	-17.17
8	116.25	8.94	8.87	0.85	-13.11	154.78	11.91	8.65	1.22	-11.69	74.12	5.70	9.24	0.47	-13.74
7	94.88	7.30	7.24	0.82	-9.68	133.15	10.24	8.11	1.09	-10.30	61.46	4.73	7.42	0.45	-11.44
6	77.01	5.92	6.35	0.71	-8.39	87.60	6.74	7.44	0.72	-9.80	52.74	4.06	6.08	0.44	-8.02
5	77.16	5.94	5.15	0.88	-5.68	100.66	7.74	5.72	1.11	-6.52	57.00	4.38	5.00	0.60	-6.94
4	77.24	5.94	4.66	0.98	-5.30	88.02	6.77	5.17	1.04	-6.20	64.86	4.99	4.58	0.79	-5.36
3	73.43	5.65	3.97	1.07	-3.91	84.84	6.53	4.38	1.17	-5.78	54.19	4.17	4.09	0.68	-4.02
2	63.82	4.91	3.35	1.05	-3.82	85.01	6.54	3.36	1.53	-3.77	49.10	3.78	3.46	0.69	-4.34
Low	73.97	5.69	2.51	1.72	-1.96	84.39	6.49	2.79	1.83	-1.32	53.18	4.09	2.64	1.03	-2.25
High-Low		5.44					10.38**					1.35			

Panel B: Expected Shortfall

	All Funds					Alive					Defunct				
Decile	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$
High	153.56	11.81	16.27	0.64	-23.64	236.59	18.20	18.65	0.90	-24.01	93.63	7.20	14.87	0.39	-23.88
9	116.33	8.95	11.05	0.68	-15.84	140.01	10.77	12.31	0.76	-18.95	80.15	6.17	10.61	0.45	-15.51
8	110.06	8.47	8.67	0.82	-11.49	159.72	12.29	9.12	1.19	-12.20	53.98	4.15	9.30	0.30	-14.36
7	105.38	8.11	7.12	0.94	-10.05	130.64	10.05	7.18	1.21	-8.64	71.22	5.48	7.58	0.54	-10.73
6	85.46	6.57	6.19	0.84	-8.10	108.63	8.36	7.16	0.97	-8.92	60.82	4.68	5.98	0.55	-8.05
5	82.76	6.37	5.81	0.86	-7.36	90.55	6.97	6.25	0.89	-6.75	56.94	4.38	5.94	0.50	-8.11
4	75.00	5.77	4.56	0.96	-4.53	89.47	6.88	5.06	1.09	-5.35	54.68	4.21	4.54	0.62	-5.87
3	63.92	4.92	3.96	0.89	-3.82	86.85	6.68	4.51	1.17	-4.76	36.65	2.82	3.88	0.37	-5.04
2	55.10	4.24	3.00	0.95	-3.85	67.85	5.22	3.43	1.12	-4.04	38.49	2.96	3.00	0.52	-4.52
Low	63.00	4.85	2.08	1.66	-1.46	79.00	6.08	2.32	2.02	-1.04	47.94	3.69	2.21	1.04	-1.77
High-Low		6.97					12.12**					3.51			

Note: The table reports the cumulative returns (CR), annualized average returns (AR), annualized standard deviation (SD), Sharpe Ratio (SR) and the Historical Simulation 5% VaR of each decile portfolio. In addition, it provides the difference between the average returns of the High and Low risk portfolios. (**) suggests that the average returns differential is significantly different than zero at a confidence level of 5%. Newey-West corrected t-tests are employed. Panel A reports the results when VaR is utilized as a risk measure. Panel B reports the results when ES is utilized as a risk measure.

Table 4: Hedge funds decile portfolio characteristics-Cornish Fisher

Panel A: Value at Risk

	All Funds					Alive					Defunct				
Decile	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$
High	153.56	11.81	15.71	0.66	-22.00	211.29	16.25	18.05	0.82	-24.08	91.32	7.02	14.36	0.39	-22.46
9	114.25	8.79	11.12	0.67	-16.37	175.47	13.50	12.68	0.96	-18.09	51.21	3.94	11.46	0.22	-17.91
8	116.81	8.99	8.47	0.90	-11.29	149.04	11.46	8.74	1.15	-12.32	85.38	6.57	8.93	0.58	-12.65
7	97.82	7.52	7.11	0.86	-10.27	120.06	9.24	7.23	1.08	-9.46	67.35	5.18	7.58	0.50	-12.33
6	69.91	5.38	6.52	0.61	-9.26	100.86	7.76	7.45	0.85	-9.15	42.98	3.31	6.24	0.31	-7.85
5	87.71	6.75	5.28	1.02	-5.17	106.20	8.17	5.99	1.13	-6.78	61.32	4.72	5.57	0.60	-7.06
4	83.26	6.40	4.73	1.06	-5.01	93.72	7.21	5.21	1.12	-5.75	64.72	4.98	4.46	0.80	-5.53
3	65.63	5.05	4.16	0.88	-4.10	86.77	6.67	4.81	1.10	-6.03	45.76	3.52	3.88	0.55	-4.21
2	53.53	4.12	3.07	0.89	-3.50	66.55	5.12	3.43	1.09	-4.28	32.29	2.48	3.26	0.34	-4.40
Low	68.21	5.25	2.46	1.57	-2.05	80.92	6.22	2.60	1.86	-1.70	52.88	4.07	2.51	1.07	-2.53
High-Low		6.57					10.03**					2.96			

Panel B: Expected Shortfall

	All Funds					Alive					Defunct				
Decile	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$
High	165.31	12.72	15.86	0.71	-23.39	223.98	17.23	17.64	0.90	-19.56	105.62	8.12	14.79	0.46	-23.99
9	110.17	8.47	10.86	0.65	-17.12	149.01	11.46	12.61	0.80	-19.91	68.53	5.27	10.18	0.38	-15.33
8	104.78	8.06	8.91	0.75	-14.01	166.05	12.77	9.38	1.21	-14.21	57.40	4.42	9.62	0.31	-14.82
7	117.56	9.04	7.18	1.07	-9.67	143.50	11.04	7.27	1.33	-8.53	73.13	5.63	7.79	0.54	-11.97
6	81.17	6.24	6.29	0.77	-8.03	105.06	8.08	7.23	0.93	-8.71	60.20	4.63	6.28	0.52	-8.53
5	75.33	5.79	5.69	0.77	-6.05	88.71	6.82	6.45	0.84	-6.51	49.26	3.79	5.53	0.43	-7.57
4	72.50	5.58	4.82	0.87	-5.71	85.81	6.60	5.25	0.99	-5.48	54.06	4.16	4.92	0.56	-6.86
3	62.49	4.81	4.08	0.84	-4.49	75.08	5.78	4.44	0.99	-4.82	40.59	3.12	4.00	0.43	-5.43
2	54.87	4.22	3.01	0.94	-3.66	73.84	5.68	3.47	1.24	-4.27	33.85	2.60	3.11	0.39	-3.97
Low	66.09	5.08	2.21	1.67	-1.55	79.25	6.10	2.48	1.90	-1.71	51.31	3.95	2.20	1.16	-1.87
High-Low		7.63					11.13**					4.18			

Note: See notes in Table 3.

Table 5: Hedge funds decile portfolio characteristics-Extreme Value Theory

Panel A: Value at Risk															
	All Funds					Alive					Defunct				
Decile	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$
High	150.83	11.60	16.35	0.62	-24.62	231.19	17.78	18.55	0.88	-22.55	76.37	5.87	15.06	0.30	-24.07
9	117.20	9.02	11.11	0.69	-16.11	147.11	11.32	12.90	0.77	-19.70	88.79	6.83	11.07	0.49	-16.30
8	112.03	8.62	8.75	0.83	-11.64	154.54	11.89	9.00	1.17	-13.61	61.27	4.71	9.26	0.36	-13.65
7	98.10	7.55	6.90	0.89	-8.94	132.37	10.18	7.22	1.22	-9.40	58.20	4.48	7.04	0.44	-11.09
6	81.58	6.28	6.45	0.76	-8.54	98.18	7.55	7.31	0.84	-9.12	61.72	4.75	6.40	0.52	-8.37
5	80.01	6.15	5.54	0.86	-6.80	93.76	7.21	6.21	0.94	-8.31	53.74	4.13	5.49	0.50	-6.80
4	83.58	6.43	4.42	1.14	-4.90	94.85	7.30	5.01	1.18	-5.15	68.98	5.31	4.33	0.90	-5.64
3	64.92	4.99	3.91	0.92	-3.68	84.74	6.52	4.32	1.19	-4.58	42.83	3.29	3.95	0.48	-4.39
2	59.73	4.59	2.99	1.07	-3.65	73.04	5.62	3.30	1.28	-3.84	34.20	2.63	3.12	0.40	-4.88
Low	62.60	4.82	2.11	1.62	-1.48	80.21	6.17	2.23	2.14	-1.03	49.57	3.81	2.28	1.06	-1.88
High-Low		6.79					11.61**					2.06			

Panel B: Expected Shortfall															
	All Funds					Alive					Defunct				
Decile	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$
High	154.38	11.88	15.73	0.67	-21.45	211.44	16.26	17.84	0.83	-19.12	99.11	7.62	14.51	0.46	-23.99
9	116.47	8.96	10.83	0.70	-15.52	156.84	12.06	12.82	0.83	-19.10	97.57	7.51	10.07	0.38	-15.33
8	108.33	8.33	9.22	0.75	-11.26	142.75	10.98	9.05	1.06	-12.16	61.30	4.72	9.88	0.31	-14.82
7	105.91	8.15	7.48	0.90	-9.92	149.38	11.49	7.95	1.27	-10.50	47.19	3.63	8.15	0.54	-11.97
6	86.89	6.68	6.32	0.84	-8.78	109.38	8.41	6.64	1.06	-8.29	60.20	4.63	6.72	0.52	-8.53
5	87.41	6.72	5.61	0.95	-7.39	104.44	8.03	6.28	1.06	-7.25	64.49	4.96	5.37	0.43	-7.57
4	69.05	5.31	4.91	0.80	-5.52	84.71	6.52	5.53	0.93	-6.26	40.36	3.10	4.98	0.56	-6.86
3	65.89	5.07	3.78	0.97	-3.92	84.16	6.47	4.55	1.12	-4.74	43.02	3.31	3.78	0.43	-5.43
2	54.49	4.19	3.11	0.90	-3.95	70.22	5.40	3.48	1.15	-3.58	36.34	2.80	3.02	0.39	-3.97
Low	61.42	4.72	2.01	1.66	-1.34	76.21	5.86	2.27	1.97	-1.16	45.50	3.50	2.10	1.16	-1.87
High-Low		7.15					10.40**					4.12			

Note: See notes in Table 3.

Table 6: Fund of funds decile portfolio characteristics- Historical Simulation

Panel A: Value at Risk															
	All Funds					Alive					Defunct				
Decile	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$
High	43.61	3.35	9.22	0.21	-15.23	73.68	5.67	8.33	0.51	-13.43	-2.59	-0.20	10.00	-0.16	-17.64
9	57.28	4.41	6.61	0.46	-11.10	72.96	5.61	6.69	0.63	-11.21	44.58	3.43	7.03	0.29	-10.71
8	65.85	5.07	6.01	0.61	-8.93	78.60	6.05	6.12	0.76	-9.19	48.60	3.74	6.00	0.39	-8.91
7	59.01	4.54	5.28	0.60	-8.20	69.75	5.37	5.45	0.73	-7.94	47.25	3.63	5.28	0.43	-8.62
6	56.71	4.36	4.70	0.63	-7.02	66.60	5.12	4.99	0.75	-7.94	41.66	3.20	4.71	0.39	-6.90
5	52.73	4.06	4.91	0.54	-8.81	68.91	5.30	5.11	0.76	-8.15	35.54	2.73	5.09	0.26	-9.50
4	55.70	4.28	4.53	0.64	-7.48	68.10	5.24	4.74	0.81	-7.67	44.77	3.44	4.36	0.47	-7.23
3	54.96	4.23	4.33	0.66	-6.51	70.82	5.45	4.63	0.88	-6.69	41.81	3.22	4.26	0.43	-6.76
2	53.86	4.14	3.97	0.69	-6.08	60.92	4.69	4.22	0.78	-5.34	45.30	3.48	4.06	0.52	-6.26
Low	53.31	4.10	3.54	0.77	-5.06	53.54	4.12	3.73	0.73	-5.08	51.57	3.97	3.45	0.75	-4.87
High-Low		-0.75					1.55					-4.17			
Panel B: Expected Shortfall															
	All Funds					Alive					Defunct				
Decile	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$
High	41.59	3.20	9.11	0.20	-13.78	74.85	5.76	8.07	0.54	-12.26	6.97	0.54	10.16	-0.08	-17.35
9	56.98	4.38	6.45	0.46	-9.68	67.13	5.16	6.42	0.59	-10.89	36.41	2.80	6.70	0.21	-9.74
8	69.60	5.35	6.09	0.65	-10.41	74.78	5.75	6.27	0.70	-9.37	58.41	4.49	6.11	0.51	-9.90
7	56.74	4.36	5.54	0.54	-8.85	67.96	5.23	5.74	0.67	-7.95	47.30	3.64	5.61	0.40	-8.38
6	57.93	4.46	5.01	0.61	-8.50	74.83	5.76	5.33	0.82	-9.28	38.15	2.93	4.94	0.31	-7.78
5	59.74	4.60	4.91	0.65	-7.94	63.81	4.91	5.08	0.69	-8.48	45.27	3.48	4.82	0.43	-7.80
4	60.07	4.62	4.28	0.76	-6.69	78.65	6.05	4.79	0.97	-6.87	40.16	3.09	4.25	0.40	-6.86
3	53.78	4.14	4.18	0.66	-6.56	74.46	5.73	4.59	0.94	-6.06	41.02	3.16	4.01	0.44	-6.47
2	45.72	3.52	4.00	0.53	-6.12	53.52	4.12	4.01	0.68	-5.80	38.54	2.96	3.98	0.40	-6.24
Low	50.64	3.90	3.57	0.70	-5.31	52.63	4.05	3.55	0.75	-4.48	46.39	3.57	3.72	0.59	-5.92
High-Low		-0.70					1.71					-3.03			

Note: See notes in Table 3.

Table 7: Fund of funds decile portfolio characteristics - Cornish Fisher

Panel A: Value at Risk

	All Funds					Alive					Defunct				
Decile	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$
High	45.14	3.47	9.16	0.23	-14.43	75.33	5.79	8.15	0.54	-13.11	11.01	0.85	10.01	-0.05	-16.41
9	57.81	4.45	6.52	0.47	-10.58	69.71	5.36	6.69	0.59	-9.90	34.95	2.69	6.67	0.19	-10.18
8	61.96	4.77	6.02	0.56	-10.04	72.74	5.60	6.19	0.68	-9.78	49.00	3.77	6.02	0.40	-9.12
7	58.92	4.53	5.35	0.59	-8.25	74.10	5.70	5.55	0.78	-7.95	43.57	3.35	5.55	0.35	-8.68
6	57.53	4.43	5.10	0.60	-8.23	66.89	5.15	5.37	0.70	-8.43	43.18	3.32	5.14	0.38	-8.37
5	55.61	4.28	4.68	0.62	-7.69	74.60	5.74	4.95	0.88	-7.85	43.74	3.36	4.67	0.42	-6.66
4	55.51	4.27	4.41	0.65	-7.17	68.74	5.29	4.63	0.84	-7.31	35.12	2.70	4.32	0.30	-7.32
3	60.81	4.68	4.18	0.79	-7.17	74.76	5.75	4.47	0.97	-6.23	45.71	3.52	4.12	0.52	-7.19
2	47.11	3.62	3.99	0.56	-5.98	50.46	3.88	4.23	0.59	-5.30	35.91	2.76	4.02	0.34	-6.23
Low	52.85	4.07	3.74	0.72	-5.43	57.40	4.42	3.76	0.80	-5.10	50.09	3.85	3.79	0.65	-6.05
High-Low		-0.59					1.38					-3.01			

Panel B: Expected Shortfall

	All Funds					Alive					Defunct				
Decile	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$
High	43.29	3.33	9.27	0.21	-14.13	76.66	5.90	8.02	0.56	-12.89	6.19	0.48	10.43	-0.09	-17.20
9	61.12	4.70	6.18	0.54	-10.38	61.08	4.70	6.38	0.52	-10.68	47.81	3.68	6.58	0.35	-10.17
8	58.61	4.51	6.01	0.52	-9.73	75.14	5.78	6.31	0.70	-9.82	41.41	3.19	5.90	0.30	-9.53
7	58.13	4.47	5.41	0.57	-9.13	64.20	4.94	5.73	0.62	-8.74	53.06	4.08	5.39	0.50	-8.82
6	56.42	4.34	5.04	0.59	-8.21	73.88	5.68	5.20	0.82	-8.52	33.45	2.57	4.94	0.24	-8.45
5	57.38	4.41	4.54	0.67	-7.89	77.56	5.97	5.18	0.88	-8.25	44.80	3.45	4.48	0.46	-7.81
4	60.58	4.66	4.78	0.68	-7.53	71.53	5.50	4.86	0.85	-7.91	43.43	3.34	4.76	0.41	-7.08
3	55.01	4.23	4.33	0.66	-6.53	72.20	5.55	4.54	0.92	-7.03	40.55	3.12	4.33	0.40	-6.88
2	51.00	3.92	4.22	0.60	-6.29	55.37	4.26	4.23	0.68	-6.51	42.33	3.26	4.13	0.45	-6.58
Low	51.07	3.93	3.46	0.73	-5.59	56.32	4.33	3.46	0.85	-4.88	44.38	3.41	3.68	0.55	-6.26
High-Low		-0.60					1.56					-2.94			

Note: See notes in Table 3.

Table 8: Fund of funds decile portfolio characteristics-Extreme Value Theory

Panel A: Value at Risk															
	All Funds					Alive					Defunct				
Decile	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$
High	42.15	3.24	9.28	0.20	-14.06	74.91	5.76	8.04	0.54	-12.77	-4.76	-0.37	10.37	-0.17	-18.41
9	59.24	4.56	6.28	0.50	-8.87	64.58	4.97	6.55	0.55	-10.23	51.53	3.96	6.47	0.40	-8.74
8	64.44	4.96	6.14	0.58	-10.09	75.50	5.81	6.18	0.72	-9.54	50.32	3.87	6.25	0.40	-10.30
7	59.91	4.61	5.54	0.58	-9.67	71.21	5.48	5.74	0.71	-9.62	51.46	3.96	5.56	0.46	-8.99
6	59.81	4.60	5.07	0.63	-7.97	72.97	5.61	5.22	0.81	-8.09	42.12	3.24	5.07	0.36	-7.69
5	58.66	4.51	4.74	0.66	-7.68	74.20	5.71	5.13	0.84	-8.32	42.91	3.30	4.75	0.40	-7.75
4	59.98	4.61	4.41	0.73	-7.12	75.00	5.77	4.62	0.95	-7.40	41.19	3.17	4.27	0.42	-6.43
3	51.51	3.96	4.17	0.62	-6.35	70.61	5.43	4.69	0.86	-6.24	42.03	3.23	4.07	0.45	-6.60
2	48.35	3.72	3.93	0.59	-6.39	52.22	4.02	4.09	0.64	-6.32	38.62	2.97	3.91	0.40	-6.02
Low	48.99	3.77	3.56	0.67	-4.78	53.03	4.08	3.60	0.75	-4.43	43.88	3.38	3.64	0.55	-5.17
High-Low		-0.53					1.68					-3.74			
Panel B: Expected Shortfall															
	All Funds					Alive					Defunct				
Decile	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$	CR	AR	SD	SR	$VaR_{5\%}$
High	38.57	2.97	9.07	0.17	-13.82	71.85	5.53	7.83	0.53	-11.78	6.53	0.50	10.38	-0.09	-16.72
9	58.96	4.54	6.10	0.52	-9.04	64.60	4.97	6.09	0.59	-9.19	41.66	3.20	6.36	0.29	-10.57
8	61.48	4.73	5.95	0.56	-9.59	62.81	4.83	6.10	0.56	-9.46	51.65	3.97	6.27	0.41	-9.70
7	59.25	4.56	5.56	0.57	-8.57	79.36	6.10	5.72	0.82	-8.96	44.10	3.39	5.52	0.36	-8.50
6	62.47	4.81	5.19	0.66	-8.59	70.10	5.39	5.50	0.73	-8.39	48.30	3.72	5.02	0.46	-8.13
5	55.73	4.29	5.03	0.58	-8.80	75.42	5.80	5.39	0.82	-8.94	43.89	3.38	4.86	0.41	-8.00
4	62.29	4.79	4.43	0.77	-7.27	78.86	6.07	4.85	0.96	-7.40	34.95	2.69	4.44	0.29	-7.23
3	57.94	4.46	4.26	0.72	-6.44	71.92	5.53	4.55	0.91	-7.30	41.57	3.20	4.04	0.45	-6.58
2	46.73	3.59	4.16	0.53	-5.75	54.73	4.21	4.36	0.65	-6.03	40.65	3.13	4.12	0.42	-5.95
Low	49.16	3.78	3.45	0.69	-5.38	54.26	4.17	3.48	0.80	-4.41	44.56	3.43	3.62	0.56	-6.30
High-Low		-0.81					1.35					-2.93			

Note: See notes in Table 3.

Table 9: Comparison with Risk-Optimal portfolio (VaR)

	CR	AR	SD	SR	$VaR_{1\%}$	$VaR_{5\%}$	$VaR_{10\%}$	$ES_{1\%}$	$ES_{5\%}$	$ES_{10\%}$	MDD	OMG	SOR	UP
Panel A: HS														
FoF-Decile 3	54.96	4.23	4.33	0.66	-18.52	-6.51	-3.63	-20.37	-11.23	-7.92	22.17	1.67	0.25	0.63
FoF-Decile 2	53.86	4.14	3.97	0.69	-16.73	-6.08	-2.34	-18.18	-10.65	-7.29	18.82	1.74	0.26	0.62
FoF-Low Risk	53.31	4.10	3.54	0.77	-14.16	-5.06	-2.49	-15.24	-9.03	-6.29	16.75	1.85	0.30	0.66
HF-Decile 3	73.43	5.65	3.97	1.07	-14.46	-3.91	-2.49	-16.57	-8.47	-5.83	14.54	2.29	0.48	0.86
HF-Decile 2	63.82	4.91	3.35	1.05	-14.47	-3.82	-1.74	-16.81	-7.57	-5.30	14.75	2.37	0.43	0.74
HF-Low Risk	73.97	5.69	2.51	1.72	-10.06	-1.96	-0.81	-11.86	-5.34	-3.26	7.59	3.88	0.76	1.03
Optimal	**106.53**	**8.19**	**3.45**	**1.97**	**-8.19**	**-3.90**	**-1.47**	**-12.47**	**-7.03**	**-4.72**	**8.79**	**4.38**	**0.97**	**1.25**
Panel B: CF														
FoF-Decile 3	70.82	5.45	4.63	0.88	-16.95	-6.69	-4.78	-19.27	-10.46	-8.06	19.05	1.92	0.36	0.76
FoF-Decile 2	60.92	4.69	4.22	0.78	-19.96	-5.34	-3.22	-20.45	-10.88	-7.54	19.87	1.85	0.30	0.65
FoF-Low Risk	53.54	4.12	3.73	0.73	-15.80	-5.08	-2.70	-16.72	-9.47	-6.58	18.09	1.81	0.29	0.64
HF-Decile 3	84.84	6.53	4.38	1.17	-13.29	-5.78	-2.51	-15.45	-8.71	-6.41	13.43	2.45	0.57	0.96
HF-Decile 2	85.01	6.54	3.36	1.53	-11.42	-3.77	-2.50	-12.28	-6.54	-4.86	10.35	3.12	0.75	1.10
HF-Low Risk	84.39	6.49	2.79	1.83	-12.66	-1.32	-0.72	-14.80	-5.52	-3.21	8.55	4.60	0.79	1.01
Optimal	**109.49**	**8.42**	**5.97**	**1.18**	**-17.17**	**-6.22**	**-2.94**	**-26.21**	**-14.05**	**-9.10**	**21.61**	**2.76**	**0.50**	**0.79**
Panel C: EVT														
FoF-Decile 3	41.81	3.22	4.26	0.43	-18.46	-6.76	-3.25	-21.05	-11.51	-8.15	22.75	1.42	0.16	0.53
FoF-Decile 2	45.30	3.48	4.06	0.52	-15.74	-6.26	-3.51	-17.16	-10.87	-7.71	18.69	1.51	0.19	0.57
FoF-Low Risk	51.57	3.97	3.45	0.75	-13.62	-4.87	-3.03	-15.13	-8.69	-6.18	15.94	1.79	0.29	0.67
HF-Decile 3	54.19	4.17	4.09	0.68	-15.17	-4.02	-3.26	-17.94	-9.39	-6.51	16.71	1.72	0.28	0.67
HF-Decile 2	49.10	3.78	3.46	0.69	-15.28	-4.34	-3.12	-17.22	-8.01	-5.72	15.60	1.74	0.27	0.64
HF-Low Risk	53.18	4.09	2.64	1.03	-9.60	-2.25	-1.17	-12.68	-6.27	-3.86	11.33	2.39	0.41	0.71
Optimal	**94.57**	**7.27**	**3.23**	**1.82**	**-8.96**	**-2.09**	**-0.64**	**-13.89**	**-6.65**	**-3.91**	**8.60**	**4.50**	**0.84**	**1.08**

Note: This table reports the cumulative returns (CR), annualized average returns (AR), annualized standard deviation (SD), Sharpe Ratio (SR), the annualized HS-VaR and HS-ES, Maximum Draw Down (MDD) Omega Ratio(OMG), Sortino Ration (SOR) and Upside Potential (UP) for the risk-optimal portfolios and the three low-risk decile portfolios of hedge funds and fund of funds.

Table 10: Comparison with Risk-Optimal portfolio (ES)

	CR	AR	SD	SR	$VaR_{1\%}$	$VaR_{5\%}$	$VaR_{10\%}$	$ES_{1\%}$	$ES_{5\%}$	$ES_{10\%}$	MDD	OMG	SOR	UP
Panel A: HS														
FoF-Decile 3	53.78	4.14	4.18	0.66	-14.98	-6.56	-3.69	-17.00	-10.48	-7.63	20.42	1.65	0.26	0.65
FoF-Decile 2	45.72	3.52	4.00	0.53	-18.21	-6.12	-3.16	-19.52	-10.07	-7.12	17.92	1.53	0.20	0.59
FoF-Low Risk	50.64	3.90	3.57	0.70	-12.13	-5.31	-2.95	-14.47	-8.76	-6.33	15.88	1.72	0.28	0.67
HF-Decile 3	63.92	4.92	3.96	0.89	-13.79	-3.82	-2.95	-16.35	-7.94	-5.65	12.65	1.94	0.39	0.81
HF-Decile 2	55.10	4.24	3.00	0.95	-10.19	-3.85	-2.25	-12.48	-6.81	-4.90	12.13	2.07	0.40	0.77
HF-Low Risk	63.00	4.85	2.08	1.66	-7.80	-1.46	-0.75	-9.33	-4.02	-2.54	5.73	3.61	0.76	1.06
Optimal	**104.87**	**8.07**	**3.73**	**1.79**	**-9.80**	**-2.85**	**-1.09**	**-16.41**	**-7.32**	**-4.57**	**10.09**	**4.40**	**0.83**	**1.07**
Panel C: EVT														
FoF-Decile 3	74.46	5.73	4.59	0.94	-15.15	-6.06	-3.65	-18.16	-10.76	-7.82	19.90	2.03	0.40	0.78
FoF-Decile 2	53.52	4.12	4.01	0.68	-12.90	-5.80	-3.86	-15.82	-9.51	-7.09	16.92	1.67	0.27	0.68
FoF-Low Risk	52.63	4.05	3.55	0.75	-12.39	-4.48	-2.77	-14.59	-8.12	-5.88	13.96	1.78	0.31	0.71
HF-Decile 3	86.85	6.68	4.51	1.17	-12.57	-4.76	-3.47	-14.48	-7.79	-5.85	12.33	2.33	0.60	1.05
HF-Decile 2	67.85	5.22	3.43	1.12	-12.32	-4.04	-2.27	-12.78	-7.44	-5.07	9.92	2.32	0.51	0.90
Low Risk	79.00	6.08	2.32	2.02	-5.44	-1.04	-0.62	-9.69	-3.86	-2.33	5.59	4.79	0.99	1.25
Optimal	**120.91**	**9.30**	**4.92**	**1.61**	**-11.98**	**-4.50**	**-2.89**	**-15.98**	**-8.27**	**-5.93**	**8.07**	**3.56**	**0.90**	**1.25**
Panel C: EVT														
FoF-Decile 3	41.02	3.16	4.01	0.44	-14.22	-6.47	-3.71	-16.38	-10.25	-7.45	19.45	1.41	0.17	0.58
FoF-Decile 2	38.54	2.96	3.98	0.40	-16.40	-6.24	-2.71	-20.18	-10.59	-7.35	18.88	1.39	0.14	0.52
FoF-Low Risk	46.39	3.57	3.72	0.59	-12.40	-5.92	-3.57	-15.20	-9.36	-6.94	17.39	1.57	0.23	0.62
HF-Decile 3	36.65	2.82	3.88	0.37	-13.86	-5.04	-3.17	-17.23	-8.91	-6.42	14.38	1.32	0.14	0.60
HF-Decile 2	38.49	2.96	3.00	0.52	-9.13	-4.52	-2.36	-11.92	-6.83	-5.16	13.45	1.49	0.21	0.64
HF-Low Risk	47.94	3.69	2.21	1.04	-9.12	-1.77	-1.15	-9.59	-4.88	-3.13	8.21	2.33	0.45	0.79
Optimal	**101.10**	**7.78**	**2.79**	**2.29**	**-8.09**	**-2.12**	**-0.22**	**-9.15**	**-5.09**	**-2.89**	**5.04**	**6.23**	**1.31**	**1.56**

Note: See notes in Table 9.

Table 11: Risk-Optimal Portfolio Composition

Panel A: Historical Simulation													
						VaR Optimal Portfolios							
Year	RV	EM	ED	GM	L	LS	MN	MS	OT	CTA	SE	SB	
2002	1.68	18.20	1.65	0.00	0.00	8.97	0.00	2.55	0.85	4.85	56.05	5.19	
2003	4.48	26.35	3.40	0.00	4.71	19.97	0.00	0.17	0.05	1.44	39.29	0.15	
2004	0.05	37.23	0.98	0.00	6.84	14.54	0.00	3.12	0.09	0.99	34.79	1.35	
2005	0.00	31.56	0.00	0.00	9.41	24.16	0.00	6.62	0.00	1.78	21.66	4.82	
2006	0.00	26.25	0.00	0.00	7.23	24.45	0.00	4.21	2.52	1.78	28.22	5.33	
2007	0.02	10.08	0.00	0.00	1.86	33.95	0.00	6.70	1.70	4.63	39.65	1.42	
2008	0.56	15.40	0.84	0.00	4.01	27.89	0.00	3.42	3.35	11.34	31.13	2.08	
2009	0.06	22.98	0.13	0.00	10.99	23.45	0.00	1.21	2.51	2.07	36.61	0.00	
2010	0.00	15.56	0.07	2.57	13.59	23.12	0.00	5.05	0.00	0.00	39.99	0.06	
2011	0.88	15.61	6.28	4.19	11.71	17.14	0.00	0.16	2.33	0.02	41.57	0.12	
2012	0.90	28.86	0.00	0.00	8.93	18.36	0.00	0.83	1.41	3.90	36.75	0.04	
2013	2.56	27.49	0.00	0.00	7.50	7.21	0.00	0.00	2.55	6.78	45.90	0.00	
2014	0.88	37.63	0.00	1.68	3.42	6.35	0.00	0.00	0.11	4.91	45.02	0.00	
						ES Optimal Portfolios							
2002	6.67	22.50	0.49	8.48	0.00	12.55	0.00	2.84	0.83	0.83	41.47	3.33	
2003	5.83	18.05	1.67	3.97	0.00	7.50	0.00	3.38	0.00	0.83	36.81	21.95	
2004	0.49	30.83	0.00	0.00	0.00	21.32	0.00	1.52	0.00	6.67	34.37	4.80	
2005	6.67	35.84	0.00	0.00	0.00	9.41	0.00	0.00	0.00	5.29	26.12	16.67	
2006	5.63	24.51	0.00	0.00	0.00	15.89	0.00	2.50	0.83	2.99	39.65	7.99	
2007	3.33	9.17	0.00	0.00	4.17	22.16	0.00	8.33	0.00	4.17	36.61	12.06	
2008	5.00	15.98	0.83	0.00	2.50	20.20	0.00	9.17	0.00	7.65	33.68	5.00	
2009	4.36	28.68	0.83	2.01	17.79	9.80	0.00	0.00	3.33	1.67	31.52	0.00	
2010	0.49	37.49	1.72	0.00	8.34	15.64	0.00	0.83	0.83	4.17	28.20	2.30	
2011	2.50	53.07	0.00	0.00	3.19	8.82	0.00	0.83	1.67	2.01	26.23	1.67	
2012	3.82	36.03	0.00	0.00	8.48	13.97	0.00	1.67	3.33	5.00	25.06	2.64	
2013	3.33	49.16	0.00	0.00	5.34	1.67	0.00	0.00	3.82	8.68	27.99	0.00	
2014	4.66	40.83	0.00	0.83	5.00	2.16	0.00	0.00	3.33	3.68	39.51	0.00	

Note: This table reports the annual average strategy contribution to the risk-optimal portfolio for all estimation methods and risk measures,

Table 11 (Cont.) Panel B: Cornish - Fisher												
VaR Optimal Portofolios												
Year	RV	EM	ED	GM	L	LS	MN	MS	OT	CTA	SE	SB
2002	1.68	18.20	1.65	0.00	0.00	8.97	0.00	2.55	0.85	4.85	56.05	5.19
2003	4.48	26.35	3.40	0.00	4.71	19.97	0.00	0.17	0.05	1.44	39.29	0.15
2004	0.05	37.23	0.98	0.00	6.84	14.54	0.00	3.12	0.09	0.99	34.79	1.35
2005	0.00	31.56	0.00	0.00	9.41	24.16	0.00	6.62	0.00	1.78	21.66	4.82
2006	0.00	26.25	0.00	0.00	7.23	24.45	0.00	4.21	2.52	1.78	28.22	5.33
2007	0.02	10.08	0.00	0.00	1.86	33.95	0.00	6.70	1.70	4.63	39.65	1.42
2008	0.56	15.40	0.84	0.00	4.01	27.89	0.00	3.42	3.35	11.34	31.13	2.08
2009	0.06	22.98	0.13	0.00	10.99	23.45	0.00	1.21	2.51	2.07	36.61	0.00
2010	0.00	15.56	0.07	2.57	13.59	23.12	0.00	5.05	0.00	0.00	39.99	0.06
2011	0.88	15.61	6.28	4.19	11.71	17.14	0.00	0.16	2.33	0.02	41.57	0.12
2012	0.90	28.86	0.00	0.00	8.93	18.36	0.00	0.83	1.41	3.90	36.75	0.04
2013	2.56	27.49	0.00	0.00	7.50	7.21	0.00	0.00	2.55	6.78	45.90	0.00
2014	0.88	37.63	0.00	1.68	3.42	6.35	0.00	0.00	0.11	4.91	45.02	0.00
ES Optimal Portfolios												
2002	5.88	32.54	3.33	5.00	0.00	18.21	0.00	0.83	1.67	0.00	29.21	3.33
2003	0.83	29.88	9.17	0.00	9.17	10.20	0.00	3.96	0.00	4.17	30.96	1.67
2004	5.83	42.38	2.50	0.91	1.67	14.96	0.00	0.79	0.00	4.13	26.83	0.00
2005	0.00	58.54	1.67	0.00	1.67	16.67	0.00	0.00	0.00	4.17	17.29	0.00
2006	0.83	31.96	5.00	0.00	5.83	20.79	0.00	0.83	0.00	11.67	17.25	5.84
2007	2.50	10.84	0.00	0.00	0.84	20.12	0.00	3.41	0.04	9.88	33.21	19.17
2008	0.83	14.05	2.50	0.00	3.33	20.08	0.00	3.33	0.83	12.75	38.12	4.17
2009	0.00	27.54	4.25	0.83	6.67	20.83	0.00	5.00	0.00	2.46	32.42	0.00
2010	0.00	28.25	1.67	0.00	9.37	15.75	0.00	6.67	1.58	0.00	36.71	0.00
2011	0.04	34.37	0.00	0.00	1.75	11.67	0.00	0.00	8.79	8.33	35.04	0.00
2012	2.50	15.25	0.00	0.00	7.50	12.58	0.00	0.00	4.08	20.83	37.25	0.00
2013	2.38	36.75	0.00	0.00	10.04	1.67	0.00	0.00	1.79	20.00	27.38	0.00
2014	0.87	30.83	0.00	0.83	5.83	3.33	0.00	0.00	3.33	13.33	41.62	0.00

Table 11 (Cont.) Panel C: EVT												
VaR Optimal Portofolios												
Year	RV	EM	ED	GM	L	LS	MN	MS	OT	CTA	SE	SB
2002	9.13	25.06	0.78	0.00	0.00	14.78	0.00	1.75	1.63	2.97	41.15	2.76
2003	9.84	23.69	3.98	0.00	2.23	9.16	0.00	4.73	0.00	0.44	44.57	1.36
2004	7.49	28.60	0.48	0.00	0.74	17.01	0.00	1.93	0.00	4.26	36.09	3.40
2005	1.01	40.69	0.00	0.00	1.13	16.21	0.00	2.66	0.00	6.48	18.01	13.83
2006	3.42	43.94	0.00	0.00	2.22	15.90	0.00	0.37	0.14	5.01	19.26	9.73
2007	0.47	14.19	0.00	0.00	4.87	12.94	0.00	2.43	0.39	3.76	43.62	17.33
2008	5.22	23.65	0.64	2.28	2.47	15.15	0.00	3.77	2.98	9.24	30.51	4.10
2009	2.59	21.70	11.27	1.74	8.69	14.20	0.00	0.15	0.00	3.22	36.45	0.00
2010	0.00	20.98	5.08	2.14	9.03	13.77	0.00	0.62	0.56	5.18	42.66	0.00
2011	2.18	32.64	1.58	0.58	8.79	23.14	0.00	1.83	0.67	2.61	25.99	0.00
2012	1.73	25.56	0.00	0.00	2.36	21.76	0.00	0.00	1.67	8.99	37.92	0.00
2013	1.85	35.74	0.00	0.00	7.41	6.57	0.00	0.00	1.71	5.99	40.73	0.00
2014	0.08	31.76	0.00	0.74	7.04	1.90	0.00	0.00	0.96	7.11	50.42	0.00
ES Optimal portfolios												
2002	10.98	26.37	0.25	4.83	0.00	16.32	0.00	4.83	1.08	5.90	29.39	0.05
2003	5.37	34.92	7.94	0.30	0.17	12.18	0.00	2.26	0.00	1.62	35.19	0.04
2004	3.35	39.01	2.71	0.06	1.82	11.48	0.00	2.10	0.00	14.88	23.71	0.88
2005	0.61	43.90	3.59	0.00	3.48	9.34	0.00	0.12	0.00	23.52	14.61	0.83
2006	1.46	37.47	6.75	0.00	3.08	12.22	0.00	1.39	0.04	13.03	16.53	8.01
2007	0.08	14.53	2.65	0.00	6.68	11.25	0.00	1.72	1.12	18.38	24.96	18.61
2008	2.83	13.18	7.12	0.55	7.08	17.16	0.00	5.79	1.12	14.56	29.73	0.88
2009	4.01	24.31	23.49	0.27	1.47	10.66	0.00	1.52	0.03	17.89	16.35	0.00
2010	0.00	20.19	15.61	0.86	6.02	13.72	0.00	0.00	5.40	11.06	27.14	0.00
2011	1.63	20.10	4.82	0.00	5.25	13.35	0.00	0.00	10.05	16.06	28.74	0.00
2012	0.56	24.88	3.29	0.00	2.73	8.62	0.00	0.01	11.55	21.44	26.92	0.00
2013	0.00	19.49	8.36	0.00	1.72	4.50	0.00	0.02	5.25	32.29	28.37	0.00
2014	0.00	20.19	2.51	0.00	1.32	1.15	0.00	0.53	8.40	43.94	21.95	0.00

Figure 1: Average Fund Return Distribution

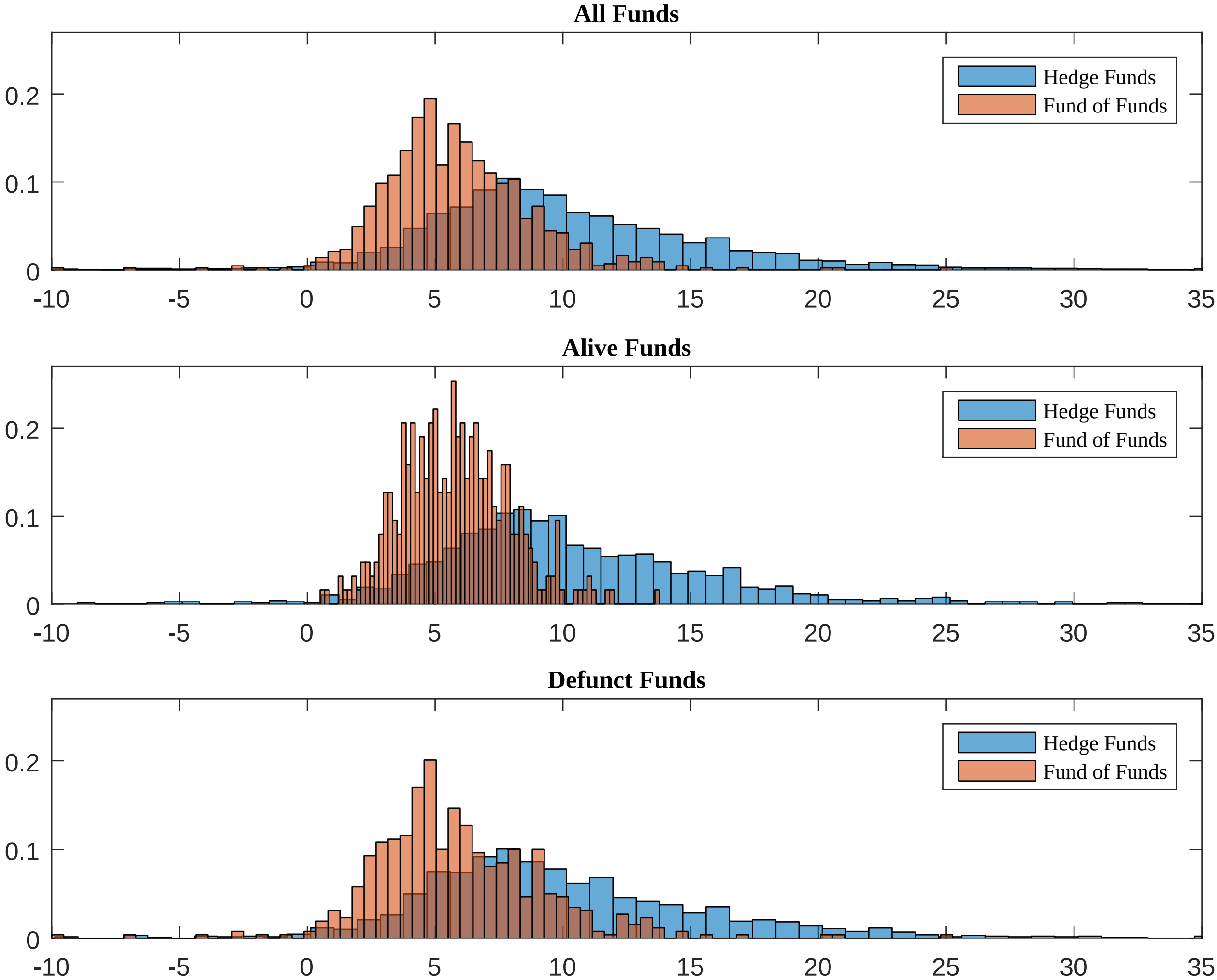

Figure 2: 5% HS VaR Fund Distribution

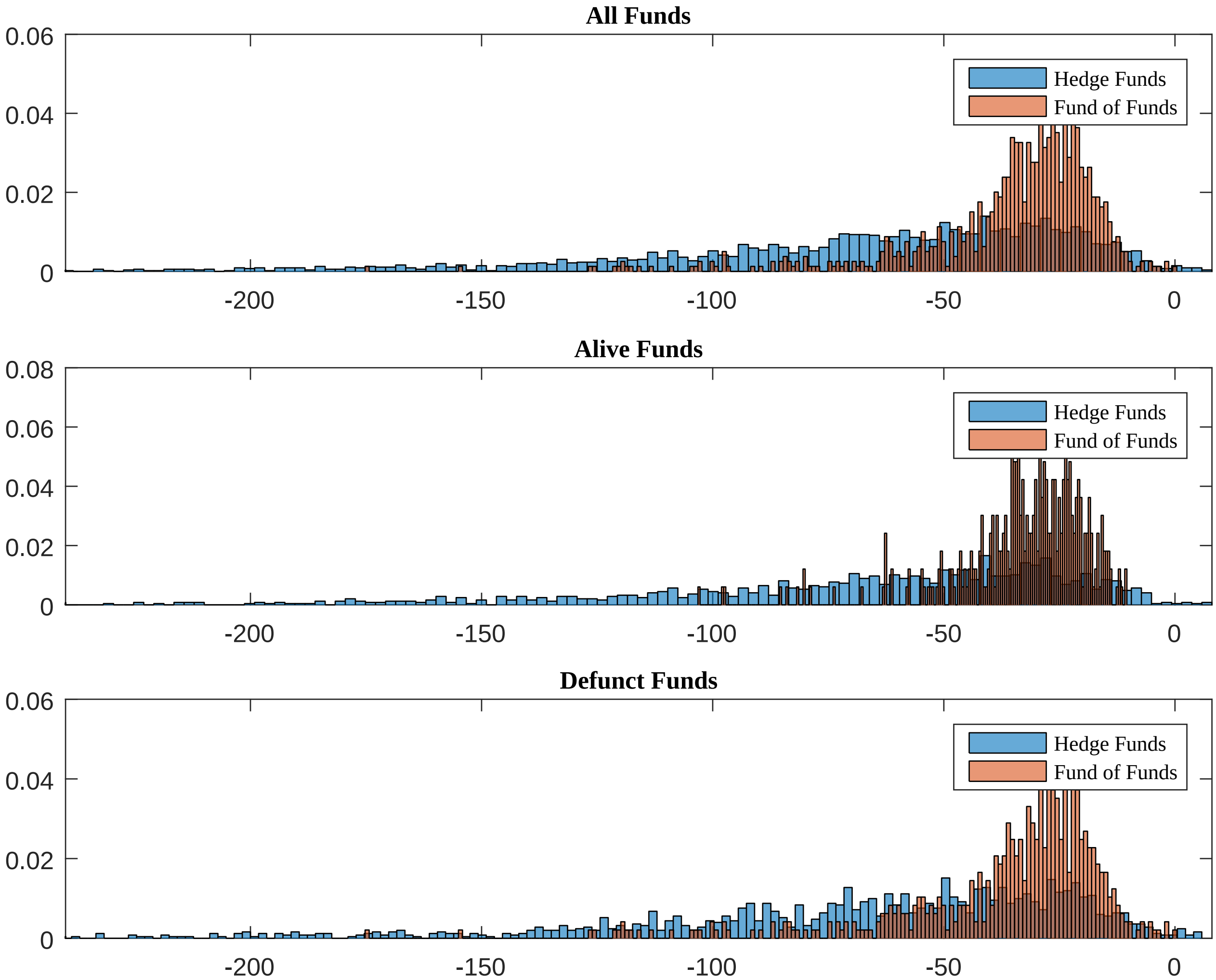

Figure 3: VaR-Optimal Portfolios vs. Fund of funds (Average Returns)

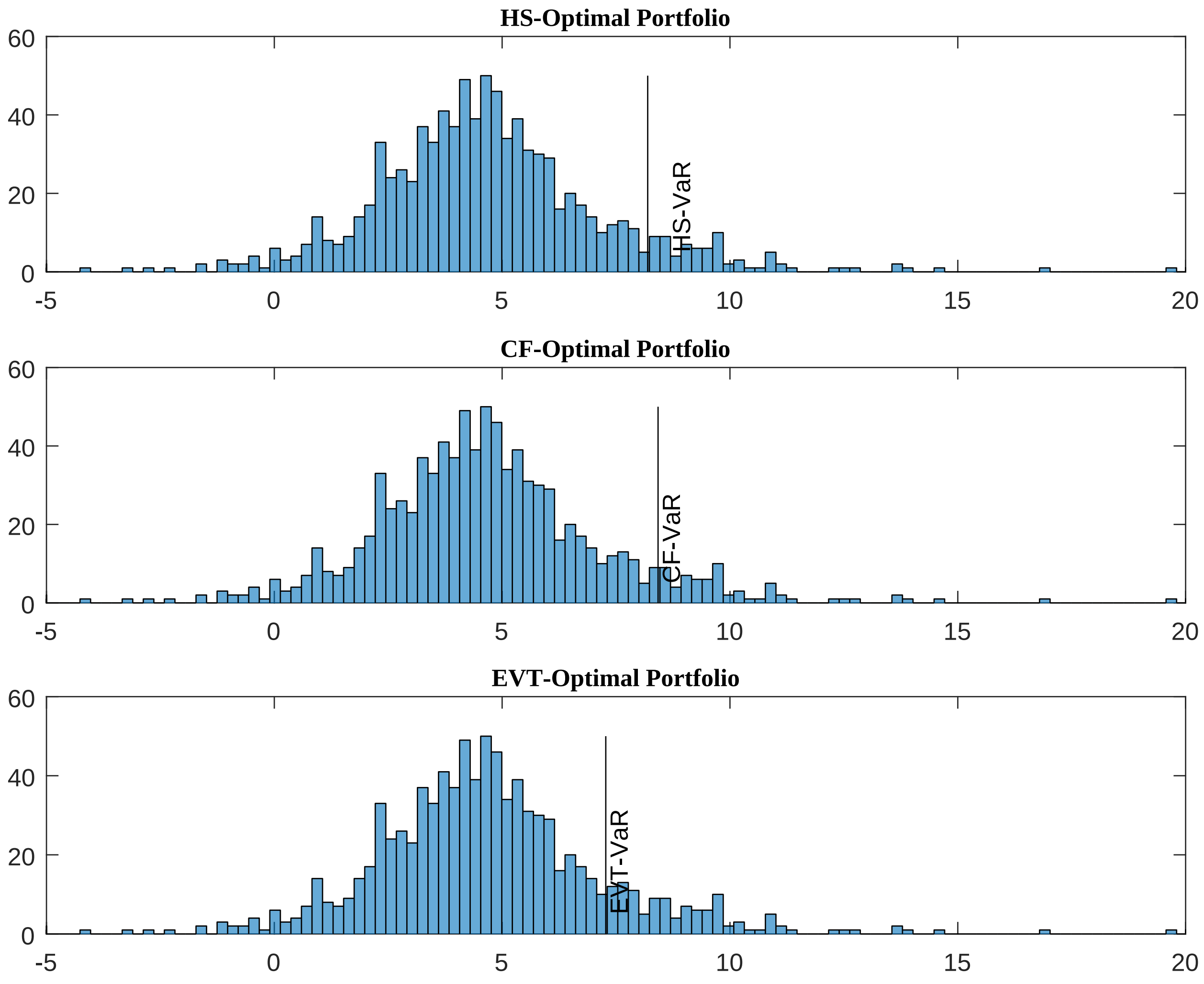

Figure 4: VaR-Optimal Portfolios vs. Fund of Funds (5% HS VaR)

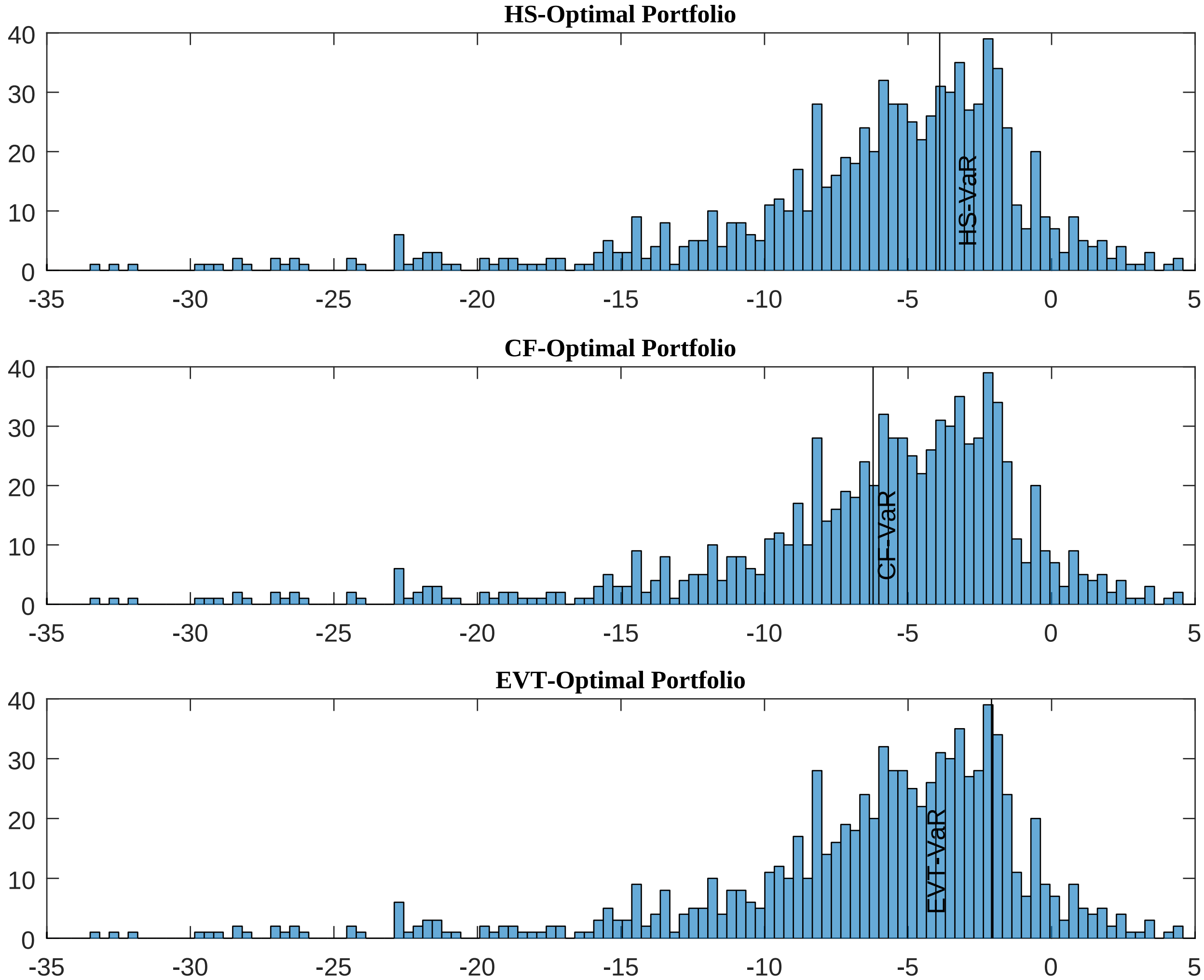

Figure 5: ES-Optimal Portfolios vs. Fund of Funds (Average Returns)

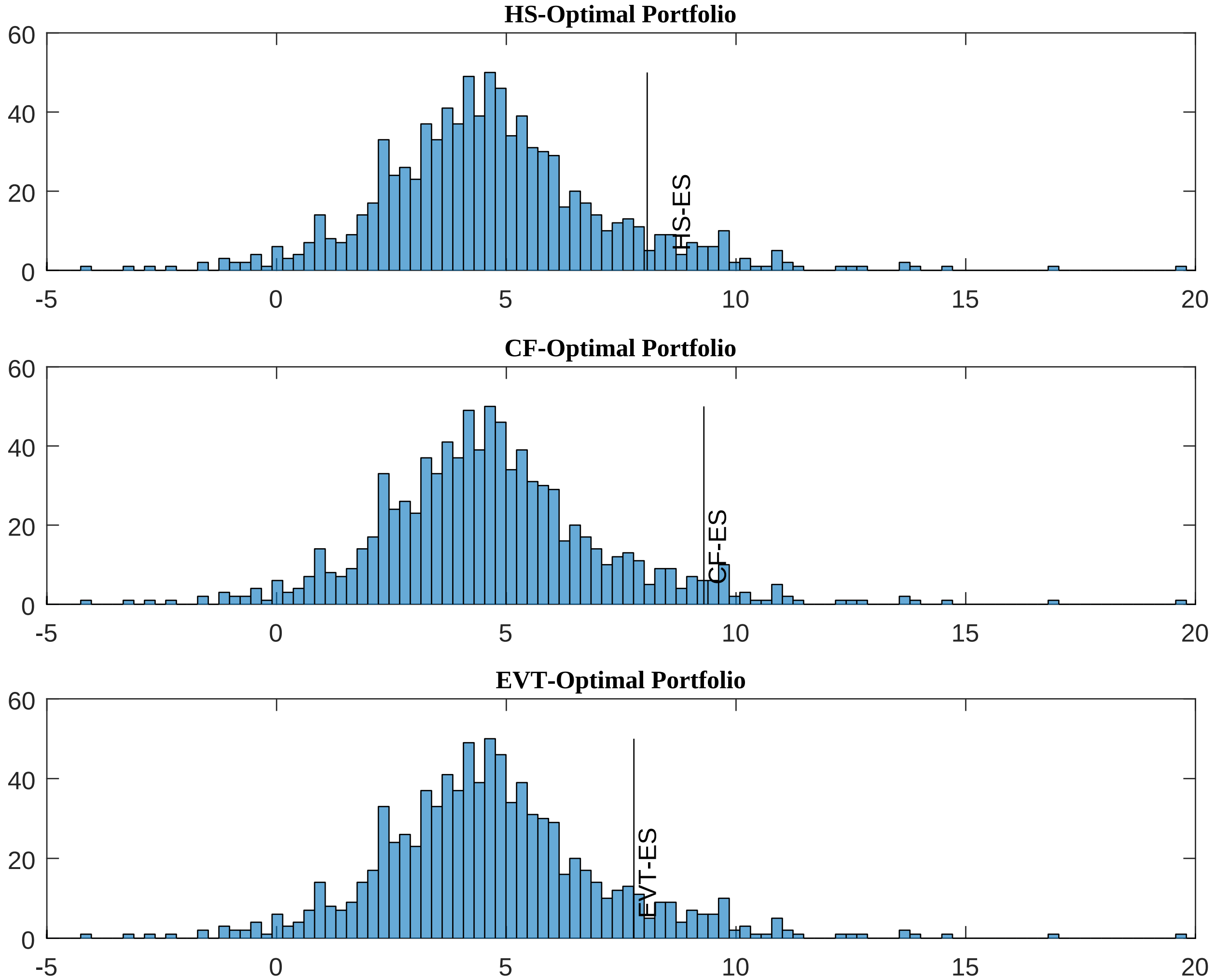

Figure 6: ES-Optimal Portfolios vs. Fund of Funds (5% HS-VaR)

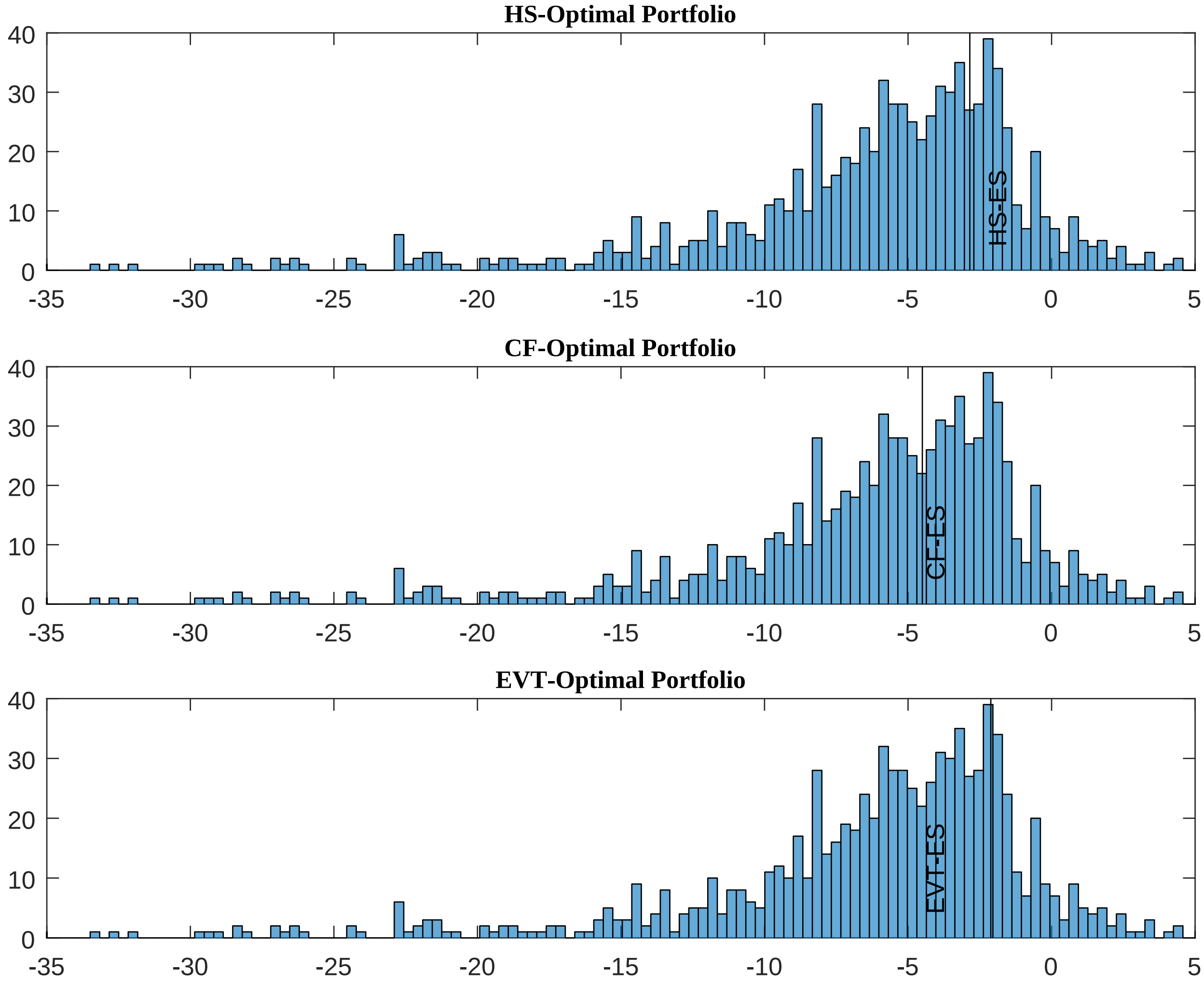

Figure 7: VaR-Optimal vs. Decile Fund of Funds Portfolios (Cumulative Returns)

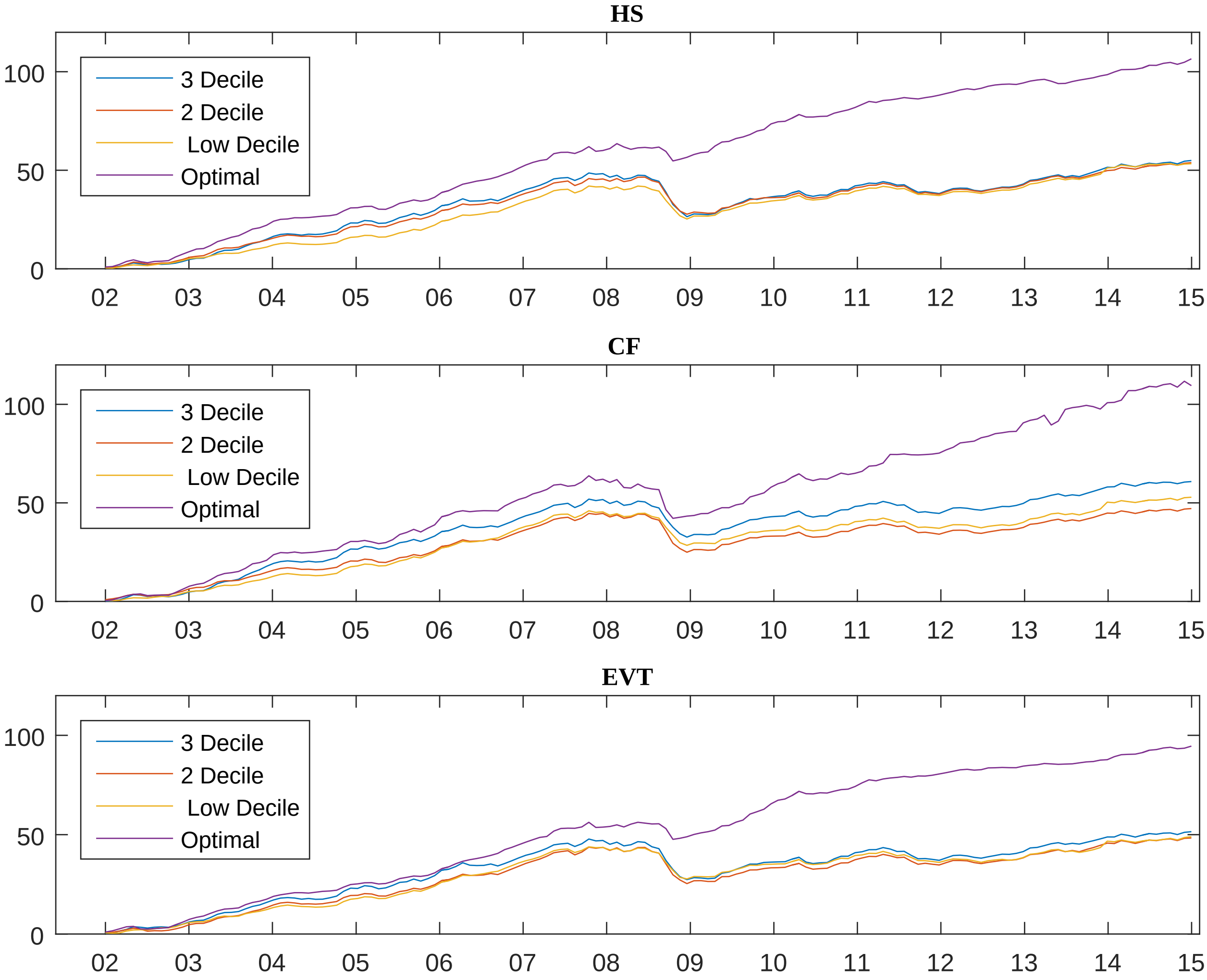

Figure 8: ES-Optimal vs. Decile Fund of Funds Portfolios (Cumulative Returns)