Journal of Banking and Finance 171 (2025) 107345

Contents lists available at ScienceDirect

Journal of Banking and Finance

journal homepage: www.elsevier.com/locate/jbf

# Downside risk and hedge fund returns

Christos Argyropoulos [a], Ekaterini Panopoulou [a,*], Spyridon Vrontos [b]

[a] Essex Business School, University of Essex, United Kingdom
[b] Department of Mathematical Sciences, University of Essex, United Kingdom

ARTICLE INFO

*JEL classification:*
G11
G23
C58

*Keywords:*
Hedge funds
Funds of hedge funds
Downside risk
Optimal diversification strategies

ABSTRACT

This study compares the predictive power of downside risk for hedge funds and fund of hedge funds returns. We find a positive relationship between downside risk and return for hedge funds but not for funds of hedge funds. This result is robust to the downside risk measure employed and additional control variables. Furthermore, we find that funds of hedge funds perform significantly worse than hedge funds during adverse equity market regimes, exhibiting an inverse (negative) risk–return relationship. Finally, we form realistic portfolios to determine whether an investor can construct a portfolio that outperforms the average fund of hedge funds. These portfolios display superior risk-adjusted performance and rank among the top performers of funds of hedge funds in our sample.

## 1. Introduction

Hedge funds (HFs) are professionally managed investment pools that employ complex strategies with nontraditional payoffs. Unlike mutual funds, HFs are not subject to strict regulation and are not required to disclose portfolio holdings or investment strategies. Given the opacity of information, past returns and measures based on them are considered valuable indicators of future HF performance. For instance, Sun et al. (2018) provide evidence that flows do, in fact, follow past performance. Therefore, can investors benefit from information based on past returns? Kosowski et al. (2007) suggest that skills cause HF alphas, which predict future returns.

Similarly, Titman and Tiu (2011) find that HFs that exhibit lower $R^2$, with respect to systematic factors, are likely to perform better in the future. However, Joenvaara et al. (2019) contend that the documented performance persistence diminishes as investor constraints limit access to top performers. Furthermore, Bali et al. (2019) argue that selecting funds based on past returns necessitates an adjustment that considers the unique nonnormal characteristics of HF returns.

This paper makes four contributions. First, we investigate how downside risk measures (RMs) can help HF investors forecast HF returns. Although Bali et al. (2007) found a positive relationship between downside risk and returns, we updated the sample to determine whether this relationship holds in the presence of additional factors found to explain HF returns, such as the Pastor and Stambaugh (2003) liquidity factor, the Bali et al. (2014) macroeconomic risk factor, and the Agarwal et al. (2017a) systematic tail risk factor. We quantify the fund's downside risk using a variety of measures. To assess the HFs' downside risk and return relationship, we compute their average after-fee risk–return profile using univariate portfolio sorts, conditional bivariate portfolio sorts, and Fama and MacBeth (1973) regressions. Depending on the RM, we find a significant monthly spread of 0.37% to 0.55% between the average returns (ARs) of the high- and low (downside)-risk portfolios. This spread decreases but remains significant even after accounting for additional risk sources.

The paper's second contribution is to determine whether downside risk predicts fund of HF (FoHF) returns. FoHFs are managed investment pools specializing in the HF industry by creating HF portfolios. According to Aiken et al. (2015b), FoHFs promote HF selection skills and insights to investors. Through their holdings in HFs, they gain an informational advantage that enables the efficient monitoring and management of their portfolios. FoHFs charge a second layer of fees for their services, which according to Brown et al. (2004) and Gao et al. (2020), account for most of the after-fee returns. To the best of our knowledge, this is the first time the predictive power of downside risk for FoHFs has been assessed and compared with HFs. This is important because FoHFs are a natural benchmark for HF portfolios, whereas many investors could not access multiple HFs due to high investment minimums. Our findings suggest that, unlike HFs, the risk–return relationship for FoHFs is insignificant.

The third contribution of the paper is to determine whether the results as mentioned earlier are significant due to specific periods of good

* Corresponding author.
*E-mail address:* a.panopoulou@essex.ac.uk (E. Panopoulou).

https://doi.org/10.1016/j.jbankfin.2024.107345
Received 27 October 2020; Accepted 18 November 2024
Available online 1 December 2024

performance. We focus our analysis on specific equity market regimes, as Sun et al. (2018) argue that good performance during weak markets predicts future performance. Specifically, we identify up and down equity market regimes by comparing the S&P500 price index with its 200-day moving average. We find that HFs' risk-taking is significantly rewarded during the up regime, but not during the down regime. High-risk HFs do not provide higher ARs than low-risk funds in the down regime. Regarding FoHFs, higher risk results in higher ARs during up regimes. However, unlike HFs, for the down regime, FoHFs show a significant deterioration in performance across all reported risk levels, accompanied by a significant inverted (negative) risk–return relationship. Our findings suggest that FoHFs do not compensate for risk-taking during market downturns, particularly when compared with the HFs.

Finally, our paper examines whether an investor can build a portfolio of HFs and achieve economic returns comparable with those of FoHFs. Agarwal et al. (2013) suggest that, under certain conditions, direct investments in HFs outperform indirect investments via FoHFs through various channels. Gao et al. (2019) find that institutional investors can earn consistent returns by investing in small HFs. To investigate such gains, we construct six HF portfolios for three investors of varying sizes. To achieve high realism in our portfolios, we follow Joenvaara et al. (2019) and impose restrictions that account for realistic HF investor constraints. When selecting funds, we focus on past returns, estimated alpha, Sharpe ratio (SR), and modified SR (MSR). We construct equally weighted portfolios of the 30 best-performing funds for each of the four selection methods. We also calculate optimal portfolios for the latter two selection methods (SR and MSR) to maximize SR and MSR, respectively. Our results suggest that, regardless of investor size, our optimal realistic portfolios rank among the top 10 % of FoHF performers, whereas equally weighted realistic portfolios perform on average as a median FoHF.

The remainder of the paper is structured as follows. Section 2 discusses the data and the main methodological approaches. Section 3 presents the empirical results for the HFs and FoHFs decile portfolios, the Fama and MacBeth (1973) regressions and the decile results conditional on the equity market regime. Section 4 discusses the realistic portfolio methodology and results, while Section 5 concludes.

## 2. Data and risk estimation

This section introduces the HF database, fund characteristics, and summary statistics. Then we define key variables used in the cross-sectional predictability of future fund returns. Finally, we present the standard risk factors used to estimate risk-adjusted returns (alphas).

### *2.1. HFs database*

We employ monthly data from the BarclayHedge database, with a sample period spanning January 1994 to December 2014. BarclayHedge is a database widely used by practitioners, but it is less frequently used in academic research, despite its comprehensive coverage of the HF sector.[1] When compared with other commercial databases, such as TASS, Eurekahedge, HFR, or Morningstar, the BarclayHedge database has several useful features. First, as documented by Joenvaara et al. (2021), the BarclayHedge database has the largest number of funds and the highest percentage of defunct funds, making it the least susceptible to survivorship bias. Defunct funds are funds that ceased reporting their performance to the data vendor. The primary reasons for the cessation of reporting are liquidation, merger, and voluntary cessation. Moreover, Joenvaara et al. (2021) compare HF databases commonly used in the literature and find that BarclayHedge, along with HFR and TASS, is one of the three high-quality individual databases. They find that BarclayHedge should be added first because it contains 45% of unique funds when constructing their union database (which combines seven databases). Second, all databases, except for TASS, HFR, and BarclayHedge, exhibit survivorship bias because they report extremely low attrition rates for the early sample. Third, BarclayHedge has the lowest percentage (11 %) of missing assets under management (AUM) information and the longest AUM time series, making it more appropriate for analyzing HF performance based on its size. For comparison, the TASS database has approximately 34 % missing AUM information[2] Finally, Joenvaara et al. (2021) show that, despite the small overlap of funds between BarclayHedge and TASS, these databases share several other important characteristics, including evidence of performance persistence in individual HF returns.

Databases may contain various biases. Following similar studies, we apply various filters to the initial sample to address these issues. First, survivorship bias occurs if the database does not include returns from defunct HFs. Our study spans from January 1994 to December 2014, and we have data on alive and defunct funds. As previously stated, BarclayHedge provides comprehensive coverage of nonsurviving funds after 1994. Our initial dataset includes 6489 alive funds and 16,748 defunct ones. We exclude funds that do not report returns monthly and those that report returns in currencies other than the US dollar. To reduce any size bias caused by small funds, we exclude those with less than \$10 million in AUM.

When a HF is added to a database, previous returns (typically one year) are automatically included. This leads to backfill bias. Our analysis removes the first 12 months of returns for all funds used. Finally, multiperiod sampling bias is the last possible data bias in an HF study. Before deciding to invest in a HF, investors typically require at least 24 months of return history. Therefore, in a HF study, including HFs with return histories shorter than 24 months would be misleading for investors seeking past performance data to make future investment decisions. In our case, a longer return history requirement makes statistical sense because it allows us to calculate RMs, run regressions, and obtain valid estimates of alphas, betas, SRs, and appraisal ratios for individual HFs in the sample. Therefore, we require all HFs in the sample to have at least 48 months of return history, after which we remove the first 12 observations to account for any backfill bias. The requirement for at least four years of historical returns results in a 15-year out-of-sample period that runs from January 1999 to December 2014.

Applying the aforementioned filters to our database results in a baseline dataset of 5324 HFs and 1810 FoHFs. This dataset includes 1832 alive HFs and 475 alive FoHFs, with the remaining funds comprising the defunct ones for both groups. Our analysis is based on the combined alive and defunct HF database. However, in some cases, we provide results for both alive and defunct funds to determine whether a specific group of funds causes the observed relationship. Furthermore, because the database reports several investment styles, we filtered the data set into 13 groups based on the similarities of their strategies. The 13 fund groups are as follows: relative value (RV), emerging markets (EM), event-driven (ED), global macro (GM), long (L), long/short (LS), multistrategy (MS), others (OT), commodity trade advisors (CTA), sector (SE), short bias (SB), market neutral (MN), and FoHF.[3]

Table 1 reports the cross-sectional average values of the descriptive statistics for both FoHFs and HFs, as well as the rejection rates of the

[1] Buraschi et al. (2014a) and Buraschi et al. (2014b) employed BarclayHedge in their empirical analyses. BarclayHedge is frequently used in the hedge fund (HF) literature as an aggregate database. See, for example, Aiken et al. (2013), Aiken et al. (2015a), Cao et al. (2016), and Hodder et al. (2014).

[2] At the end of 2016, the largest individual database was BarclayHedge, with an asset under management (AUM) of approximately \$1.3 trillion, whereas the aggregate database of TASS, HFR, and BarclayHedge had \$1.8 trillion (Joenvaara et al., 2021).

[3] The online appendix includes a table with descriptive statistics for each individual strategy.

**Table 1**
Descriptive Statistics of Funds of Hedge Funds and Hedge Fund Returns.

| | All Funds | | Alive | | Defunct | |
|---|---|---|---|---|---|---|
| | FoHFs | HFs | FoHFs | HFs | FoHFs | HFs |
| Mean | 0.42 | 0.71 | 0.48 | 0.75 | 0.40 | 0.69 |
| Standard Deviation | 2.14 | 3.93 | 1.90 | 3.77 | 2.22 | 4.02 |
| Sharpe Ratio | 0.15 | 0.20 | 0.22 | 0.27 | 0.12 | 0.17 |
| Max | 5.83 | 13.13 | 5.90 | 13.43 | 5.81 | 12.97 |
| Min | −7.86 | −11.99 | −7.28 | −11.84 | −8.07 | −12.06 |
| Median | 0.63 | 0.72 | 0.65 | 0.77 | 0.62 | 0.70 |
| Kurtosis | 7.73 | 6.98 | 8.07 | 7.02 | 7.61 | 6.95 |
| Skewness | −0.97 | −0.20 | −0.91 | −0.15 | −0.99 | −0.23 |
| Absolute Skewness | 1.21 | 0.87 | 1.17 | 0.79 | 1.22 | 0.91 |
| Jarque–Bera | 0.82 | 0.69 | 0.89 | 0.70 | 0.80 | 0.68 |

Notes: The table shows the average values of the sample mean, median, standard deviation, Sharpe ratio, skewness, absolute skewness, and kurtosis of the returns of HFs and FoHFs (all, alive, and defunct). The mean, median, and standard deviation values are reported in monthly percentages. It also reports the rejection rates of the Jarque–Bera test for normality. The data are obtained from the BarclayHedge database and cover January 1994 to December 2014.

Jarque–Bera test for normality. Overall, our findings confirm the presence of excessive kurtosis and negative skewness, as reported in the literature. This finding is consistent with the findings of Amin and Kat (2003) and Davies et al. (2009), who report a trade-off between the moments of the return distribution of HF portfolios. When comparing HFs and FoHFs, we find that the former has higher ARs (0.71%) than the latter (0.42 %) and a larger average standard deviation and return range. Despite the increased average risk of HFs, their SR remains higher than that of FoHFs. These performance differences are consistent across both alive and defunct funds, suggesting that no particular group of funds drives the aggregate results. Finally, the Jarque–Bera test rejection rates show that at least 69% of the HF return series reject the normality hypothesis, whereas 82 % of the FoHFs do.

### 2.2. Risk estimation

Traditionally, quantifying an asset's risk entails calculating the return standard deviation or developing a factor model that attributes the variation in return, or at least a portion of it, to specific factors. However, the skewness and excess kurtosis of HF returns would result in an underestimation of risk by the return standard deviation (Agarwal and Naik, 2004). From a factor model perspective, Fung and Hsieh (2001) and Fung and Hsieh (2004) propose a seven-factor model to explain HF returns under a linear specification, where some of the factors represent nonlinearities in HF strategies. Focusing directly on forecasting HF returns, Vrontos et al. (2008), Avramov et al. (2013), and Panopoulou and Vrontos (2015) argue that combining multiple factor models can provide additional explanatory power on HF returns than stand-alone models. Nonetheless, models fail to explain much of the HFs' return variation, even with "nonlinear" factors and/or combining specifications, because they do not completely conform to the empirical properties of HF returns.

Meanwhile, Gupta and Liang (2005) examine HF capital adequacy and find significant variation in HF risk and capitalization that traditional RMs such as standard deviation cannot detect. Instead, they propose value at risk (VaR) as a more appropriate RM for assessing the capital adequacy of HFs. Agarwal and Naik (2004) suggest that expected shortfall (ES) is more appropriate than the VaR measure, whereas Liang and Park (2007) find evidence of a significant relationship between the ES and tail risk (TR) RMs and returns. In a more recent paper, Agarwal et al. (2017b) calibrate a tail-dependency systemic measure using individual fund ES. In addition to explaining the cross section of returns, VaR and ES can predict fund failure. Bali et al. (2007) observe an increase in the VaR of HFs before the fund discontinues reporting to the database. Similarly, Liang and Park (2010) use a battery of RMs, including VaR, ES, TR, and semi-deviation (SeD), with the Cox proportional-hazard model to find that downside RMs, such as ES, are superior in predicting HF failure. Finally, in addition to financial risks, VaR and ES could aggregate information on operational risk losses, which, according to Brown et al. (2008), can contribute to a fund's failure.

For our analysis, we use an estimation window of 36 raw returns, which we roll forward until the end of the out-of-sample period or the fund's delisting, to calculate the 5% empirical VaR, ES, TR, CVaR, and SeD, as follows:

$$\mathrm{VaR}_t(q) = F_q^{-1}\left(\{r_i\}_{i=1}^{t-1}\right),$$

where $F_q^{-1}$ denotes the $q$ empirical quantile of the sample of returns, and $r_i$ is the return for time $i$. Given the sample size of 36 observations, we follow Bali et al. (2007) to calculate the 5%VaR as the interpolated quantity between the third (34/36=94.44 %) and second (35 /36 = 97.22%) ranked returns in our rolling window,[4]

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

where $\Delta$ is the partition of the tail, $N(\Delta)$ is the number of elements within the partition $\Delta$ and $F_a^{-1}$ denotes the $a$ empirical quantile of the sample of returns,

$$CVaR_t(q) = -(\mu + \Omega(q)\sigma),$$

where $\Omega(q)$ is the Cornish Fischer expansion for the $q$ quantile, $\mu$ and $\sigma$ is the average returns and standard deviation of the in-sample period ending at $t-1$, respectively,

$$TR_t(q) = \sqrt{E_{t-1}\left[(r_t - E_{t-1}(r_t))^2 \middle| r_t \le VaR_t\right]}$$

and

$$SeD_t(q) = \sqrt{E_{t-1}\left[(\min(r_t-\mu,0))^2 \middle| r_t \le \mu\right]}.$$

### 2.3. Fund characteristics and risk factors

In the following empirical analysis, we select a set of control variables from the pool of fund characteristics and financial risk factors. Specifically, the control variables' vector X includes time-varying fund characteristics such as the past monthly return (Return(−1)), a function of AUM as a proxy for the fund's size and the age of the funds. Furthermore, when applicable, we include static characteristics of individual funds reported once in the database: a Management Fee (Management) indicator, a Performance Fee (Performance) indicator, a liquidity constraint (Liquidity) variable, reported in days and defined as the sum of the notice and lock up periods, a fund leverage indicator (Leverage), a Minimum Investment (Min Investment) variable, and finally a Highwater Mark (HWM) indicator variable.

With respect to risk factors, we use the risk factors in Fung and Hsieh (2004) seven-factor model, namely the S&P500 index monthly total

[4] Bali et al. (2007) and Liang and Park (2010) calculate downside risk measures (RMs) using a lower minimum of 24 observations and a maximum of 60 observations (if available). We chose a short rolling in-sample period to estimate downside RMs because we wanted to include as many funds as possible in the analysis. One of the biases in HF databases is the backfill bias, which occurs when a HF is included in a database and previous returns (usually one year) are automatically added. In our analysis, we remove the first 12 months of returns for all funds used, requiring that the fund have 48 observations. Increasing the rolling in-sample period would reduce the cross section of available funds and lead to survivorship bias, as HFs have a typical lifetime of around 5 years.

return of the S&P500 index (S&P), the size spread factor calculated as the difference between the monthly total return of the Russell 2000 index minus the monthly total return of the S&P500 monthly total return (SCMLC), the bond market factor defined as the monthly change in the 10-year Treasury constant maturity yield (BD10RET), the credit spread factor defined as the monthly change in the Moody's Baa yield less 10year Treasury constant maturity yield (BAAMTSY), the bond trend following factor (PTFSBD), the currency trend following factor (PTFSFX) and the commodity trend following factor (PTFSCOM), augmented by the Fama and French (1993) book-to-market factor (HML), the Carhart (1997) momentum factor (UMD), Fama and French (2015) investment (CMA) and profitability (RWA) factors, the Pastor and Stambaugh (2003) liquidity (LIQ) factor, the Bali et al. (2014) macroeconomic risk (MRI) factor and the Agarwal et al. (2017a) systematic tail risk (STR) factor.

## 3. Empirical results

This section uses alternative tests to investigate the relationship between risk and future fund returns. First, we analyze the predictive power of all alternative downside RMs for future fund returns using univariate portfolio tests. Then, we examine whether the observed relationship can be attributed to the effects or particular sample periods. We report the results of Fama–MacBeth cross-sectional regressions controlling for various characteristics and factors. Furthermore, we report the results of conditional bivariate portfolios containing all downside RMs and alternative factors found in the literature to explain the funds' returns. Finally, we conduct decile portfolio analysis on specific subsamples of the sample period to assess funds' risk–return relationship over time. For the following analysis, we report VaR, ES, and CVaR as positive quantities.

### 3.1. Univariate portfolio sorts

Tables 2 and 3 report the ARs, RM estimates, Fung Hsieh's nine-factor alphas (9FH–$\alpha$), and t-statistics for decile portfolios of HFs and FoHFs for all risk classification measures. We only report the full results for the VaR case; for the other measures, we only report the spreads between the high- and low-risk decile portfolios. We find that returns decrease as risk levels increase for HF VaR-sorted portfolios (Table 2, Panel A). The AR and 9FH $-\ \alpha$ spread between the high- and low-risk portfolios are positive (37 basis points (bps) and 27 bps, respectively) but insignificant. Similar results are reported for the sorted portfolios on alternative RMs (Table 2, Panels B–E), with a positive spread between the high- and low-risk decile portfolios' RM, AR and 9FH $-\ \alpha$. SeD and TR have the highest return spreads, with significant values of 54 and 55 bps, respectively. In these cases, the spread of the risk-adjusted return (9FH $-\ \alpha$) is 41 bps and significant.

Fig. 1 depicts the results as mentioned above in the form of return histograms for each VaR-sorted decile portfolio across all funds.[5] The figure shows that the low decile portfolio has the lowest dispersion of returns, with its shape indicating a significantly higher likelihood of positive rather than negative returns. The number and magnitude of negative returns are the lowest among the decile portfolio cases (the red bar represents the zero-returns bin), because the left tail of the distribution overlaps with the middle part of the return distributions of the remaining decile portfolios.

To better understand the effect of alive and defunct funds on our main result, we report portfolio results separately. We find a positive and significant spread in AR and 9FH $-\ \alpha$ for the alive funds' portfolios. Meanwhile, for the defunct funds' portfolios, the relationship is still positive but insignificant. Similar to the results of Bali et al. (2007), when we pool together alive and defunct funds, the significance of the reported average relationship is diminished, owing to the large number of defunct funds, ex-post, do not identify a positive relationship between risk and returns.

Table 3 reports the characteristics of each FoHF decile portfolio. Overall, we cannot find a clear relationship between risk and return. We observe a relatively flat AR profile, with a negative 9 bps AR differential and a negative 19 bps differential in 9FH–$\alpha$, which is significant at the 10% level. This is to be expected given that investing in FoHFs is equivalent to investing in a diversified portfolio of HFs. Hence, downside RMs should have a less direct and significant effect on expected FoHF returns. Interestingly, when we compare the risk levels of HFs and FoHFs decile portfolios, we find that the low-risk FoHFs portfolios are riskier than the HFs low-risk portfolios. For the alive group of funds, the relationship between risk and return is indistinguishable from zero, with the return (9FH $-\ \alpha$) differential positive (negative) and insignificant (insignificant). In contrast, the return and the 9FH $-\ \alpha$ spreads are negative for the group of defunct funds, with the latter being significant at the 10% significance level. Alternatively sorted portfolios yield similar results (Table 3, Panels B–E). Specifically, for the ES- and CF VaR-sorted portfolios, we find a significant negative 9FH $-\ \alpha$ spread for the groups of all and defunct funds, but not for the SeD- and TR-sorted portfolios. Fig. 2 illustrates the return distribution characteristics of the FoHF decile portfolios. Similar to the HF case, the empirical distribution of the low-risk portfolio has a lower kurtosis than the other portfolios. However, the deep end of its left tail is comparable with the tails of the high- to middle-risk portfolios.[6]

### 3.2. Multivariate cross-sectional regressions

In addition to univariate portfolio sorts, we run Fama and MacBeth (1973) regressions of future fund returns in month $t+1$ on fund RMs and additional fund characteristics and risk factors in month:

$$r_{i,t+1} = \alpha + \beta_1 RM_{i,t} + \boldsymbol{\beta}_2 \mathbf{X}_{i,t} + \varepsilon_{i,t}$$

where $r_{i,t+1}$ denotes fund i's return in month $t+1$, $RM_{i,t}$ denotes one of the alternative RMs of fund i in month $t$, and $\mathbf{X}_{i,t}$ is a vector of fund characteristics, factor exposures, and the nine-factor FH fund's $R^2$. To account for potential serial correlation in monthly slope coefficients, we apply the Newey and West (1987) adjustment with 36 lags.

Table 4 summarizes our findings regarding HFs and FoHFs. In columns (2) and (5), we only use the RM as an explanatory variable. For HFs and the VaR measure (Panel A, column (2)), the coefficient estimate is 0.0328, which is statistically significant at the 5% level (t-statistic = 2.11). When we include fund characteristics as control variables (column (3)), our results are qualitatively similar, with statistically significant estimates of 0.0285. Expanding the control variables set to include factor sensitivities (column (4)), we find that VaR has a slightly lower impact on future returns, with an estimate of 0.0154, marginally significant at the 10% level. Panels B–E present the Fama–MacBeth estimates for our alternative RMs. Our findings are robust to the choice of RM and indicate that risk significantly and positively impacts future fund returns.

Columns (5), (6), and (7) in Table 4 show the cross-sectional regression results for FoHFs using the same specifications as HFs. Our

[5] For brevity, we only present the VaR graphs here. Similar distribution shapes apply to the remaining decile portfolio returns. This set of results is available upon request.

[6] We constructed value-weighted decile portfolios to account for the effect of the funds' size. Overall, the value-weighted results suggest that medium-sized and smaller funds drive the observed relationship between HFs. At the same time, for the funds of HFs (FoHFs), the relationship between risk and return is generally insignificant. Finally, to account for potential sample variation, we use the Bali et al. (2007) data frame and methodology to find comparable results. Sections 2.1–2.3 of the Online Appendix provide a more in-depth discussion.

**Table 2**
Hedge Funds Decile Portfolios.

| Panel A: VaR | All Funds | | | | Alive Funds | | | | Defunct Funds | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | RM | AR | 9FH–$\alpha$ | t-stat | RM | AR | 9FH–$\alpha$ | t-stat | RM | AR | 9FH–$\alpha$ | t-stat |
| High | 6.01 | 0.95 | 0.64 | 3.31 | 6.44 | 1.29 | 1.03 | 4.98 | 6.39 | 0.66 | 0.37 | 1.54 |
| 9 | 3.88 | 0.95 | 0.58 | 6.51 | 4.58 | 1.18 | 0.84 | 6.92 | 3.79 | 0.72 | 0.36 | 3.32 |
| 8 | 3.19 | 0.78 | 0.37 | 7.56 | 3.50 | 1.00 | 0.65 | 8.61 | 2.99 | 0.59 | 0.22 | 3.70 |
| 7 | 2.50 | 0.64 | 0.31 | 7.46 | 2.74 | 0.83 | 0.49 | 7.37 | 2.63 | 0.46 | 0.18 | 2.41 |
| 6 | 1.79 | 0.71 | 0.38 | 7.53 | 2.14 | 0.84 | 0.50 | 10.34 | 2.20 | 0.59 | 0.26 | 3.22 |
| 5 | 1.53 | 0.57 | 0.30 | 13.43 | 1.70 | 0.80 | 0.51 | 12.19 | 1.58 | 0.42 | 0.19 | 8.87 |
| 4 | 1.48 | 0.51 | 0.24 | 6.44 | 1.31 | 0.66 | 0.42 | 13.92 | 1.50 | 0.38 | 0.12 | 3.15 |
| 3 | 0.85 | 0.49 | 0.24 | 11.43 | 1.16 | 0.70 | 0.40 | 17.49 | 1.02 | 0.41 | 0.17 | 2.83 |
| 2 | 0.73 | 0.47 | 0.25 | 6.94 | 0.77 | 0.55 | 0.31 | 22.55 | 0.87 | 0.39 | 0.18 | 3.48 |
| Low | 0.17 | 0.58 | 0.37 | 15.72 | 0.14 | 0.69 | 0.48 | 13.62 | 0.23 | 0.49 | 0.29 | 6.32 |
| High–Low | 5.84 | 0.37 | 0.27 | | 6.30 | 0.59 | 0.55 | | 6.16 | 0.17 | 0.08 | |
| | | [1.45] | [1.33] | | | [2.22] | [2.57] | | | [0.56] | [0.34] | |
| Panel B: ES | RM | AR | 9FH–$\alpha$ | | RM | AR | 9FH–$\alpha$ | | RM | AR | 9FH–$\alpha$ | |
| High–Low | 7.15 | 0.39 | 0.29 | | 7.66 | 0.63 | 0.60 | | 7.24 | 0.16 | 0.06 | |
| | | [1.42] | [1.40] | | | [2.20] | [2.65] | | | [0.50] | [0.25] | |
| Panel C: CF VaR | RM | AR | 9FH–$\alpha$ | | RM | AR | 9FH–$\alpha$ | | RM | AR | 9FH–$\alpha$ | |
| High–Low | 6.38 | 0.41 | 0.32 | | 7.07 | 0.59 | 0.61 | | 6.52 | 0.15 | 0.07 | |
| | | [1.53] | [1.56] | | | [2.07] | [2.59] | | | [0.44] | [0.28] | |
| Panel D: SeD | RM | AR | 9FH–$\alpha$ | | RM | AR | 9FH–$\alpha$ | | RM | AR | 9FH–$\alpha$ | |
| High–Low | 3.12 | 0.54 | 0.41 | | 3.35 | 0.75 | 0.75 | | 3.04 | 0.34 | 0.18 | |
| | | [2.06] | [2.13] | | | [2.55] | [3.33] | | | [1.15] | [0.85] | |
| Panel E: TR | RM | AR | 9FH–$\alpha$ | | RM | AR | 9FH–$\alpha$ | | RM | AR | 9FH–$\alpha$ | |
| High–Low | 2.30 | 0.55 | 0.41 | | 2.42 | 0.72 | 0.72 | | 2.34 | 0.38 | 0.21 | |
| | | [2.03] | [2.08] | | | [2.51] | [3.18] | | | [1.23] | [0.95] | |

Notes: The table reports the risk–return relationship of the equally weighted decile portfolio of HFs for the out-of-sample period (Jan. 1999–Dec. 2014). Panel A reports the results for the VaR-sorted hedge funds for the group of all, alive, and defunct group of funds. For each group of funds, the columns present the risk measure (RM) for each decile portfolio, the monthly average returns (AR), and the nine-factor model alpha (9FH − $\alpha$) with the associated Newey-West t-stats (36 lags). Panels B to E report the differentials between the high- and low-risk portfolios for the expected shortfall (ES), Cornish Fischer value at risk (CFVaR), semi-deviation (SeD) and tail risk (TR), respectively. The reported measures were calculated over 203,276 return observations for the group of alive funds and 274,481 return observations for the group of defunct funds.

**Table 3**
Fund of Hedge Funds Decile Portfolios.

| Panel A: VaR | All Funds | | | | Alive Funds | | | | Defunct Funds | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | RM | AR | 9FH–$\alpha$ | t-stat | RM | AR | 9FH–$\alpha$ | t-stat | RM | AR | 9FH–$\alpha$ | t-stat |
| High | 4.79 | 0.39 | 0.04 | 0.28 | 4.26 | 0.56 | 0.22 | 2.61 | 5.19 | 0.28 | −0.03 | −0.19 |
| 9 | 3.29 | 0.49 | 0.14 | 1.82 | 3.07 | 0.55 | 0.25 | 5.17 | 3.21 | 0.39 | 0.03 | 0.33 |
| 8 | 2.69 | 0.48 | 0.18 | 3.30 | 2.44 | 0.57 | 0.24 | 7.37 | 3.02 | 0.45 | 0.13 | 1.64 |
| 7 | 2.49 | 0.48 | 0.19 | 4.39 | 2.52 | 0.58 | 0.28 | 5.41 | 2.40 | 0.38 | 0.10 | 1.67 |
| 6 | 2.50 | 0.52 | 0.23 | 3.12 | 2.40 | 0.62 | 0.32 | 6.03 | 2.26 | 0.45 | 0.17 | 2.05 |
| 5 | 2.07 | 0.48 | 0.21 | 2.84 | 2.05 | 0.60 | 0.29 | 4.60 | 2.08 | 0.38 | 0.13 | 1.54 |
| 4 | 1.85 | 0.45 | 0.18 | 3.71 | 1.91 | 0.53 | 0.28 | 6.15 | 1.61 | 0.40 | 0.14 | 2.27 |
| 3 | 1.75 | 0.49 | 0.23 | 2.72 | 1.66 | 0.53 | 0.26 | 3.93 | 1.83 | 0.43 | 0.18 | 1.90 |
| 2 | 1.38 | 0.44 | 0.22 | 3.68 | 1.18 | 0.51 | 0.29 | 6.43 | 1.49 | 0.40 | 0.19 | 2.74 |
| Low | 1.23 | 0.47 | 0.23 | 3.18 | 1.32 | 0.49 | 0.27 | 5.33 | 1.10 | 0.43 | 0.20 | 2.39 |
| High–Low | 3.56 | −0.09 | −0.19 | | 2.94 | 0.06 | −0.04 | | 4.09 | −0.15 | −0.23 | |
| | | [−0.46] | [−1.84] | | | [0.40] | [−0.63] | | | [−0.72] | [−1.85] | |
| Panel B: ES | RM | AR | 9FH–$\alpha$ | | RM | AR | 9FH–$\alpha$ | | RM | AR | 9FH–$\alpha$ | |
| High–Low | 4.35 | −0.05 | −0.17 | | 3.26 | 0.08 | −0.04 | | 4.72 | −0.09 | −0.21 | |
| | | [−0.24] | [−1.62] | | | [0.48] | [−0.62] | | | [−0.42] | [−1.76] | |
| Panel C: CF VaR | RM | AR | 9FH–$\alpha$ | | RM | AR | 9FH–$\alpha$ | | RM | AR | 9FH–$\alpha$ | |
| High–Low | 3.74 | −0.07 | −0.21 | | 2.59 | 0.05 | −0.06 | | 4.23 | −0.12 | −0.23 | |
| | | [−0.35] | [−2.02] | | | [0.30] | [−0.79] | | | [−0.57] | [−1.74] | |
| Panel D: SeD | RM | AR | 9FH–$\alpha$ | | RM | AR | 9FH–$\alpha$ | | RM | AR | 9FH–$\alpha$ | |
| High–Low | 1.12 | 0.14 | 0.02 | | 0.78 | 0.12 | 0.02 | | 1.25 | 0.06 | −0.05 | |
| | | [1.10] | [0.40] | | | [0.96] | [0.54] | | | [0.38] | [−0.52] | |
| Panel E: TR | RM | AR | 9FH–$\alpha$ | | RM | AR | 9FH–$\alpha$ | | RM | AR | 9FH–$\alpha$ | |
| High–Low | 0.83 | −0.13 | −0.02 | | 0.51 | 0.11 | 0.02 | | 0.96 | 0.05 | −0.05 | |
| | | [−0.92] | [−0.40] | | | [0.86] | [0.41] | | | [0.31] | [−0.58] | |

Notes: The table reports the risk–return relationship of the equally weighted decile portfolio of FoHFs for the out-of-sample period (Jan. 1999–Dec. 2014). Panel A reports the results for the VaR-sorted hedge funds for the group of All, alive and defunct funds. For each group of funds, the columns present the risk measure (RM) for each decile portfolio, the monthly average returns (AR), and the nine-factor model alpha (9FH − $\alpha$) with the associated t-stat in brackets. The last two rows of Panel A report the differential between the high- and low-risk portfolios for the RM, AR and 9FH–$\alpha$ alongside the associated Newey–West t-stats (36 lags). Panels B–E report the differentials between the high- and low-risk portfolios for the expected shortfall (ES), Cornish Fischer value at risk (CFVaR), semi-deviation (SeD) and tail risk (TR), respectively. The reported measures were calculated for 59,730 return observations for the group of alive funds and 115,466 return observations for the group of defunct funds.

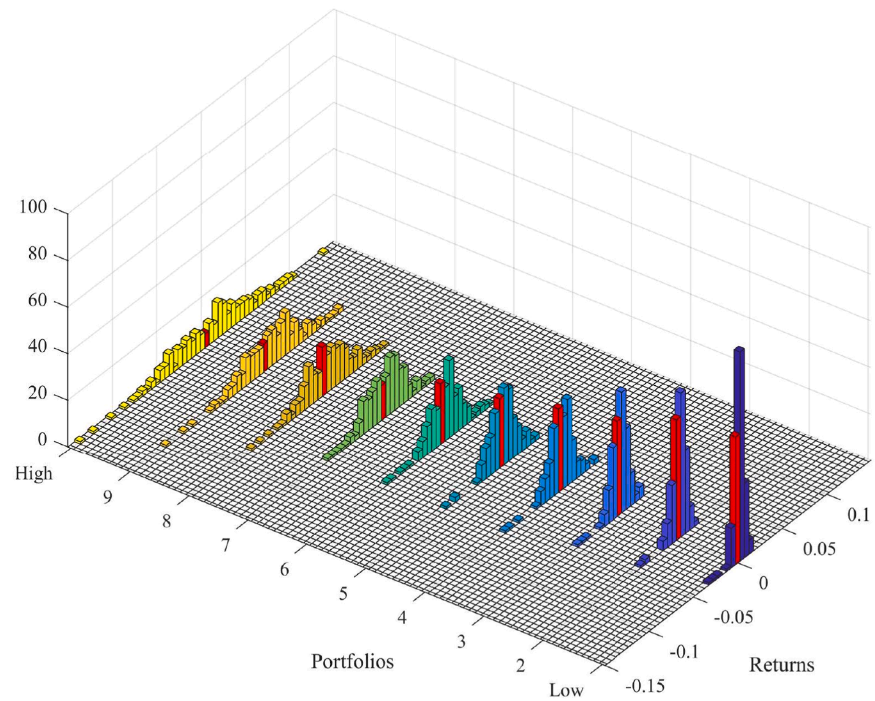


**Fig. 1.** Hedge Funds, VaR Decile Portfolio Return Distribution
Note: The figure reports the shape of the empirical distribution of returns for each hedge fund decile portfolio and the whole out-of-sample period. The red bar represents the zero-return bin for each portfolio (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

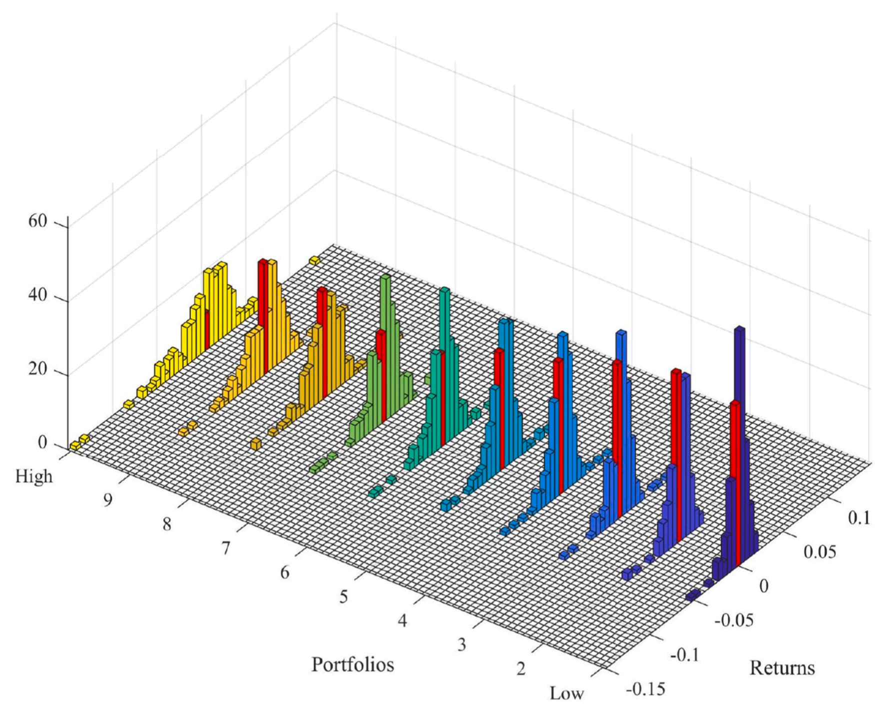


**Fig. 2.** Fund of Hedge Funds, VaR Decile Portfolio Return Distribution
Note: The figure reports the histogram of the out-of-sample returns of each funds of hedge funds decile portfolio. The red bar represents the zero-return bin for each portfolio (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

findings corroborate the analysis for FoHFs so far (Table 3) and point to a rather flat relationship between risk (Panels A–E) and future returns, regardless of the RM used. When all characteristics and financial factors are considered, the relationship remains insignificant.

We now examine the economic significance of the cross-sectional relationship between VaR and future returns using Fama–MacBeth regressions and portfolio-level analysis. Our portfolio sorts (Table 3) show that the VaR spread between deciles 10 and 1 for all funds is 5.84%, which, multiplied by the slope coefficients in the regressions between 0.0154 and 0.0328, yields estimated monthly premia ranging from 9.0

**Table 4**
Fama–McBeth Regressions.

| | Hedge Funds | | | Funds of Hedge Funds | | |
|---|---|---|---|---|---|---|
| | No Controls | Fund Controls | Fund and Financial Controls | No Controls | Fund Controls | Fund and Financial Controls |
| Panel A: VaR | | | | | | |
| Constant | 0.4438 | 2.262 | 1.6445 | 0.4969 | -1.146 | -0.2457 |
| | [5.3067] | [1.8998] | [2.2271] | [4.4437] | [-0.7817] | [-0.4338] |
| Risk Measure | 0.0328 | 0.0285 | 0.0154 | 0.0063 | -0.0082 | 0.0901 |
| | [2.1077] | [2.0862] | [1.4459] | [0.1856] | [-0.3229] | [0.7858] |
| Panel B: ES | | | | | | |
| Constant | 0.4243 | 2.1779 | 1.643 | 0.4918 | -0.4371 | -0.4451 |
| | [5.5726] | [1.8680] | [2.1339] | [4.8580] | [-0.4934] | [-0.6032] |
| Risk Measure | 0.0268 | 0.0252 | 0.0138 | 0.0045 | -0.0114 | 0.0422 |
| | [2.0616] | [2.3251] | [1.8467] | [0.1694] | [-0.5136] | [0.7358] |
| Panel C: CF VaR | | | | | | |
| Constant | 0.4227 | 2.1835 | 1.6294 | 0.4927 | -0.8764 | 0.2957 |
| | [5.0451] | [1.8494] | [2.1834] | [4.8157] | [-0.7284] | [0.7621] |
| Risk Measure | 0.0363 | 0.0342 | 0.0174 | 0.0051 | -0.0145 | -0.0157 |
| | [2.2194] | [2.3509] | [1.4955] | [0.1484] | [-0.4899] | [-0.4135] |
| Panel D: SeD | | | | | | |
| Constant | 0.3618 | 2.1644 | 1.5434 | 0.4051 | -0.8957 | 0.0797 |
| | [4.3230] | [1.8016] | [2.0131] | [3.5365] | [-0.8503] | [0.1834] |
| Risk Measure | 0.0984 | 0.0883 | 0.0659 | -0.0661 | 0.0037 | -0.0564 |
| | [2.7462] | [2.7577] | [3.3014] | [-1.2443] | [0.0443] | [-0.8726] |
| Panel E:TR | | | | | | |
| Constant | 0.3768 | 2.1356 | 1.5892 | 0.4178 | 1.2454 | 1.9144 |
| | [5.3164] | [1.8359] | [2.0301] | [3.6140] | [1.0702] | [1.2044] |
| Risk Measure | 0.1275 | 0.1174 | 0.0782 | -0.0745 | 0.092 | -0.1268 |
| | [2.5730] | [2.8358] | [3.3551] | [-1.0532] | [0.5490] | [-0.8306] |

Notes: The table reports the Fama and MacBeth (1973) regression results for hedge funds (HFs) and fund of HFs (FoHFs). The table presents three specifications for each group of funds. Columns (2), (5) include only the risk measure (RM) as an explanatory variable. Columns (3) and (6) include the RM, the previous period's return, and eight fund characteristics. Columns (4) and (7) include the RM, the complete risk factors, and fund characteristics. The table reports only the constant and RM coefficient and the associated Newey–West t-stats (36 lags) in brackets. Panel A reports the VaR-sorted HFs results, whereas Panels B–E report the results for the expected shortfall (ES), Cornish Fischer value at risk (CFVaR), semi-deviation (SeD) and tail risk (TR) RMs, respectively. Reported measures were calculated on 477,757 return observations for the group of HFs and 175,196 return observations for the group of FoHFs, conditional on reporting the additional measures included in the regression specification.

to 15.2 bps per month. Similar premia hold for the remaining RMs in HFs, whereas the risk premium in FoHFs is negligible, as suggested by the insignificant risk–return relationship.

### *3.3. Conditional bivariate portfolio analysis*

Our multivariate Fama and MacBeth (1973) regression results show that risk significantly impacts future returns for HFs, but the effect on FoHFs is relatively insignificant. We now determine whether the documented risk effect is due to other confounding risk factors. To this end, we perform dependent bivariate portfolio sorts based on the potential risk factors and RMs considered. In particular, we double-sort using the factor loadings from the Fung and Hsieh (2004) model (PTFSBD, PTFSFX, PTFSCOM, S&P, SCMLC, BD10RET, and BAAMTSY), the factor loadings from the Fama and French (2015) model (MKT, HML, SMB, RMW, and CMA), the loading on the Pastor and Stambaugh (2003) traded liquidity factor (LIQ), the loading on the Bali et al. (2014) macroeconomic risk index (MRI) and the loading on the Agarwal et al. (2017a) systematic tail risk factor (STRF). We also double sort on managerial skill as proxied by the $R^2$ from the nine-factor Fung Hsieh model. First, we form quintile portfolios based on risk factor loadings, and then within each risk factor quintile, we sort funds into five portfolios based on RMs. To facilitate the exposition, we only report the spread portfolio's return (Q5 − Q1) and the associated 9FH–$\alpha$ differentials.

Table 5 reports the findings for HFs (Panels A1–A5) and FoHF (Panels B1–B5). The double-sorted portfolio results suggest that funds' risk factor loadings cannot explain the positive relationship between risk and return. In general, for the HFs, we observe that for VaR portfolios (Panel A1), the monthly AR difference (Q5 − Q1) ranges from 0.02% (PTFSCOM) to 0.38% (9FH–$\alpha$) and in some cases, this positive return difference is statistically significant at the 5 % level. For example, controlling for the credit spread risk factor (BAAMTSY), HFs in the highest VaR quintile generate a higher monthly return of 0.29 % compared with the lower risk decile, or approximately 3.5 % per annum. This shows that the risk-adjusted return spread between high-risk and low-risk funds is still positive. More importantly, the risk-adjusted (9FH − $\alpha$) return difference between quintiles 5 and 1 ranges from 0.09 % to 0.48 %, with most cases being statistically significant. For example, when conditioning on $R^2$, we find a high economically and statistically significant spread between the high and low VaR quantiles of 0.38% per month (4.56% per annum), along with a risk-adjusted return difference of 0.48 % per month (5.76% per annum). Focusing on alternative RMs (Panels A2–A5), our findings are qualitatively similar and reinforce the impact of downside risk on future returns when a variety of factors are considered.

We observe a starkly different picture with regard to FoHFs, which is consistent with our previous results. When risk factors and managerial ability are considered, our double-sorted FoHF portfolios (Table 5, Panels B1–B5) do not produce a significant return spread between high- and low-risk portfolios. The respective spreads are very close to zero (less than 10 bps), and in most cases they are negative. In terms of 9FH–$\alpha$ differentials (risk-adjusted returns), we observe only a few cases of mixed positive and negative alpha spreads. For example, conditioning on the size factor and VaR, the 9FH–$\alpha$ spread between the high- and low-risk portfolios is −0.17, which is statistically significant. When we factor in credit market risk and the semi-deviation, we find a 15-bps positive and significant risk-adjusted return differential.

To summarize, this set of findings shows that including a plethora of risk factors does not affect the positive and statistically significant impact of downside risk in HF returns, whereas the relationship for FoHFs is rather muted.

**Table 5**
Bivariate Sorts.

| Panel A: Hedge Funds | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Size | S&P | PTFSBD | PTFSFX | PTFSCOM | SCMLC | BD10RET | BAAMTSY | HML | UMD | CMA | RMW | LIQ | MRI | STRF | $9FH - R^2$ |
| Panel A1: VaR | | | | | | | | | | | | | | | | |
| Q5− Q1 | 0.32 | 0.13 | 0.23 | 0.16 | 0.02 | 0.13 | 0.25 | 0.29 | 0.25 | 0.13 | 0.23 | 0.11 | 0.21 | 0.12 | 0.26 | 0.38 |
| t-stat | [1.78] | [1.06] | [1.31] | [0.89] | [0.12] | [0.90] | [1.43] | [1.84] | [1.42] | [0.89] | [1.80] | [0.73] | [1.76] | [0.75] | [1.53] | [2.14] |
| FH 9-Factor | 0.23 | 0.21 | 0.35 | 0.26 | 0.09 | 0.18 | 0.31 | 0.37 | 0.36 | 0.21 | 0.36 | 0.19 | 0.26 | 0.29 | 0.38 | 0.48 |
| t-stat | [1.62] | [1.89] | [2.15] | [2.08] | [0.70] | [2.26] | [2.60] | [3.15] | [3.59] | [1.85] | [5.09] | [1.58] | [3.98] | [2.34] | [4.60] | [5.52] |
| Panel A2: ES | | | | | | | | | | | | | | | | |
| Q5 − Q1 | 0.35 | 0.14 | 0.23 | 0.19 | 0.03 | 0.11 | 0.26 | 0.31 | 0.27 | 0.15 | 0.21 | 0.10 | 0.21 | 0.14 | 0.26 | 0.36 |
| t-stat | [1.77] | [1.01] | [1.27] | [0.98] | [0.19] | [0.72] | [1.44] | [1.83] | [1.52] | [0.82] | [1.38] | [0.67] | [1.71] | [0.85] | [1.43] | [1.97] |
| FH 9-Factor | 0.24 | 0.23 | 0.35 | 0.29 | 0.06 | 0.15 | 0.33 | 0.37 | 0.36 | 0.22 | 0.34 | 0.18 | 0.28 | 0.29 | 0.39 | 0.46 |
| t-stat | [1.67] | [1.97] | [2.05] | [2.04] | [0.38] | [1.60] | [2.87] | [3.08] | [4.02] | [1.47] | [3.13] | [1.39] | [4.15] | [2.40] | [3.64] | [4.46] |
| Panel A3: CF VaR | | | | | | | | | | | | | | | | |
| Q5 − Q1 | 0.31 | 0.14 | 0.23 | 0.28 | 0.04 | 0.10 | 0.24 | 0.27 | 0.24 | 0.13 | 0.20 | 0.07 | 0.18 | 0.12 | 0.24 | 0.34 |
| t-stat | [1.61] | [1.00] | [1.22] | [1.42] | [0.24] | [0.70] | [1.26] | [1.60] | [1.40] | [0.74] | [1.47] | [0.48] | [1.39] | [0.70] | [1.37] | [1.87] |
| FH 9-Factor | 0.22 | 0.20 | 0.34 | 0.38 | 0.04 | 0.13 | 0.29 | 0.33 | 0.33 | 0.18 | 0.32 | 0.14 | 0.22 | 0.25 | 0.36 | 0.44 |
| t-stat | [1.53] | [1.64] | [1.93] | [2.38] | [0.26] | [1.38] | [2.29] | [2.61] | [3.50] | [1.39] | [3.46] | [1.06] | [3.38] | [2.04] | [3.81] | [4.17] |
| Panel A4: SeD | | | | | | | | | | | | | | | | |
| Q5 − Q1 | 0.40 | 0.30 | 0.34 | 0.29 | 0.11 | 0.27 | 0.39 | 0.41 | 0.38 | 0.29 | 0.36 | 0.25 | 0.31 | 0.23 | 0.40 | 0.48 |
| t-stat | [2.18] | [2.38] | [1.93] | [1.49] | [0.69] | [2.12] | [2.14] | [2.55] | [2.34] | [1.83] | [2.85] | [1.65] | [2.68] | [1.36] | [2.41] | [2.68] |
| FH 9-Factor | 0.29 | 0.37 | 0.44 | 0.39 | 0.18 | 0.30 | 0.46 | 0.46 | 0.47 | 0.35 | 0.49 | 0.32 | 0.35 | 0.40 | 0.52 | 0.58 |
| t-stat | [2.04] | [2.80] | [2.63] | [2.58] | [1.26] | [4.04] | [3.24] | [3.64] | [4.84] | [2.77] | [6.73] | [2.37] | [4.76] | [2.79] | [5.81] | [5.76] |
| Panel A5: TR | | | | | | | | | | | | | | | | |
| Q5 − Q1 | 0.43 | 0.27 | 0.32 | 0.11 | 0.06 | 0.23 | 0.37 | 0.41 | 0.37 | 0.27 | 0.31 | 0.21 | 0.31 | 0.23 | 0.36 | 0.45 |
| t-stat | [2.15] | [2.14] | [1.86] | [0.69] | [0.39] | [1.77] | [2.13] | [2.64] | [2.21] | [1.52] | [2.14] | [1.41] | [2.95] | [1.35] | [2.19] | [2.47] |
| FH 9-Factor | 0.30 | 0.35 | 0.43 | 0.18 | 0.13 | 0.27 | 0.42 | 0.47 | 0.46 | 0.33 | 0.44 | 0.29 | 0.36 | 0.37 | 0.49 | 0.56 |
| t-stat | [2.10] | [2.98] | [2.65] | [1.26] | [0.86] | [3.36] | [3.51] | [3.83] | [5.32] | [2.27] | [4.23] | [2.22] | [6.08] | [2.97] | [5.39] | [5.21] |
| Panel B: Funds of Hedge Funds | | | | | | | | | | | | | | | | |
| | Size | S&P | PTFSBD | PTFSFX | PTFSCOM | SCMLC | BD10RET | BAAMTSY | HML | UMD | CMA | RMW | LIQ | MRI | STRF | $9FH - R^2$ |
| Panel B1: VaR | | | | | | | | | | | | | | | | |
| Q5− Q1 | -0.06 | -0.08 | -0.05 | -0.07 | -0.16 | -0.14 | -0.05 | -0.02 | -0.01 | -0.06 | 0.02 | -0.11 | -0.06 | -0.08 | -0.03 | -0.03 |
| t-stat | [-0.42] | [-1.11] | [-0.53] | [-0.58] | [-1.29] | [-1.45] | [-0.45] | [-0.28] | [-0.06] | [-0.48] | [0.16] | [-1.11] | [-0.73] | [-0.61] | [-0.30] | [-0.22] |
| FH 9-Factor | -0.17 | 0.00 | 0.02 | 0.00 | -0.13 | -0.11 | 0.01 | 0.03 | 0.05 | -0.02 | 0.08 | -0.04 | -0.01 | 0.01 | 0.02 | 0.03 |
| t-stat | [-2.57] | [0.02] | [0.20] | [0.00] | [-1.19] | [-1.79] | [0.14] | [0.50] | [0.87] | [-0.15] | [1.03] | [-0.47] | [-0.14] | [0.07] | [0.29] | [0.33] |
| Panel B2: ES | | | | | | | | | | | | | | | | |
| Q5 − Q1 | -0.04 | -0.07 | -0.06 | -0.03 | -0.14 | -0.15 | -0.04 | -0.01 | -0.01 | -0.06 | 0.01 | -0.12 | -0.04 | -0.12 | -0.05 | -0.02 |
| t-stat | [-0.27] | [-1.04] | [-0.63] | [-0.20] | [-1.22] | [-1.63] | [-0.33] | [-0.11] | [-0.13] | [-0.44] | [-0.07] | [-1.22] | [-0.47] | [-0.86] | [0.47] | [0.16] |
| FH 9-Factor | -0.14 | -0.02 | 0.00 | 0.02 | -0.12 | -0.12 | 0.00 | 0.03 | 0.04 | -0.02 | 0.07 | -0.07 | 0.01 | -0.04 | 0.01 | 0.02 |
| t-stat | [-2.52] | [-0.27] | [0.03] | [0.19] | [-1.19] | [-1.86] | [0.00] | [0.44] | [0.52] | [-0.16] | [0.77] | [-0.73] | [0.18] | [-0.32] | [0.07] | [0.18] |
| Panel B3: CF VaR | | | | | | | | | | | | | | | | |
| Q5 − Q1 | -0.06 | -0.11 | -0.06 | -0.07 | -0.16 | -0.19 | -0.05 | -0.02 | -0.03 | -0.08 | -0.02 | -0.16 | -0.07 | -0.13 | -0.06 | -0.02 |
| t-stat | [-0.42] | [-1.46] | [-0.58] | [-0.51] | [-1.31] | [-2.05] | [-0.40] | [-0.20] | [-0.33] | [-0.57] | [-0.18] | [1.55] | [-0.76] | [-1.03] | [-0.55] | [-0.15] |
| FH 9-Factor | -0.16 | -0.04 | -0.01 | -0.01 | -0.14 | -0.16 | -0.01 | 0.02 | 0.02 | -0.04 | 0.04 | -0.09 | -0.03 | -0.04 | 0.00 | 0.01 |
| t-stat | [-2.68] | [-0.55] | [-0.12] | [-0.14] | [-1.20] | [-2.28] | [-0.13] | [0.30] | [0.25] | [-0.31] | [0.43] | [-0.96] | [-0.33] | [-0.40] | [-0.01] | [0.11] |
| Panel B4: SeD | | | | | | | | | | | | | | | | |
| Q5 − Q1 | 0.10 | 0.04 | 0.07 | 0.06 | -0.04 | -0.03 | 0.05 | 0.12 | 0.09 | 0.04 | 0.12 | 0.02 | 0.07 | -0.01 | 0.08 | 0.08 |
| t-stat | [0.72] | [0.60] | [0.67] | [0.43] | [-0.37] | [-0.37] | [0.42] | [1.32] | [0.93] | [0.30] | [1.28] | [0.25] | [0.95] | [-0.05] | [0.76] | [0.60] |
| FH 9-Factor | -0.01 | 0.10 | 0.11 | 0.09 | -0.03 | -0.01 | 0.08 | 0.15 | 0.13 | 0.08 | 0.17 | 0.06 | 0.11 | 0.08 | 0.12 | 0.1 |
| t-stat | [-0.21] | [1.61] | [1.28] | [0.96] | [-0.34] | [-0.12] | [0.90] | [2.06] | [1.88] | [0.75] | [2.17] | [0.79] | [1.85] | [0.78] | [1.64] | [1.10] |
| Panel B5: TR | | | | | | | | | | | | | | | | |
| Q5 − Q1 | 0.09 | 0.00 | 0.04 | 0.05 | -0.07 | -0.06 | 0.04 | 0.08 | 0.05 | 0.04 | 0.09 | -0.05 | 0.04 | -0.05 | 0.04 | 0.05 |
| t-stat | [0.69] | [0.05] | [0.39] | [0.44] | [-0.64] | [-0.70] | [0.42] | [1.00] | [0.58] | [0.30] | [0.84] | [-0.51] | [0.45] | [-0.37] | [0.42] | [0.36] |
| FH 9-Factor | -0.01 | 0.06 | 0.09 | 0.09 | -0.06 | -0.04 | 0.07 | 0.11 | 0.10 | 0.07 | 0.15 | 0.00 | 0.07 | 0.04 | 0.09 | 0.07 |
| t-stat | [-0.19] | [0.98] | [1.03] | [0.97] | [-0.64] | [-0.68] | [0.88] | [1.49] | [1.32] | [0.63] | [1.65] | [0.00] | [0.97] | [0.31] | [1.15] | [0.70] |

Notes: The table reports the bivariate portfolio sorts of hedge funds (HFs) and funds of HFs (F0HFs). Panel A reports the results for the hedge funds, while Panel B reports the results for the funds of hedge funds. We first form quintile portfolios using the factor loadings from the Fung and Hsieh (2004) model (PTFSBD, PTFSFX, PTFSCOM, S &P, SCMLC, BD10RET, BAAMTSY), the factor loadings from the Fama and French (2015) model (MKT, HML, SMB, RMW, and CMA), the loading on the Pastor and Stambaugh (2003) traded liquidity factor (LIQ), the loading on the Bali et al. (2014) macroeconomic risk index (MRI), the loading on the (Agarwal et al., 2017a) systematic tail risk factor (STRF) and on managerial skill as proxied by the $R^2$ from the nine-factor Fung Hsieh model. Within each quintile portfolio, we form quintile portfolios based on the risk measures (RMs). Subpanels report the spread between the high- and low-risk portfolios, its alpha and the associated Newey–West t-stats (36 lags) in brackets for all the alternative RMs. Reported measures are calculated over 477,757 return observations for the hedge funds and 175,196 return observations for the FoHFs.

### 3.4. Subsample analysis

We follow Cao et al. (2015) and use the S&P500 price index to identify up and down equity market regimes to assess the risk–return relationship of funds in good and bad financial periods. These regimes correspond to the index's 200-day moving average, which defines good and bad market conditions. Specifically, at each point in our data sample (monthly), we check whether the S&P 500 price index (on the last trading day of the month) is above (below) its 200-day moving average. If the end-of-month value is greater than or equal to (less than) the moving average, the following month is considered an up (down) equity market. After classifying the market regimes, we recalculate the risk decile portfolios' performance in the respective periods.

Table 6 shows the decile portfolio results for both the "Up" and "Down" market regimes. For HFs (Table 6, Panel A), we find that all decile portfolios report VaR that corresponds to gains during up days with a positive spread of 4.59 % between high- and low-risk portfolios. The return differential is 0.55% and statistically significant (at 10 %). This result is to be expected, as high-risk HFs benefit the most from good market conditions, as their risk-taking yields gains. We find similar results for all downside RMs (Table 6, Panels B–E). For example, the return spread based on SeD and TR is highly significant at 0.82% and 0.84%, respectively. During down days, the risk of HFs increases, with an estimated VaR ranging from 0.44 % (low-risk portfolio) to 10.96 % (high-risk portfolio), with a significant spread (between high- and low-risk portfolios) of 10.52%. However, the increased risk does not translate into a higher AR during the down days. In contrast, the decile portfolios' returns follow a roughly U-shaped pattern as risk increases, with an insignificant associated spread of − 0.02%. Similar findings apply to the remaining RMs, with return spreads ranging from −0.07% (SeD) to −0.12% (ES). Overall, we find that risk is compensated during good financial conditions, but excess risk does not result in excess returns during market downturns.

In terms of FoHFs (Table 6, columns (5)–(8)), we find that on good days, the spreads between the ARs of the high- and low-risk portfolios are positive and significant. In the case of VaR, the respective average return spread of 0.28 %; similar values apply to the remaining RMs. In all cases, FoHFs yield lower returns and spreads than HFs. During market downturns (down days), we observe a significant risk spread of 5.22% between the high- and low-risk FoHF portfolios and a negative and significant return spread of −0.89% for the VaR case. In more detail, as we move from the highest risk portfolio to the lowest one, AR increases from −0.74% to 0.16%. Similar results pertain with respect to the remaining RMs (Table 6, Panels B–E), indicating a negative relationship between risk and return.

When we compare FoHFs with HFs, we observe that during good times, high-risk HFs outperform high-risk FoHFs (1.20 % vs. 0.90 % for the VaR case), whereas low-risk FoHFs provide similar ARs to the respective HFs' portfolio (0.65 % vs. 0.62 % for the VaR case). However, during bad times, roughly half of the FoHF decile portfolios record losses, with the remaining ones recording returns close to zero up to a maximum of 0.16% for the low-risk funds. In the HF case, all decile portfolios produce positive returns. Finally, in line with the diversification effect, risk spreads for FoHFs are lower than for HFs in both good and bad times.

## 4. Realistic portfolios

This section assesses whether our findings for the cross section of HF returns translate into economic gains for institutional investors comparable with direct investments in FoHFs. We construct an array of HF portfolios and calculate their performance metrics, which we then compare with the distribution of FoHF performance metrics found in our database. To account for the FoHFs' diversification effect, we create portfolios of up to 30 HFs. Furthermore, we follow Joenvaara et al. (2019) and impose restrictions on the pool of available HFs to account for realistic investor constraints. In more detail, we assume a 12-month holding period, 365-day lockup and redemption period, and 30-day notice period. Finally, we impose a size constraint by restricting the assets under management (AUM) placed at each fund to 10% of the

**Table 6**
S&P 500 Up and Down Days.

| | HFs | | | | FoHFs | | | |
|---|---|---|---|---|---|---|---|---|
| | Up Days | | Down Days | | Up Days | | Down Days | |
| Panel A: VaR | RM | AR | RM | AR | RM | AR | RM | AR |
| High | 4.68 | 1.20 | 10.96 | 0.40 | 3.86 | 0.90 | 6.82 | −0.74 |
| 9 | 3.03 | 1.20 | 5.91 | 0.41 | 2.67 | 0.90 | 4.25 | −0.41 |
| 8 | 2.60 | 0.99 | 4.65 | 0.31 | 1.85 | 0.81 | 3.30 | −0.23 |
| 7 | 2.35 | 0.81 | 3.50 | 0.26 | 1.78 | 0.78 | 2.96 | −0.16 |
| 6 | 1.61 | 0.87 | 2.89 | 0.36 | 1.66 | 0.75 | 2.88 | 0.03 |
| 5 | 1.40 | 0.70 | 1.85 | 0.28 | 1.31 | 0.70 | 2.80 | −0.02 |
| 4 | 1.16 | 0.67 | 1.86 | 0.15 | 1.18 | 0.65 | 2.52 | 0.01 |
| 3 | 0.76 | 0.59 | 1.35 | 0.27 | 1.02 | 0.69 | 2.18 | 0.06 |
| 2 | 0.54 | 0.55 | 1.34 | 0.29 | 0.95 | 0.63 | 1.93 | 0.04 |
| Low | 0.09 | 0.65 | 0.44 | 0.42 | 0.76 | 0.62 | 1.59 | 0.16 |
| High–Low | 4.59 | 0.55 | 10.52 | −0.02 | 3.10 | 0.28 | 5.22 | −0.89 |
| t-stat | | 1.69 | | −0.05 | | 2.00 | | −4.10 |
| Panel B: ES | RM | AR | RM | AR | RM | AR | RM | AR |
| High–Low | 5.46 | 0.62 | 9.99 | −0.12 | 2.99 | 0.34 | 6.16 | −0.89 |
| t-stat | | 1.75 | | −0.33 | | 2.35 | | −3.94 |
| Panel C: CF VaR | RM | AR | RM | AR | RM | AR | RM | AR |
| High–Low | 4.71 | 0.63 | 9.05 | −0.07 | 2.06 | 0.30 | 5.93 | −0.86 |
| t-stat | | 1.81 | | −0.20 | | 1.95 | | −3.73 |
| Panel D: SeD | RM | AR | RM | AR | RM | AR | RM | AR |
| High–Low | 2.62 | 0.82 | 3.88 | −0.07 | 0.96 | 0.42 | 1.28 | −0.47 |
| t-stat | | 2.36 | | −0.22 | | 3.03 | | −2.93 |
| Panel E: TR | RM | AR | RM | AR | RM | AR | RM | AR |
| High–Low | 1.69 | 0.84 | 3.03 | −0.10 | 0.66 | 0.40 | 1.04 | −0.48 |
| t-stat | | 2.37 | | −0.29 | | 3.01 | | −2.84 |

Notes: The table reports the subsample (up and down days) analysis results for hedge funds (HFs) and funds of HFs (FoHFs). RM denotes the risk measure, and AR denotes the average returns. The last two rows for each panel report the RM and return differential between the high- and low-risk portfolios and the associated Newey–West t-stats (36 lags) for the average return differential.

fund's AUM. As a starting point, we assume three initial investment sizes: 100 million, 500 million, and 1 billion, for which we calculate the portfolios described above. We use the BarclayHedge FoHF index to approximate the growth of the invested AUM.

To select individual HFs, at each rebalancing point *t* in the out-of-sample period, we rank HFs based on their past returns and estimated FH nine-factor alpha, SR and modified SR (MSR).[7] We create an equally weighted portfolio of the top 30 performers for each ranking approach to simulate investors who only consider past performance. In addition to the equally weighted SR and MSR cases, we create two additional portfolios by selecting between 20 and 30 funds and assigning optimal weights to maximize the SR and MSR. In this way, we attempt to further filter the risk information embedded in the HFs' past performance.

Table 7 reports the performance of the realistic portfolios over the out-of-sample period. Panel A presents the results for the small initial investment of $100 million. Among the realistic portfolios, we find that optimal-weighted portfolios offer better risk-adjusted performance as they have a significantly reduced risk profile compared to the equally weighted ones. The latter group of realistic portfolios offers superior average returns in only the top 30 returns and top 30 alpha portfolios. As expected, the top 30 SR and top 30 MSR portfolios have significantly lower risk levels, resulting in superior risk-adjusted performance compared with the equally weighted top 30 returns and top 30 alpha portfolios. However, they do not perform as well as their optimally weighted counterparts, which offer similar AR, but with significantly lower risk. For example, we observe that the optimal SR and MSR portfolios 1% VaR are three times and ten times lower than the lowest equally weighted portfolios 1 % VaR (top 30SR1%VaR), respectively. Between the optimal portfolios, the SR portfolio outperforms the MSR portfolio, providing significantly lower risk levels with marginally higher returns and alpha.

Panel B reports the realistic portfolio results for a medium initial investment of 500 million. Compared with the small-size portfolio, the recorded performance has diminished slightly in all reported measures. Due to size constraints, we find that the top 30 SR and top 30 MSR portfolios offer approximately 5 bps lower AR than their smaller initial investment counterparts, while the top 30 returns and top 30 alpha portfolios AR is approximately 27 bps lower. As expected, the optimal portfolios outperform the equally weighted portfolios in almost every category except AR. Compared with their small initial investment counterparts mentioned above, we find a significantly increased 1 % VaR and slightly lower risk-adjusted performance. Interestingly, we find that the optimal MSR portfolio outperforms the optimal SR portfolio in terms of risk-adjusted performance in all but the SR measure. The optimal MSR portfolio has higher risk levels than the optimal SR portfolio.

Finally, for the large initial investment (Table 7, Panel C), we find a minor deterioration in the performance of realistic portfolios. Similar to the results of Joenvaara et al. (2019), the size effect further reduces performance, as evidenced by the lower returns and alpha. Such effects are more pronounced in the top 30 Alpha portfolio, which experiences a roughly 28-bps decrease in both AR and alpha when compared with the previous initial investment case. On the other hand, only the SR and MSR selected portfolios show a significant increase in risk. The difference in ARs between equally weighted and optimal SR and MSR portfolios has decreased. However, the latter group still offers better risk-adjusted performance due to lower risk levels. Finally, we find that the optimal MSR portfolio outperforms the rest across all risk-adjusted performance metrics.

Table 8 reports an approximation of the unconditional empirical distribution of FoHF performance measures. Specifically, for each FoHF in the out-of-sample period, we compute each reported measure. The decile values are then calculated for each measure individually and used to rank the performance of realistic portfolios compared with FoHFs in our sample. Focusing on the realistic cases of small initial investment portfolios (Table 7, Panel A), we find that, except for ARs and alpha measures, the optimal SR and MSR portfolios rank within the top 10 % of FoHF performers for the remaining measures. Furthermore, the equally weighted realistic portfolios consistently the median in almost all the risk-adjusted performance measures, with mixed results for the VaR metrics. For the medium initial investment case (Table 7, Panel B), we find that MSR ranks within the top 10% FoHFs found in the database in all but the maximum drawdown measure, where it ranks within the 20% top performers. The optimal SR portfolio follows closely, but drops below the 10% top performers for the maximum drawdown and upside potential measure. The performance of the equally weighted cases is similar to the previous case, as they rank nearly above the median FoHF performers on all risk-adjusted performance measures. Finally, for large initial investments (Table 7, Panel C), we find that the optimally weighted MSR portfolio ranks in the top 10% performers in terms of risk-adjusted performance and risk.

To summarize, we can construct portfolios of HFs that rank among the best FoHF performers by applying simple selection and optimization methods. Furthermore, while simple equally weighted portfolios can produce significant results for smaller investors, optimizing the risk–return and downside risk–return relationship is robust to investor size. The performance differences between the optimal SR and MSR point to the former for the low initial investment case and to the latter for the remaining cases. As a result, institutional investors of any size, subject to typical investor constraints, can construct optimal risk–return portfolios of HFs that will rank among the top-performing FoHFs.

## 5. Conclusions

This paper examines and compares the risk–return profiles of HFs and FoHFs. Information on the formulation of HF portfolios is limited, but the literature suggests that FoHFs add value to a potential investor. Furthermore, evidence shows that HF investors regard past performance as one of the most important predictors of future performance.

We constructed decile portfolios of both HFs and FoHFs using a variety of downside RMs and compared their risk–return profiles. Our findings indicate a significant spread of 0.37% to 0.55% per month between the ARs of high- and low-risk (downside) HF portfolios, depending on the RM. This spread decreases but remains significant, even after accounting for additional sources of risk. By contrast, the risk–return relationship for FoHFs is insignificant. Furthermore, our conditional bivariate portfolio results and Fama and MacBeth (1973) regressions support these findings. To determine whether the above results are influenced by specific periods of good performance, we identify up and down equity market regimes and recalculate the decile portfolio performance for each case. Our results suggest that in both up- and down-cycle regimes, HFs maintain a relatively positive risk–return relationship. However, FoHFs maintain such a relationship only during the up regime, revealing a significant negative risk–return relationship during the down regime.

Finally, we construct realistic HF portfolios to determine whether direct investments in HFs can outperform indirect investments through FoHFs. In terms of risk-adjusted returns, we find that our optimally weighted HF portfolio ranks among the top 10% performers of FoHFs.

## CRediT authorship contribution statement

**Christos Argyropoulos:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software,

[7] The modified Sharpe ratio (MSR) is the fund's expected excess returns over the empirical 5% value at risk (VaR). We use this measure in conjunction with the traditional SR to account for the fact that VaR is a more reliable RM for HFs than the traditional standard deviation. Bali et al. (2007) and Liang and Park (2010) provide a more in-depth discussion of the suitability of SD and downside RMs for HF returns.

**Table 7**
Realistic Portfolios.

| Panel A: Hedge Funds 100 Million | AR | Alpha | SR | Sortino | Upside | MDD | SD | 1 % VaR | 5 %VaR | 10 %VaR |
|---|---|---|---|---|---|---|---|---|---|---|
| Top 30 SR | 0.561 | 0.381 | 0.401 | 0.649 | 1.161 | 8.717 | 0.984 | 3.858 | 0.864 | 0.255 |
| Top 30 MSR | 0.472 | 0.297 | 0.281 | 0.418 | 0.91 | 10.249 | 1.088 | 4.519 | 1.183 | 0.481 |
| Top 30 Alpha | 0.809 | 0.442 | 0.196 | 0.355 | 0.951 | 19.102 | 3.275 | 7.033 | 4.326 | 2.871 |
| Previous “Month” Top 30 Return | 1.082 | 0.315 | 0.168 | 0.283 | 0.82 | 35.694 | 5.447 | 11.988 | 8.606 | 5.438 |
| Optimal SR | 0.523 | 0.358 | 1.061 | 2.652 | 4.015 | 3.151 | 0.335 | 0.396 | −0.014 | −0.144 |
| Optimal MSR | 0.535 | 0.366 | 0.640 | 1.753 | 2.814 | 4.027 | 0.576 | 0.978 | 0.391 | 0.161 |
| **Panel B: Hedge Funds 500 Million** | **AR** | **Alpha** | **SR** | **Sortino** | **Upside** | **MDD** | **SD** | **1 % VaR** | **5 %VaR** | **10 %VaR** |
| Top 30 SR | 0.516 | 0.314 | 0.279 | 0.387 | 0.810 | 11.990 | 1.253 | 5.388 | 1.159 | 0.454 |
| Top 30 MSR | 0.491 | 0.301 | 0.274 | 0.413 | 0.891 | 10.814 | 1.182 | 4.805 | 1.246 | 0.449 |
| Top 30 Alpha | 0.541 | 0.140 | 0.112 | 0.175 | 0.730 | 21.700 | 3.333 | 8.445 | 4.922 | 3.351 |
| Previous “Month” Top 30 Return | 0.811 | 0.164 | 0.131 | 0.218 | 0.771 | 35.745 | 4.904 | 10.84 | 7.668 | 5.538 |
| Optimal SR | 0.478 | 0.291 | 0.531 | 0.718 | 1.220 | 7.127 | 0.586 | 1.232 | 0.034 | −0.063 |
| Optimal MSR | 0.489 | 0.309 | 0.466 | 0.913 | 1.665 | 5.840 | 0.692 | 1.373 | 0.597 | 0.267 |
| **Panel C: Hedge Funds 1 Billion** | **AR** | **Alpha** | **SR** | **Sortino** | **Upside** | **MDD** | **SD** | **1 % VaR** | **5 %VaR** | **10 %VaR** |
| Top30 SR | 0.450 | 0.231 | 0.194 | 0.240 | 0.602 | 15.312 | 1.458 | 6.601 | 1.150 | 0.606 |
| Top 30 MSR | 0.430 | 0.221 | 0.195 | 0.27 | 0.722 | 12.935 | 1.355 | 5.646 | 1.691 | 0.774 |
| Top 30 Alpha | 0.287 | −0.141 | 0.037 | 0.053 | 0.586 | 22.913 | 3.213 | 9.505 | 4.989 | 3.523 |
| Previous “Month” Top 30 Return | 0.805 | 0.194 | 0.149 | 0.250 | 0.811 | 26.952 | 4.273 | 9.605 | 6.489 | 4.840 |
| Optimal SR | 0.457 | 0.275 | 0.445 | 0.575 | 1.039 | 7.873 | 0.653 | 1.410 | 0.267 | −0.064 |
| Optimal MSR | 0.476 | 0.294 | 0.465 | 0.876 | 1.609 | 5.191 | 0.666 | 1.910 | 0.510 | 0.196 |

Notes: The table reports performance measures for realistic portfolios during the out-of-sample period. The columns present the monthly average returns (AR), the Fung and Hsieh (2004) alpha, Sharpe ratio (SR), Sortino ratio, upside potential, maximum drawdown (MDD), standard deviation (SD), and the historical simulation 10 %, 5 %, and 1 %VaR.

**Table 8**
FoHFs Out-of-Sample Performance Distribution.

| Decile | AR | Alpha | SR | Sortino | Upside | MDD | SD | 1 % VaR | 5 % VaR | 10 % VaR |
|---|---|---|---|---|---|---|---|---|---|---|
| Q10 | 0.04 | −0.31 | −0.06 | −0.14 | 0.44 | 5.59 | 1.05 | 2.45 | 1.25 | 0.65 |
| Q20 | 0.19 | −0.11 | 0.01 | −0.05 | 0.54 | 7.47 | 1.29 | 3.41 | 1.63 | 0.96 |
| Q30 | 0.28 | −0.01 | 0.06 | 0.01 | 0.60 | 8.83 | 1.47 | 4.25 | 2.00 | 1.19 |
| Q40 | 0.35 | 0.07 | 0.10 | 0.06 | 0.68 | 9.87 | 1.65 | 5.07 | 2.36 | 1.40 |
| Q50 | 0.42 | 0.15 | 0.13 | 0.13 | 0.73 | 11.17 | 1.83 | 5.90 | 2.69 | 1.66 |
| Q60 | 0.48 | 0.21 | 0.17 | 0.19 | 0.81 | 12.49 | 2.01 | 6.65 | 3.03 | 1.92 |
| Q70 | 0.55 | 0.29 | 0.22 | 0.28 | 0.92 | 14.16 | 2.28 | 7.61 | 3.54 | 2.24 |
| Q80 | 0.63 | 0.39 | 0.28 | 0.39 | 1.09 | 17.06 | 2.68 | 8.88 | 4.26 | 2.75 |
| Q90 | 0.78 | 0.55 | 0.40 | 0.65 | 1.51 | 21.77 | 3.49 | 11.28 | 5.50 | 3.64 |

Notes: The table approximates the unconditional empirical distribution for each fund of hedge funds (FoHF) performance measure over the out-of-sample period. The columns present the monthly average returns (AR), the Fung and Hsieh (2004) alpha, Sharpe ratio (SR), Sortino ratio, upside potential, maximum draw down (MDD), standard deviation (SD), and the historical simulation 10 %, 5 %, 1 % VaR. Each row reports the quantile point for each measure on the total FoHF in the sample.

Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ekaterini Panopoulou:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Spyridon Vrontos:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

## Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jbankfin.2024.107345.

## Data availability

The authors do not have permission to share data.

## References

Agarwal, V., Naik, N.Y., 2004. Risks and portfolio decisions involving hedge funds. Rev. Financ. Stud. 17 (1), 63–98. https://doi.org/10.1093/rfs/hhg044.

Agarwal, V., Nanda, V.K., Ray, S., 2013. Institutional investment and intermediation in the hedge fund industry. SSRN Electr. J. https://doi.org/10.2139/ssrn.2288102.

Agarwal, V., Arisoy, Y.E., Naik, N.Y., 2017a. Volatility of aggregate volatility and hedge fund returns. J. Financ. Econ. 125 (3), 491–510. https://doi.org/10.1016/j.jfineco.2017.06.015.

Agarwal, V., Ruenzi, S., Weigert, F., 2017b. Tail risk in hedge funds: a unique view from portfolio holdings. J. Financ. Econ. 125 (3), 610–636. https://doi.org/10.1016/j.jfineco.2017.06.006.

Aiken, A.L., Clifford, C.P., Ellis, J.A., 2013. Out of the dark: hedge fund reporting biases and commercial databases. Rev. Financ. Stud. 26 (1), 208–243. https://doi.org/10.1093/rfs/hhs100.

Aiken, A.L., Clifford, C.P., Ellis, J.A., 2015a. Hedge funds and discretionary liquidity restrictions. J. Financ. Econ. 116 (1), 197–218. https://doi.org/10.1016/j.jfineco.2015.01.002.

Aiken, A.L., Clifford, C.P., Ellis, J.A., 2015b. The value of funds of hedge funds: evidence from their holdings. Manag. Sci. 61 (10), 2415–2429. https://doi.org/10.1287/mnsc.2014.2032.

Amin, G.S., Kat, H.M., 2003. Hedge funds performance 1900–2000: do the “money machines” really add value. J. Financ. Quant. Anal. 38, 251–274.

Avramov, D., Barras, L., Kosowski, R., 2013. Hedge fund return predictability under the magnifying glass. J. Financ. Quant. Anal. 48 (4), 1057–1083. https://doi.org/10.1017/S0022109013000422.

Bali, T.G., Gokcan, S., Liang, B., 2007. Value at Risk and the cross-section of hedge fund returns. J. Bank. Finance 31 (4), 1135–1166. https://doi.org/10.1016/j.jbankfin.2006.10.005.

Bali, T.G., Brown, S.J., Caglayan, M.O., 2014. Macroeconomic risk and hedge fund returns. J. Financ. Econ. 114 (1), 1–19. https://doi.org/10.1016/j.jfineco.2014.06.008.

Bali, T.G., Brown, S.J., Caglayan, M.O., 2019. Upside potential of hedge funds as a predictor of future performance. J. Bank. Finance 98, 212–229. https://doi.org/10.1016/j.jbankfin.2018.11.003.
Brown, S.J., Goetzmann, W.N., Liang, B., 2004. Fees on fees in funds of funds. SSRN Electr. J. 2, 76–93. https://doi.org/10.2139/ssrn.335581.
Brown, S.J., Fraser, T.L., Liang, B., 2008. Hedge fund due diligence: a source of alpha in a hedge fund portfolio strategy. SSRN Electr. J. 6, 22–33. https://doi.org/10.2139/ssrn.1016904.
Buraschi, A., Kosowski, R., Trojani, F., 2014a. When there is no place to hide: correlation risk and the cross-section of hedge fund returns. Rev. Financ. Stud. 27 (2), 581–616. https://doi.org/10.1093/rfs/hht070.
Buraschi, A., Kosowski, R., Sritrakul, W., 2014b. Incentives and endogenous risk taking: a structural view on hedge fund alphas. J. Finance 69 (6), 2819–2870. https://doi.org/10.1111/jofi.12167.
Cao, C., Rapach, D.E., Zhou, G., 2015. Which hedge fund styles hedge against bad times? [Working paper]. SSRN Electr. J. https://doi.org/10.2139/ssrn.2311464.
Cao, C., Goldie, B.A., Liang, B., Petrasek, L., 2016. What is the nature of hedge fund manager skills? Evidence from the risk-arbitrage strategy. J. Financ. Quant. Anal. 51 (3), 929–957. https://doi.org/10.1017/S0022109016000387.
Carhart, M.M., 1997. On persistence in mutual fund performance. J. Finance 52 (1), 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x.
Davies, R.J., Kat, H.M., Lu, S., 2009. Fund of hedge funds portfolio selection: a multiple-objective approach. J. Deriv. Hedge Funds 15 (2), 91–115. https://doi.org/10.1057/jdhf.2009.1.
Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 33 (1), 3–56. https://doi.org/10.1016/0304-405X(93)90023-5.
Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. J. Financ. Econ. 116 (1), 1–22. https://doi.org/10.1016/j.jfineco.2014.10.010.
Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: empirical tests. J. Polit. Economy 81 (3), 607–636. https://doi.org/10.1086/260061.
Fung, W., Hsieh, D.A., 2001. The risk in hedge fund strategies: theory and evidence from trend followers. Rev. Financ. Stud. 14 (2), 313–341. https://doi.org/10.1093/rfs/14.2.313.
Fung, W., Hsieh, D.A., 2004. Hegde fund benchmarks: a risk based approach. Financ. Anal. J. 60 (5), 65–80. https://doi.org/10.2469/faj.v60.n5.2657.
Gao, C., Haight, T.D., Yin, C., 2019. Size, age, and the performance life cycle of hedge funds [Working paper]. SSRN Electr. J. https://doi.org/10.2139/ssrn.3169312.
Gao, C., Haight, T.D., Yin, C., 2020. Fund selection, style allocation, and active management abilities: evidence from funds of hedge funds' holdings. Financ. Manage 49 (1), 135–159. https://doi.org/10.1111/fima.12258.
Gupta, A., Liang, B., 2005. Do hedge funds have enough capital? A value-at-risk approach. J. Financ. Econ. 77 (1), 219–253. https://doi.org/10.1016/j.jfineco.2004.06.005.
Hodder, J.E., Jackwerth, J.C., Kolokolova, O., 2014. Recovering delisting returns of hedge funds. J. Financ. Quant. Anal. 49 (3), 797–815. https://doi.org/10.1017/S0022109014000465.
Joenväärä, J., Kosowski, R., Tolonen, P., 2019. The effect of investment constraints on hedge fund investor returns. J. Financ. Quant. Anal. 54 (4), 1539–1571. https://doi.org/10.1017/S0022109018001333.
Joenväärä, J., Kauppila, M., Kosowski, R., Tolonen, P., 2021. Hedge fund performance: are stylized facts sensitive to which database one uses? Crit. Finance Rev. 10 (2), 271–327. https://doi.org/10.1561/104.00000104.
Kosowski, R., Naik, N.Y., Teo, M., 2007. Do hedge funds deliver alpha? A Bayesian and bootstrap analysis. J. Financ. Econ. 84 (1), 229–264. https://doi.org/10.1016/j.jfineco.2005.12.009.
Liang, B., Park, H., 2007. Risk measures for hedge funds: a cross-sectional approach. Eur. Financ. Manag. 13 (2), 333–370. https://doi.org/10.1111/j.1468-036X.2006.00357.x.
Liang, B., Park, H., 2010. Predicting hedge fund failure: a comparison of risk measures. J. Financ. Quant. Anal. 45 (1), 199–222. https://doi.org/10.1017/S0022109009990482.
Newey, W.K., West, K.D., 1987. A simple positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55 (3), 703–708. https://doi.org/10.2307/1913610. JSTOR.
Pástor, Ľ., Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. J. Polit. Economy 111 (3), 642–685. https://doi.org/10.1086/374184.
Panopoulou, E., Vrontos, S., 2015. Hedge fund return predictability; To combine forecasts or combine information. J. Bank. Finance 56, 103–122. https://doi.org/10.1016/j.jbankfin.2015.03.004.
Sun, Z., Wang, A.W., Zheng, L., 2018. Only winners in tough times repeat: hedge fund performance persistence over different market conditions. J. Financ. Quant. Anal. 53 (5), 2199–2225. https://doi.org/10.1017/S0022109018000200.
Titman, S., Tiu, C., 2011. Do the best hedge funds hedge? Rev. Financ. Stud. 24 (1), 123–168. https://doi.org/10.1093/rfs/hhq105.
Vrontos, S.D., Vrontos, I.D., Giamouridis, D., 2008. Hedge fund pricing and model uncertainty. J. Bank. Finance 32 (5), 741–753. https://doi.org/10.1016/j.jbankfin.2007.05.011.