# Risk and Return in Hedge Funds and Funds-of-Hedge Funds: A Cross-Sectional Approach

Lee, Hee Soo[1]

## Abstract

The objective of this study is to examine whether the available data on individual hedge funds (HFs) and funds-of-hedge funds (FOHFs) can reveal the risk-return trade-off and, if so, to find an appropriate risk measure that captures the cross-sectional variation in HF and FOHF returns and compare the risk-return relationship in HFs and FOHFs. Using the "live funds" and the "dead funds" datasets provided by Hedge Fund Research Inc. (HFR), we concentrate on alternative risk measures such as semi-deviation, VaR, expected shortfall and tail risk and compare them with standard deviation in terms of their ability to describe the cross-sectional variation in expected returns of HFs and FOHFs. Firstly, the risk measures are analysed at the portfolio level of HFs and FOHFs by adopting the Fama and French (1992) approach. Secondly, the various estimated risk measures are compared at the individual HF and FOHF levels by using univariate and multivariate cross-sectional regressions. The results show that the available data on HFs and FOHFs exhibits different risk-return trade-offs. The Cornish-Fisher expected shortfall or Cornish-Fisher tail risk could be an appropriate risk measure for HF return. Although appropriate alternative risk measures for the HFs are found, it is difficult to determine the risk measures that best capture the cross-sectional variation in FOHF returns.

**Keywords** Hedge funds; funds-of-hedge funds; VaR; expected shortfall; tail risk

**JEL Codes: G32**

---

[1] Yonsei University
Email:heesoo@yonsei.ac.kr
**Acknowledgments:** I am grateful to the comments from participants in the Finance and Corporate Governance Conference, Melbourne (2010) on the early version of the paper. I would also thank to the two blind reviewers for their insightful comments and suggestions.

## Introduction

The hedge fund industry has grown significantly over the past 60 years. Extended from US based investments to Europe, Asia and Australia, the hedge fund industry expanded dramatically during the period of 1980s through to early 2000s. The rapid growth of hedge fund industry was achieved through increased number of new financial instruments and improved technology, which helped to develop sophisticated investment strategies, during the same periods. In addition, the performance based incentive fee structure has attracted high-skilled professionals to invest in hedge funds. Both assets under management (AUM) in hedge funds and the number of funds increased from around US$39 billion with 610 funds in 1990 to US$1,900 billion with 9,237 funds in 2010 (HFR 2010). Following a decade of notable growth, assets under management (AUM) of the hedge fund industry decreased remarkably in 2008 due to the Global Financial Crisis (GFC). The International Financial Services London (IFSL) estimated that AUM would decline by more than 20% to US$1,500 billion in 2008. Being the biggest on record, the decrease was caused by the combination of negative performance, rush in redemptions and liquidations of fund (IFSL 2009).

Traditional investment strategies adopted by institutional investors had failed to satisfy their objectives in terms of return and risk, which had led investors to seek new ways of diversification. Many high-net-worth individuals, as well as institutional investors, have shown growing interest in hedge funds. With fund-of-hedge funds (FOHFs) being vehicles that provide combined investments in individual hedge funds (HFs), investment in them has been open to a wide range of investors. On the other hand, only institutions and high-net-worth individuals are allowed to invest in HFs. A large part of growth in the hedge fund industry was due to an increase in the number of FOHFs. The HFR Industry Report in 2010 reported that most investors have increasingly adopted FOHFs as the preferred investment vehicles and they were estimated to account for 20% to 25% of global hedge fund industry assets at the end of 2009.

FOHFs became more favoured by various investors given that FOHFs usually demand less initial investment than the HFs. As the name indicates, FOHFs invest in a number of HFs for the purpose of diversifying fund risk. This allows investors to allocate assets in dynamic market conditions. Additionally, FOHFs have a different fee structure from that of HFs. While a HF charges a management and incentive fee, a FOHF charges extra fees at the underlying HF level as well as management and incentive fees at the FOHF level. As a consequence, in some cases, FOHF investors might pay more fees than the total realised return in the investment. It is an interesting question as to whether it is worthwhile for investors to pay these extra fees.

Theoretically, holding a portfolio of HFs must be less risky than investing in HFs. Despite the increasing significance of FOHFs in the development of the hedge fund industry, the risk and return characteristics of FOHFs are not well established in the literature. Most existing research on hedge fund performance showed that hedge funds exhibited better performance on a risk-adjusted basis relative to standard asset categories such as equity and bonds (Ackerman, McEnally & Ravenscraft 1999; Asness, Krail & Lie 2001; Brown, Goetzmann & Ibbotson 1999 among others). On the other hand, the extant evidence on FOHF performance was that they had a tendency to underperform hedge fund indices by small but significant amounts (Brown, Goetzmann & Liang 2004; Liang 2004). Furthermore, a number of studies showed that the returns announced by HFs and FOHFs were not normally distributed with excess kurtosis and negative skewness (Agarwal & Naik 2004; Amin & Kat 2003; Fung & Hsieh 1997). Due to the nature of negative skewness and excess kurtosis in HFs and FOHFs returns, any risk estimation which assumes a normal distribution of returns would severely underestimate the actual risk exposure. Nevertheless, according to Amenc et al. (2004) only 2 % of European multi-managers have paid attention to the skewness and kurtosis of the return distribution. Also, they revealed that most European multi-managers have continued to prefer the traditional mean-variance framework to monitor manager performance. This was confirmed by the fact that 82% of multi-managers adopted the Sharpe ratio as an important indicator (Amenc et al. 2004).

The objective of this study is to examine whether the available data on HFs and FOHFs can reveal the risk-return trade-off and, if so, to find an appropriate risk measure that captures the cross-sectional variation in HF and FOHF returns. The current research extended Liang and Park (2007) by focusing on the comparison of the risk-return trade-off in HFs and FOHFs and including recent hedge fund data which covers a period of Global Financial Crisis. Understanding the risk-return relationship in HFs and FOHFs will greatly help investors build more profitable investment strategies.

With the dramatic growth of HFs and FOHFs, it is essential to find the most appropriate risk measures that capture the cross-sectional variation in these types of funds. Traditional risk management such as mean-variance analysis, the Sharpe ratio and Jensen's alpha assume a normal distribution measure of returns. As a consequence, the traditional measures of returns incorporate the standard deviation. This would appear to be inappropriate for risk measures of HFs and FOHFs. In order to overcome this problem, the focus in this study is on alternative risk measures such as semi-deviation, Value-at-Risk (VaR), expected shortfall and tail risk. They were compared with standard deviation in terms of their ability to describe the cross-sectional variation in expected returns of HFs and FOHFs.

Firstly, the various estimated risk measures were analysed at the portfolio level of HFs and FOHFs by adopting the Fama and French (1992) approach. Secondly, the estimated risk measures were compared at the individual HF and FOHF levels by using univariate[2] and multivariate cross-sectional regressions. Additional independent variables were incorporated into the analysis in order to distinguish age, size and liquidity effects from the relationship between risk and expected return. These regressions were run with and without investment strategy dummy variables. The results from both HF and FOHF data were then analysed to show if any difference existed between them.

Liang and Park (2007) analysed the risk-return trade-off with the same risk measures adopted in this study but using only HF data. They found that the expected shortfall using the Cornish-Fisher expansion captured the cross-sectional variation in expected returns of HFs better than did other risk measures studied. In the present study, the risk and return characteristics of FOHFs turned out to be different from those of HFs. However, the cross-sectional regression results using HFs were similar with those of Liang and Park (2007) except for the regression involving VaR.

There is invariably a clear trade-off between risk and expected return. One cannot be viewed without consideration of the other. A risk-return target employed by hedge funds is not the same as that of traditional investments such as stocks, bonds and mutual funds. Most hedge fund investors expect high returns to compensate them for the corresponding risks to which they are exposed. Risk measures for HF and FOHF investments are particularly important due to the illiquid character of the investments due to the long lock-up periods on capital and the infrequent redemption notice periods enforced on investors.

In the next section the data, descriptive statistics and results of normality testing of HF and FOHF returns are described. The methods used to estimate risk measures and to test

[2] The univariate regression model is a simple regression model where one variable is regressed on another variable.

the cross-sectional relation between hedge fund returns and risk measures are then presented. Subsequently, the empirical results are presented before concluding in the last section.

## Data

It is difficult to identify a representative hedge fund database among a number of hedge fund databases. It is well known that hedge funds report their information only on a voluntary basis due to limited regulatory oversight. Since hedge funds are not permitted to advertise publicly, they report fund information voluntarily to a data collection agency in order to attract potential investors. As a result, conflicting results of studies based on different databases have been produced (Ackermann et al. 1999; Brown et al. 2004; Malkiel & Saha 2005 among others). This makes the comprehensive nature and integrity of hedge fund data questionable.

This study adopted the Hedge Fund Research (HFR) database, which is a database that is commonly used by academics and practitioners. There are three major hedge fund databases employed in the literature, namely the HFR, Lipper TASS and CISDM (Centre for International Securities and Derivatives Markets) databases. Each database supplies its own family of indices. HFR provides two separate databases. One is the Dead Fund Database, while the other is called the Live Fund Database. As indicated in the name, the Live Fund database includes information about all hedge funds which are currently reporting to HFR, while the Dead Fund database consists of information regarding all hedge funds which have discontinued reporting to HFR.

In the empirical investigation carried out in this study, the monthly returns of HFs and FOHFs in the HFR database were examined over the period from January, 1990 to December, 2009. The estimation period starts in January, 1990 and test period runs from January, 1995 to December, 2009. Monthly returns are defined as the difference in net asset value during the month divided by the net asset value at the beginning of the month. Returns are net of fees including management fees, incentive fees and other fund expenses. In reality, the actual returns that investors receive differ from reported returns owing to factors such as redemption fees and the bid-ask spread offered by fund. It should be noted that reported returns are the basis for actual returns investors obtain in practice. The utilisation of monthly returns creates substantial advantages over annual returns due to the increased accuracy of the risk measures. Accuracy of the risk measure is crucial for risk management purposes.

It has been acknowledged in the literature that hedge fund databases have trouble with several biases (Ackermann et al. 1999; Brown et al. 1999; Malkiel & Saha 2005). The sample of HFR data adopted in this study included dead funds as well as live funds in order to moderate survivorship bias. To guarantee a sufficient number of appropriate observations for estimating risk measures, the sample was restricted to funds with a minimum of 36 months of data. The majority of funds in the database reported returns net of all fees on a monthly basis, whereas some funds reported only gross return quarterly. To provide data with consistency, those funds reporting gross returns or quarterly returns were removed from the sample. Additionally, funds with missing data were deleted.

For the purpose of this research the hedge fund database was divided into two classes. One class contained the HF data, while the other was comprised of the FOHF data. The original database consisted of 6297 live funds and 8520 dead funds with monthly return and assets under management (AUM) from January, 1990 to December, 2009. The live fund database included 4413 HFs and 1884 FOHFs, while the dead fund database contained 6350 HFs and 2170 FOHFs. HFs were categorised into 4 classes according to their investment strategies. They were Equity Hedge, Event Driven, Macro, and Relative Value. Two index funds were deleted from the live HF sample to make HFs distinct from portfolio hedge funds.

The FOHFs adopted one of the four strategies including Conservative, Diversified, Market Defensive and Strategic. After the removal of funds which did not meet the data requirements of this research, 2003 HFs and 879 FOHFs remained in the Live Fund database, while 2303 HFs and 816 FOHFs comprised the Dead Fund database. Table 1 shows the descriptive statistics for the returns of the live, dead and combined fund data (of the other two).

Table 1
Statistical Summary of HF and FOHF Returns: January, 1995 to December, 2009

| | | Live Fund | | Dead Fund | | Combined Fund | |
|---|---|---|---|---|---|---|---|
| | | HF | FOHF | HF | FOHF | HF | FOHF |
| Number of Funds | | 2003 | 879 | 2303 | 816 | 4306 | 1695 |
| Average Monthly return (%) | Mean | 0.83 | 0.34 | 0.73 | 0.40 | 0.77 | 0.37 |
| | Median | 0.76 | 0.4 | 0.64 | 0.38 | 0.71 | 0.39 |
| Standard Deviation (%) | Mean | 4.45 | 2.43 | 4.37 | 2.41 | 4.41 | 2.42 |
| | Median | 3.74 | 2.04 | 3.41 | 1.96 | 3.58 | 2.02 |
| Skewness | Mean | -0.36 | -1.24 | -0.21 | -0.95 | -0.28 | -1.10 |
| | Median | -0.18 | -1.13 | -0.07 | -0.82 | -0.12 | -0.98 |
| Kurtosis | Mean | 7.86 | 8.08 | 6.71 | 7.64 | 7.24 | 7.86 |
| | Median | 5.32 | 6.37 | 4.67 | 5.43 | 4.94 | 6.02 |
| Maximum Monthly Return (%) | Mean | 14.41 | 5.91 | 13.79 | 6.92 | 14.08 | 6.40 |
| | Median | 11.22 | 4.58 | 9.23 | 4.05 | 10.18 | 4.33 |
| Minimum Monthly Return (%) | Mean | -14.17 | -9.11 | -12.56 | -8.01 | -13.31 | -8.58 |
| | Median | -11.44 | -7.74 | -9.40 | -6.67 | -10.42 | -7.22 |

Table 1 presents the number of funds, the mean and median values of the average monthly returns, standard deviation, skewness, kurtosis[3], as well as maximum monthly return and minimum monthly return in the Live, Dead and Combined HFR databases. Summary statistics are presented for HF returns and FOHF returns. As can be seen from this Table 1, the average return of HFs was higher than that of FOHFs and HFs were more volatile than FOHFs. Both HFs and FOHFs showed negative skewness and FOHFs had thicker tails in the return distribution than HFs. The average monthly return and standard deviation of the 4306 combined HFs were 0.77% and 4.41%, respectively, with average skewness of -0.28, and average kurtosis of 7.24. Compared to HFs, 1695 combined FOHFs showed the average monthly return of 0.37%, standard deviation of 2.42%, skewness of -1.10, and kurtosis of 7.86.

It has been well established in the literature that the reported returns of HFs and FOHFs are not normally distributed and exhibit excess kurtosis and negative skewness (Agarwal & Naik 2004; Amin & Kat 2003; Brown et al. 2004; Fung & Hsieh 1997; Lo 2001). Table 2 presents the proportion of rejection in the Jarque-Bera and Lilliefors normality test [4] for HF and FOHF returns.

---

[3] Skewness and Kurtosis are defined as follows: Skewness = $\frac{E(R-\mu)^3}{\sigma^3}$ , Kurtosis = $\frac{E(R-\mu)^4}{\sigma^4}$ , where $R$ is returns, $\mu$ denotes the mean of $R$ and $\sigma$ denotes the standard deviation of $R$.
[4] The Lilliefors test is more appropriate when the sample size is small. The Lilliefors test was conducted as the number of funds in several strategies such as Conservative and Market Defensive is small.

Table 2
Normality Test for HF and FOHF Returns

| Fund Group | Investment Strategy | Live Fund | | Dead Fund | | Combined Fund | |
|---|---|---|---|---|---|---|---|
| | | % rejection in J-B test | % rejection in Lilliefors test | % rejection in J-B test | % rejection in Lilliefors test | % rejection in J-B test | % rejection in Lilliefors test |
| HF | Equity Hedge | 69% | 57% | 56% | 49% | 62% | 52% |
| | Event Driven | 84% | 78% | 72% | 66% | 78% | 72% |
| | Macro | 57% | 45% | 54% | 48% | 55% | 47% |
| | Relative Value | 85% | 84% | 77% | 71% | 80% | 77% |
| FOHF | Conservative | 96% | 93% | 80% | 76% | 88% | 84% |
| | Diversified | 83% | 77% | 67% | 58% | 75% | 68% |
| | Market Defensive | 63% | 48% | 60% | 48% | 61% | 48% |
| | Strategic | 74% | 64% | 67% | 66% | 71% | 65% |
| All Hedge Funds | | 71% | 62% | 61% | 55% | 66% | 58% |
| All Fund-of-Hedge Funds | | 82% | 76% | 70% | 64% | 76% | 70% |

As expected, rejection rate in the J-B test (Lilliefors test) was high, showing 66% (58%) on average in the combined HFs and 76% (70%) in the combined FOHFs. The average rejection rate of FOHFs was higher than that of HFs, but there was a great fluctuation across investment strategies. Among the strategy classes in the combined HFs, Relative Value and Event Driven showed high J-B test rejection rate of 80% and 76% respectively, while Macro yielded lower rejection rate of 55%. The strategy of Conservative in the combined FOHFs showed high J-B test rejection rate of 88%, while Market Defensive presented rejection rate of 61%. It is interesting to note that the rejection rates for live funds are higher than those for dead funds.

## Description of Approach

### *Estimation of Risk Measures*

All the risk measures studied in this article were estimated in order to test cross-sectional variation in HF and FOHF returns. Eight risk measures including the standard deviation, semi-deviation, nonparametric VaR, Cornish- Fisher VaR, nonparametric expected shortfall, Cornish- Fisher expected shortfall, nonparametric tail risk and Cornish- Fisher tail risk were estimated using the same procedure.[5]

Monthly returns over the previous 36 to 60 months (as available) were used to estimate risk measures for each month within the test period. The test period started from January, 1995 and the estimation window started from January, 1990. That is, monthly returns between January, 1990 and December, 1994 were used to estimate risk measures as of January, 1995. This calculation was repeated by rolling the sample forward by one month ahead until the risk measure of December, 2009 was calculated. As a consequence, 180 months of time-series data for each risk measure was obtained. As the number of funds at each month and their available return history were different across the sample, the number of estimated risk measures at each month was not identical. Funds having a return history of less

[5] These eight risk measures are well defined in Liang and Park (2007).

than 36 months at a particular month were excluded from the estimation sample for that month.

### *Test at the Portfolio Level of HFs and FOHFs: Fama and French Method*

As mentioned above, the estimation period for risk measures started in January, 1990 and the test period was between January, 1995 and December, 2009. Having calculated risk measures for each month in the test period using the previous 36 to 60 monthly returns (as available), portfolios were formed on each risk measure at each month. For each month, returns of HFs and FOHFs were ranked on the basis of their risk measure to construct 10 decile portfolios. Portfolio #1 contained the least average risk measure, while portfolio #10 included the highest average risk measure. This portfolio formation method is much the same as Fama and French (1992), with the exception that portfolios were updated on a monthly basis rather than yearly. For example, in January, 1995 risk measures for each fund were estimated by the return history from January, 1990 to December, 1994 and all funds were ranked into 10 equally weighted portfolios based on the rank of estimated risk measures. Once the portfolios were formed, the portfolio returns in January, 1995 (one month ahead estimation window) were calculated as the equal-weighted average of returns on individual funds in the same portfolio. By rolling over one month ahead, the risk measures were estimated for each fund and ranked according to the updated risk measures to form new portfolios. That is, the second estimation window for updating portfolios was from February, 1990 to January, 1995 and portfolios returns were computed in February, 1995. This procedure was repeated until 180th portfolios based on the estimation period between December, 2004 and November, 2009 was constructed. As a consequence, 180 time series of returns for the 10 equally weighted portfolios based on risk measures were obtained. These portfolios were generated and tested for i) live HFs and live FOHFs, ii) dead HFs and dead FOHFs, and iii) combined HFs and combined FOHFs. Then, as in the standard asset pricing literature, the difference between the returns of the most risky portfolio (portfolio #10) and the returns of the least risky portfolio (portfolio #1) were used in order to test the risk-return trade-off for each risk measure.

### *Test at the Individual Level of HFs and FOHFs: A Cross-sectional Regression*

The cross-sectional regression approach of Fama and Macbeth (1973) was used to test the risk-return trade–off in HFs and FOHFs. The test period began in January, 1995 and finished in December, 2009 (180 months). Similar to Fama and French (1992), the cross-sectional one-month-ahead predictive regression was run to investigate the predictive power of risk measures at the individual fund level. The data from January, 1990 to December, 1994 was used to estimate the risk measures and then the January, 1995 cross-sectional returns were regressed on the lagged calculated risk measures. This procedure was repeated by rolling the sample forward by one month to generate risk measures and run the cross-sectional regressions until the whole sample was exhausted by December, 2009. For each month, the cross-sectional returns of the HFs and the FOHFs were separately regressed on the eight risk measures discussed above in order to compare their ability for describing the cross-sectional variation in expected returns. As a consequence, each fund group had 180 sets of time series coefficient estimates of the eight risk measures which were used in the corresponding 180 cross-sectional regressions.

Univariate cross-sectional regressions were run for the 180 months using the following model:

$$R_{it} = \alpha_t + \beta_t RM_{i,t-1} + \varepsilon_{it} \quad (1)$$

where $R_{it}$ is the realised return of fund *i* in month *t* and $RM_{i,t-1}$ is the risk measure for fund *i* in month *t-1*. $RM_{i,t-1}$ is specified by the standard deviation (SD), semi-deviation[6] (SEMD), nonparametric VaR[7] (VaR_np), Cornish-Fisher VaR[8] (VaR_cf), nonparametric expected shortfall[9] (ES_np), Cornish-Fisher expected shortfall[10] (ES_cf), nonparametric tail risk[11] (TR_np) and Cornish-Fisher tail risk[12] (TR_cf) measures.

Additional independent variables were incorporated into the analysis in order to distinguish age, size and liquidity effects from the relationship between risk and expected return. These characteristics of funds were reported to be related to the cross-section of hedge fund returns in the literature. Ammann and Moerth (2005), Hedges (2003) and Herzberg and Mozes (2003) found that fund size impacted on hedge fund performance. Bali, Gokcan and Liang (2007) and Liang and Park (2007) showed that fund age as well as size explained, to some extent, the expected return of a fund. Liang (1999), Liang and Park (2007) and Aragon (2007) found the liquidity premium in hedge fund returns using the lockup provision of the fund, so it was an another explanatory variable. Accordingly, monthly cross-sectional regressions were performed for the following univariate specifications to demonstrate the relationship between return and fund characteristics.

$$R_{it} = \alpha_t + \beta_t Age_{i,t-1} + \varepsilon_{it} \quad (2)$$

$$R_{it} = \alpha_t + \beta_t Ln(AUM)_{i,t-1} + \varepsilon_{it} \quad (3)$$

$$R_{it} = \alpha_t + \beta_t Lockup_i + \varepsilon_{it} \quad (4)$$

Age was calculated on a daily basis. Fund size was measured by ln(AUM), where AUM is a fund's assets under management and fund liquidity was measured by the lockup period on a daily basis.[13]

Age, size and lockup effects were, therefore, controlled in order to study the relationship between expected return and risk measure for HFs and FOHFs. Multivariate cross-sectional regressions for 180 months were run using the following model.

$$R_{it} = \alpha_{i,t} + \beta_{1t} RM_{i,t-1} + \beta_{2t} Age_{i,t-1} + \beta_{3t} Ln(AUM)_{i,t-1} + \beta_{4t} Lockup_i + \varepsilon_{i,t} \quad (5)$$

For each risk measure, empirical tests were performed for i) live HFs and live FOHFs, ii) dead HFs and dead FOHFs, as well as iii) combined HFs and combined FOHFs using both the Live and Dead Fund databases. Following Fama and MacBeth (1973), the time series of the parameter estimates from the cross-sectional regression were used to test the risk-return trade-off. That is, the time series means of the monthly regression slopes were used to determine which risk measures on average have non-zero expected premiums during the January, 1995 to the December, 2009 periods.

---

6 Compared to the standard deviation, semi-deviation is derived only from negative deviation from the mean. That is returns below the mean return increase semi-deviation, whereas returns above mean return do not.

7 Nonparametric VaR with 95% confidence level (VaR_np (95%)) was calculated as the 5th percentile of all observations in an estimation window.

8 This is a parametric VaR using the Cornish-Fisher expansion with 95% confidence level (VaR_cf (95%)).

9 Once VaR_np (95%) was estimated within a monthly estimation window from January, 1995 to December, 2009, all returns less than or equal to VaR_np (95%) became the sample. Nonparametric expected shortfall with 95% confidence level (ES_np (95%)) was computed as the average of the new sample.

10 Cornish-Fisher expected shortfall with 95% confidence level (ES_cf (95%)) was calculated with the same method as ES_np (95%), except the returns from the estimation window were sorted on the basis of VaR_cf (95%) instead of VaR_np (95%).

11 Tail risk is derived from the deviation of returns from the mean return within each estimation window, for returns less than VaR. Nonparametric tail risk at the 95% confidence level (TR_np (95%)) was estimated with returns lower than VaR_np (95%).

12 Cornish-Fisher tail risk at the 95% confidence level (TR_cf (95%)) was calculated with returns below VaR_cf (95%).

13 The lockup period of a fund without a lockup provision was set to 0.

Despite the fact that all funds in the HF and FOHF databases are regarded as a single asset class, the HFs and FOHFs are heterogeneous according to their strategies. Thus, the style effects were adjusted by adding strategy dummy variables to the univariate regression as well as multivariate regression. The univariate regression model for HFs and FOHFs with strategy dummy variables[14] is as follows:

$$R_{it} = \sum_{s=1}^{4} D_s\, \alpha_{s,t} + \beta_t RM_{i,t-1} + \varepsilon_{i,t} \tag{6}$$

In addition, univariate regression models for HFs and FOHFs with strategy dummy variables for age, size and liquidity effects are as follows.

$$R_{it} = \sum_{s=1}^{4} D_s\, \alpha_{s,t} + \beta_t Age_{i,t-1} + \varepsilon_{i,t} \tag{7}$$

$$R_{it} = \sum_{s=1}^{4} D_s\, \alpha_{s,t} + \beta_t Ln(AUM)_{i,t-1} + \varepsilon_{i,t} \tag{8}$$

$$R_{it} = \sum_{s=1}^{4} D_s\, \alpha_{s,t} + \beta_t Lockup_{i,t-1} + \varepsilon_{i,t} \tag{9}$$

Similarly, the multivariate regression model for HFs and FOHFs with strategy dummy variables is specified as follows.

$$R_{it} = \sum_{s=1}^{4} D_s\, \alpha_{s,t} + \beta_{1t} RM_{i,t-1} + \beta_{2t} Age_{i,t-1} + \beta_{3t} Ln(AUM)_{i,t-1} + \beta_{4t} Lockup_i + \varepsilon_{i,t} \tag{10}$$

## Empirical Results

### *Results at the Portfolio Level of HFs and FOHFs*

Table 3 shows the cross-sectional relation at the portfolio level between the Cornish-Fisher expected shortfall (ES_cf) at the 95% confidence level and expected returns for all HFs and FOHFs based on the sample of live, dead and combined funds. The time-series (180 months) average returns and ES_cf of the ten portfolios formed by ranking the ES_cf are presented in the Table 3.

The results from the alternative eight risk measures are similar[15]. As an example of monotonicity of average returns, we focused on a particular risk measure, Cornish-Fisher expected shortfall, given in Table 3. The results in Table 3 indicated that, for ES_cf, when moving from a low risk portfolio to a high risk portfolio, there was almost a monotonic increase in the average return of HFs in the live and the combined fund. The monotonically increasing risk-return relation did not appear for the case of dead HFs. This might be caused by the fact that some funds with very high risk and negative return eventually joined the Dead Fund database. By contrast, all the samples of live, dead and combined FOHFs rarely showed this monotonically increasing risk-return relationship. It can be observed in Table 3 that when they were compared within the same portfolio, the average value of the ES_cf risk measures for all HFs were always greater than that corresponding to the FOHFs except for the low ES_cf portfolio.

[14] The HF strategy dummy variables are categorised into Equity Hedge, Event Driven, Macro, and Relative Value, while the FOHF strategy dummy variables are categorized into Conservative, Diversified, Market Defensive, and Strategic.

[15] The results for the other risk measures are not presented due to limited space. These results are available from the author upon request.

Table 3

Average Returns of HF and FOHF Portfolios Formed According to 95% Cornish-Fisher Expected Shortfall: January, 1995 to December, 2009

| | | | Low ES_cf | 2 ES_cf | 3 ES_cf | 4 ES_cf | 5 ES_cf | 6 ES_cf | 7 ES_cf | 8 ES_cf | 9 ES_cf | High ES_cf | All |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| HF | Live | ES_cf | 0.64 | 2.16 | 3.30 | 4.47 | 5.71 | 6.98 | 8.58 | 10.57 | 13.66 | 23.16 | 7.92 |
| | | Return | 0.82 | 0.74 | 0.79 | 0.94 | 1.00 | 0.99 | 1.12 | 1.07 | 1.21 | 1.56 | 1.02 |
| | Dead | ES_cf | 0.56 | 2.03 | 3.17 | 4.29 | 5.46 | 6.83 | 8.52 | 10.76 | 14.10 | 23.85 | 7.95 |
| | | Return | 0.64 | 0.48 | 0.52 | 0.49 | 0.48 | 0.65 | 0.57 | 0.63 | 0.54 | 0.41 | 0.58 |
| | Combined | ES_cf | 0.60 | 2.09 | 3.23 | 4.39 | 5.63 | 6.96 | 8.64 | 10.84 | 14.01 | 23.40 | 7.98 |
| | | Return | 0.76 | 0.63 | 0.70 | 0.73 | 0.78 | 0.84 | 0.91 | 0.96 | 0.98 | 1.12 | 0.84 |
| FOHF | Live | ES_cf | 0.84 | 1.65 | 2.22 | 2.76 | 3.35 | 3.95 | 4.55 | 5.26 | 6.36 | 10.47 | 4.14 |
| | | Return | 0.63 | 0.63 | 0.69 | 0.69 | 0.72 | 0.68 | 0.76 | 0.73 | 0.73 | 0.60 | 0.68 |
| | Dead | ES_cf | 0.71 | 1.72 | 2.35 | 2.93 | 3.54 | 4.19 | 4.90 | 6.10 | 8.13 | 14.50 | 5.58 |
| | | Return | 0.66 | 0.51 | 0.61 | 0.53 | 0.49 | 0.56 | 0.62 | 0.33 | 0.61 | 0.31 | 0.57 |
| | Combined | ES_cf | 0.74 | 1.64 | 2.24 | 2.79 | 3.39 | 4.01 | 4.67 | 5.52 | 7.02 | 12.75 | 4.47 |
| | | Return | 0.63 | 0.62 | 0.68 | 0.66 | 0.59 | 0.62 | 0.67 | 0.65 | 0.53 | 0.49 | 0.62 |

*Note*: Portfolios are formed on a monthly basis. For each month, 10 equally weighted portfolios are formed on the basis of ranked values according to 95% Cornish-Fisher expected shortfall estimated from the previous 36 to 60 monthly returns (as available) for each HF and FOHF. This table shows the 95% Cornish-Fisher expected shortfall and returns of each portfolio calculated from HFs and FOHFs. The reported 95% Cornish-Fisher expected shortfall is the time-series (180 months) average of the average 95% Cornish-Fisher expected shortfall of all HFs and FOHFs in each portfolio. The reported return is the time-series (180 months) average of the monthly equal-weighted portfolio returns (in percent).

Table 4 shows the average return differential between low risk portfolio and high risk portfolio. The p-value in bracket was obtained from the nonparametric Wilcoxon test[16] for the average return differential for live funds, dead funds, and combined funds.

Although the return differentials between the high risk portfolio and the low risk portfolio were not the same across the eight risk measures, the test results were, nevertheless, similar. From Table 4, the live HF samples showed that the average return of the low risk portfolio differed significantly from the average return of high risk portfolio at the conventional significant level. This was true for all risk measures. In the case of the dead HFs, there were no significant differences between the average returns of the low risk portfolio and the high risk portfolios. Funds in the combined HFs presented similar results across all the risk measures except for the portfolio formed by VaR_cf which showed insignificant result. The differences in the average returns of the low risk and the high risk portfolios for risk measures including the SD, SEMD, VaR_np, ES_np, TR_np and TR_cf were all significant at the 5% level, whereas, for ES_cf they were significant at the 10% level.

[16] It is well established in the literature that the reported returns of HFs and FOHFs are not normally distributed and, therefore, a parameter t-test is not appropriate.

Table 4
Test for Average Return Differential Between the Most Risky Portfolio and the Least Risky Portfolio

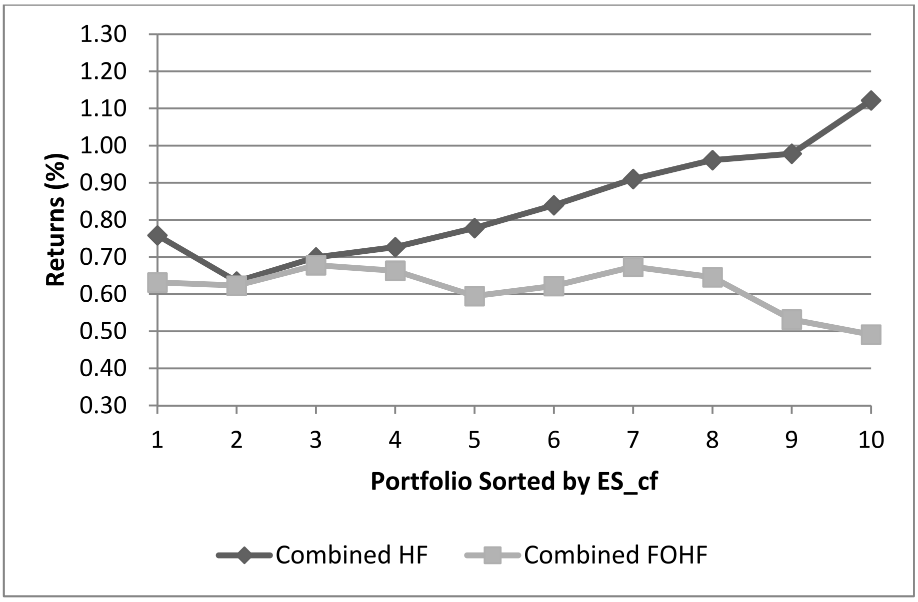
| Return Differential | HF | | | FOHF | | |
|---|---|---|---|---|---|---|
| | Live | Dead | Combined | Live | Dead | Combined |
| High SD - Low SD | 0.9459%<br>(0.0099) | 0.1104%<br>(0.2234) | 0.6567%<br>(0.0108) | 0.1683%<br>(0.1229) | -0.0812%<br>(0.8474) | -0.0799%<br>(0.6290) |
| High SEMD - Low SEMD | 0.9367%<br>(0.0104) | 0.1283%<br>(0.2499) | 0.6126%<br>(0.0114) | 0.1405%<br>(0.0931) | -0.1312%<br>(0.7466) | -0.0854%<br>(0.5129) |
| High VaR_np - Low VaR_np | 0.8742%<br>(0.0540) | -0.1744%<br>(0.2622) | 0.4081%<br>(0.0287) | 0.0236%<br>(0.3706) | -0.4198%<br>(0.5651) | -0.2345%<br>(0.9427) |
| High VaR_cf - Low VaR_cf | 0.7354%<br>(0.0554) | -0.2204%<br>(0.5367) | 0.3828%<br>(0.1254) | -0.0078%<br>(0.3509) | -0.3355%<br>(0.4097) | -0.2098%<br>(0.9411) |
| High ES_np - Low ES_np | 0.9234%<br>(0.0143) | -0.1481%<br>(0.4260) | 0.4281%<br>(0.0399) | -0.0170%<br>(0.3006) | -0.3134%<br>(0.6398) | -0.1605%<br>(0.5970) |
| High ES_cf - Low ES_cf | 0.7466%<br>(0.0169) | -0.2220%<br>(0.3239) | 0.3634%<br>(0.0614) | -0.0331%<br>(0.2834) | -0.3477%<br>(0.5234) | -0.1402%<br>(0.7245) |
| High TR_np - Low TR_np | 0.9715%<br>(0.0130) | -0.0089%<br>(0.1799) | 0.5840%<br>(0.0127) | -0.0089%<br>(0.1799) | -0.1633%<br>(0.7713) | -0.1033%<br>(0.5012) |
| High TR_cf - Low TR_cf | 0.8794%<br>(0.0087) | -0.0620%<br>(0.2461) | 0.5185%<br>(0.0245) | 0.0085%<br>(0.2566) | -0.1161%<br>(0.9394) | -0.0979%<br>(0.4493) |

The results for the FOHFs contrasted with those of HFs. All portfolios in the live, dead, and combined FOHFs did not indicate a significant average return differential between the low risk portfolio and the high risk portfolio in all eight risk measures. These results can be expected from the fact that the FOHFs did not show any monotonically increasing relationship between risk and return as shown in Table 3. It should be noted that in almost all of the FOHF portfolios, the average differential calculated by subtracting the average return of the low risk portfolio from the average return of the high risk portfolio was a negative value[17]. Also, it can be observed that the value of return differential for all HFs was always higher than that corresponding to the FOHFs. This was true for all eight risk measures.

As a consequence, the cross-sectional relationship between risk and return of FOHFs was observed to be not the same as that of HFs. Figure 1 presents returns of the combined HF and combined FOHF portfolios formed by ranking the ES_cf in order to compare the cross-sectional relationship between the risk and return of HFs and FOHFs. The figures for the alternative eight risk measures were very similar[18].

[17] For the live FOHF portfolios formed by SD, SEMD and VaR_np, the average return differential between the low risk portfolio and high risk portfolio was a positive value.
[18] The figures for the other risk measures are not presented due to limited space. These figures are available from the author upon request.

Figure 1
Returns of Portfolios Sorted by ES_cf: January, 1995 to December, 2009




As can be seen from the Figure 1, the ES_cf risk measure presented different risk-return trade-off between HFs and FOHFs. The generally accepted risk-return relationship was found in the case of the HFs. However, FOHFs did not show the monotonically increasing risk-return relationship. This result suggested that, even though HFs were more volatile than FOHFs, investing in FOHFs could be riskier than investing in HFs if the investment decision was only based on this risk-return relationship.

Overall, while the risk-return trade-off for HFs can be found from the available data, the FOHFs barely disclose a clear relationship between risk and return. As indicated above, the results from the analysis across the eight alternative risk measures at the portfolio level were similar. This made it difficult to conclude that there was an appropriate risk measure capturing cross-sectional relationship between risk and return for both HFs and FOHFs. One lesson from this analysis is that investors should bear in mind the different risk-return relationships between FOHFs and HFs, and be more cautious about investment in the FOHFs than in HFs due to the unanticipated risk-return relationship of FOHFs.

*Results at the Individual HF and FOHF level: A Cross-sectional Regression*

According to the empirical results from the analysis at the portfolio level, the available data on HFs seemed to reveal the risk-return trade-off. However, all risk measures presented a similar significance level for testing the difference of average returns between the low risk portfolio and the high risk portfolio. This result made it difficult to determine an appropriate risk measure to capture the cross-sectional variation. Furthermore, it should be noted that fund specific information could be lost when we test at the portfolio level, although aggregating may produce more reliability in the statistical testing process.

Before conducting cross-sectional regressions for risk measures, univariate cross-sectional regressions of HF and FOHF returns on age, size and liquidity were performed to test the significance of these fund characteristics. Table 5 shows the results of these regressions.

Table 5
Univariate Cross-sectional Regressions of HF and FOHF Returns on Age, Size and Liquidity: January, 1995 to December, 2009

Panel A : Cross-Sectional Regressions for HFs

| Model | | Age | | ln(A) | | Lockup | |
|---|---|---|---|---|---|---|---|
| | | Beta | R^2 | Beta | R^2 | Beta | R^2 |
| Without Fund Strategy Dummy Variables | Live | -0.0001 (0.0002) | 0.62% | -0.1102 (0.0000) | 0.57% | 0.0002 (0.0316) | 0.83% |
| | Dead | -0.0001 (0.0000) | 1.03% | -0.1036 (0.0000) | 0.61% | 0.0006 (0.0094) | 1.89% |
| | Combined | -0.0001 (0.0000) | 0.39% | -0.0996 (0.0000) | 0.40% | 0.0005 (0.0044) | 0.70% |
| With Fund Strategy Dummy Variables | Live | -0.0001 (0.0000) | 7.01% | -0.1013 (0.0000) | 7.32% | 0.0002 (0.0608) | 6.93% |
| | Dead | -0.0001 (0.0000) | 5.79% | -0.1036 (0.0000) | 6.04% | 0.0005 (0.0011) | 5.86% |
| | Combined | -0.0001 (0.0000) | 5.53% | -0.0937 (0.0000) | 5.74% | 0.0005 (0.0000) | 5.51% |

Panel B : Cross-Sectional Regressions for FOHFs

| Model | | Age | | ln(A) | | Lockup | |
|---|---|---|---|---|---|---|---|
| | | Beta | R^2 | Beta | R^2 | Beta | R^2 |
| Without Fund Strategy Dummy Variables | Live | 0.0000 (0.9171) | 0.63% | -0.0150 (0.1971) | 1.57% | 0.0002 (0.0283) | 0.92% |
| | Dead | 0.0000 (0.1074) | 1.40% | 0.0407 (0.0180) | 2.20% | 0.0002 (0.2648) | 1.98% |
| | Combined | 0.0000 (0.4256) | 0.54% | 0.0202 (0.0978) | 1.09% | 0.0001 (0.2495) | 0.73% |
| With Fund Strategy Dummy Variables | Live | 0.0000 (0.9590) | 10.40% | -0.0041 (0.7179) | 11.56% | 0.0002 (0.0309) | 10.66% |
| | Dead | 0.0000 (0.3981) | 9.71% | 0.0235 (0.0668) | 9.60% | 0.0001 (0.6371) | 9.80% |
| | Combined | 0.0000 (0.4949) | 8.89% | 0.0239 (0.0591) | 9.54% | 0.0001 (0.1850) | 8.99% |

*Note:* The average slope is the time-series (180 months) average of the monthly cross-sectional regression slopes for January, 1995 to December, 2009. The p-value in brackets is obtained from a standard t-test. Age is calculated on a daily basis. Fund size is measured by ln(A) where A is funds' assets under management. Fund liquidity is measured by lockup period on a daily basis. Panel A shows the results from univariate cross-sectional regressions for HFs without HF strategy dummy variables as defined in equation (2) to (4) and with HF strategy dummy variables as defined in equation (7) to (9). Panel B shows the results from univariate cross-sectional regressions for FOHFs without FOHF strategy dummy variables as defined in equation (2) to (4) and with FOHF strategy dummy variables as defined in equation (7) to (9).

For HFs, all three variables were significant at the 1% level in all regression models except for the lockup period variable for live HFs. The younger HFs provided significantly higher returns than the older HFs. The smaller the HFs, the higher the returns. The HFs with longer lockup period had significantly higher returns than the HFs with shorter lockup period. This was the case for the live, dead and combined HFs. The results for FOHFs were different from those for the HFs. It is interesting to note that the age appeared not important to all FOHF returns. Fund size seemed to be a significant factor for dead and combined FOHF returns, while it seemed not to be for live FOHF returns. In contrast, lockup variable showed significance at the 5% level only for the live FOHF returns. Results from the cross-sectional regression model for the dead and the combined FOHFs showed that the direction of the time-series average of the regression slope for size was different from that for the dead and the combined HFs. The larger FOHFs in the dead and the combined sample provided higher returns than the smaller FOHFs.

Table 6 shows the results of univariate and multivariate cross-sectional regressions of HF and FOHF returns on the ES_cf with a set of fund characteristics that include fund age, size and liquidity. [19]

The time-series average of the coefficients from the cross-sectional regressions of the one-month ahead returns on the risk measure were used to determine which explanatory variables on average had non-zero expected premiums. Panel A presents the results from cross-sectional regressions for the HFs, while Panel B shows the results from cross-sectional regressions for the FOHFs. In each regression model in Table 6, the first row indicates the average of the time-series coefficients, $\beta_t$, for one or more covariates over the 180 months from January, 1995 to December, 2009. The p-values from a standard t-test appear in parentheses and the average $R^2$ for each regression model is presented in the last column of Table 6.

It is interesting to note that the $R^2$ of the univariate regression model with an independent risk measure variable in Table 6 was much higher than that of the corresponding univariate regression model using fund characteristics as explanatory variables in Table 5. This result meant that risk measures had much higher ability to explain hedge fund returns than fund characteristics such as fund age, size and liquidity.

[19] The results from univariate and multivariate cross-sectional regression of HF and FOHF returns on the other risk measures are not reported due to limited space. These results are available from the author upon request.

Table 6
Average Values of the 180 Regression Slopes from the Month-by-month Regressions of HF and FOHF Returns on 95% Cornish-Fisher Expected Shortfall, Age, Size and Liquidity: January, 1995 to December, 2009

Panel A : Cross-Sectional Regressions for HFs

| Model | | | ES_cf | Age | ln(A) | Lockup | R^2 |
|---|---|---|---|---|---|---|---|
| Univariate Regression | Without Strategy Dummy Variables | Live | 0.0380<br>(0.0058) | | | | 7.34% |
| | | Dead | 0.0144<br>(0.3511) | | | | 6.26% |
| | | Combined | 0.0256<br>(0.0043) | | | | 5.24% |
| | With Strategy Dummy Variables | Live | 0.0342<br>(0.0060) | | | | 13.89% |
| | | Dead | 0.015<br>(0.2567) | | | | 10.17% |
| | | Combined | 0.0219<br>(0.0127) | | | | 10.31% |
| Multivariate Regression | Without Strategy Dummy Variables | Live | 0.0379<br>(0.0034) | 0.0000<br>(0.6203) | -0.0633<br>(0.0009) | 0.0001<br>(0.6813) | 9.84% |
| | | Dead | 0.0078<br>(0.6110) | 0.0000<br>(0.2764) | -0.0102<br>(0.5962) | 0.0003<br>(0.1475) | 7.04% |
| | | Combined | 0.0243<br>(0.0902) | 0.0000<br>(0.4232) | -0.0231<br>(0.1368) | 0.0003<br>(0.1211) | 6.57% |
| | With Strategy Dummy Variables | Live | 0.0353<br>(0.0412) | 0.0000<br>(0.4726) | -0.0585<br>(0.0008) | 0.0000<br>(0.6715) | 15.82% |
| | | Dead | 0.0129<br>(0.3323) | 0.0000<br>(0.2299) | -0.0101<br>(0.5436) | 0.0004<br>(0.0262) | 11.46% |
| | | Combined | 0.0209<br>(0.0349) | 0.0000<br>(0.1920) | -0.0193<br>(0.1454) | 0.0003<br>(0.0146) | 11.25% |

Table 6 *(Continued)*

Panel B : Cross-Sectional Regressions for FOHFs

| Model | | | ES_cf | Age | ln(A) | Lockup | R^2 |
|---|---|---|---|---|---|---|---|
| Univariate Regression | Without Strategy Dummy Variables | Live | 0.0049<br>(0.8076) | | | | 11.43% |
| | | Dead | 0.0073<br>(0.7112) | | | | 8.48% |
| | | Combined | 0.0008<br>(0.9665) | | | | 8.33% |
| | With Strategy Dummy Variables | Live | -0.0051<br>(0.7709) | | | | 17.79% |
| | | Dead | 0.0007<br>(0.9710) | | | | 15.74% |
| | | Combined | -0.0034<br>(0.8393) | | | | 14.65% |
| Multivariate Regression | Without Strategy Dummy Variables | Live | 0.0006<br>(0.9779) | 0.0000<br>(0.5202) | -0.0061<br>(0.6187) | 0.0002<br>(0.1287) | 15.11% |
| | | Dead | 0.0099<br>(0.6349) | -0.0001<br>(0.1801) | 0.0347<br>(0.0883) | 0.0003<br>(0.1300) | 13.78% |
| | | Combined | 0.0051<br>(0.7883) | 0.0000<br>(0.2290) | 0.0272<br>(0.0762) | 0.0002<br>(0.1873) | 11.69% |
| | With Strategy Dummy Variables | Live | -0.0099<br>(0.5917) | 0.0000<br>(0.3735) | -0.0025<br>(0.8328) | 0.0002<br>(0.0641) | 21.71% |
| | | Dead | 0.0023<br>(0.9140) | -0.0001<br>(0.1040) | 0.0302<br>(0.1243) | 0.0001<br>(0.4564) | 20.66% |
| | | Combined | -0.001<br>(0.9579) | 0.0000<br>(0.1265) | 0.0253<br>(0.0850) | 0.0002<br>(0.1471) | 17.74% |

*Note:* The average coefficients are the time-series (180 months) average of the monthly cross-sectional regression slopes for January, 1995 to December, 2009. The p-value in brackets is obtained from a standard t-test. Age is calculated on a daily basis. Fund size is measured by ln(A) where A is funds' assets under management. Fund liquidity is measured by lockup period on a daily basis. Panel A shows results from univariate and multivariate cross-sectional regressions for HFs without HF strategy dummy variables as defined in equation (1) and (5) and with HF strategy dummy variables as defined in equation (6) and (10). Panel B shows results from univariate and multivariate cross-sectional regressions for FOHFs without FOHF strategy dummy variables as defined in equation (1) and (5) and with FOHF strategy dummy variables as defined in equation (6) and (10).

In order to compare alternative risk measures the univariate and multivariate cross-sectional regression results are summarised in Table 7. Panel A shows results from HF regression, while Panel B presents those from FOHF regression. In each regression model in Table 7, the first row indicates the average of the time-series coefficients, $\beta_t$, for risk measure covariate over the 180 months from January, 1995 to December, 2009. The symbols ***, ** and * indicate whether the risk measure coefficient for each regression model is significantly different from zero at the 1%, 5% and 10% level of significance, respectively. The average $R^2$ for each regression model appears in parentheses.

## Table 7

Average Values of the 180 Regression Slopes from the Month-by-month Regressions of HF and FOHF Returns on Eight Risk Measures: January, 1995 to December, 2009

Panel A : Regressions for HFs

| Risk Mesure | Without Strategy Dummy Variables | | | | | | With Strategy Dummy Variables | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Univariate Regression | | | Multivariate Regression | | | Univariate Regression | | | Multivariate Regression | | |
| | Live | Dead | Combined | Live | Dead | Combined | Live | Dead | Combined | Live | Dead | Combined |
| SD | 0.1012** | 0.0341 | 0.0724* | 0.0966** | 0.0180 | 0.0701* | 0.1037* | 0.0413 | 0.0701* | 0.1007 | 0.0351 | 0.0668 |
| | (8.93%) | (5.83%) | (6.31%) | (11.36%) | (7.65%) | (7.64%) | (15.25%) | (10.88%) | (11.24%) | (17.09%) | (12.20%) | (12.21%) |
| SEMD | 0.1504** | 0.0538 | 0.1101* | 0.1441** | 0.0338 | 0.1073* | 0.1509** | 0.0634 | 0.1053* | 0.1468* | 0.0558 | 0.1013* |
| | (9.57%) | (6.46%) | (6.90%) | (12.03%) | (8.26%) | (8.24%) | (15.84%) | (11.36%) | (11.75%) | (17.71%) | (12.64%) | (12.72%) |
| VaR_np | 0.0568* | 0.0117 | 0.0370 | 0.0534* | 0.0034 | 0.0354* | 0.0556 | 0.0137 | 0.0334 | 0.0536 | 0.0104 | 0.0315 |
| | (8.77%) | (6.15%) | (6.24%) | (11.28%) | (7.85%) | (7.62%) | (15.03%) | (11.08%) | (11.16%) | (16.95%) | (12.38%) | (12.14%) |
| VaR_cf | 0.0578* | 0.016 | 0.0415 | 0.0547* | 0.008 | 0.0405 | 0.0547 | 0.0186 | 0.0376 | 0.0531 | 0.0162 | 0.0365 |
| | (8.92%) | (7.33%) | (6.45%) | (11.36%) | (8.09%) | (7.82%) | (15.13%) | (11.16%) | (11.30%) | (17.00%) | (12.46%) | (12.29%) |
| ES_np | 0.0447** | 0.0126 | 0.0295* | 0.0435** | 0.0083 | 0.0283* | 0.0418** | 0.0161 | 0.0258* | 0.0422* | 0.0137 | 0.0247* |
| | (8.46%) | (5.71%) | (5.93%) | (11.06%) | (7.50%) | (7.29%) | (14.78%) | (10.63%) | (10.88%) | (16.80%) | (11.91%) | (11.85%) |
| ES_cf | 0.038*** | 0.0144 | 0.0256** | 0.0379*** | 0.0078 | 0.0243* | 0.0342*** | 0.0150 | 0.0219** | 0.0353** | 0.0129 | 0.0209** |
| | (7.34%) | (6.26%) | (5.24%) | (9.84%) | (7.04%) | (6.57%) | (13.89%) | (10.17%) | (10.31%) | (15.82%) | (11.46%) | (11.25%) |
| TR_np | 0.0449** | 0.0148 | 0.0307* | 0.0438** | 0.0103 | 0.0294* | 0.0430** | 0.0187 | 0.0279* | 0.0431* | 0.0160 | 0.0266* |
| | (8.74%) | (5.78%) | (6.16%) | (11.31%) | (7.58%) | (7.51%) | (15.10%) | (10.69%) | (11.10%) | (17.08%) | (11.97%) | (12.06%) |
| TR_cf | 0.0390*** | 0.0150 | 0.0268** | 0.0388** | 0.0089 | 0.0254* | 0.0363*** | 0.0169 | 0.0238** | 0.0370** | 0.0144 | 0.0226* |
| | (7.76%) | (6.19%) | (5.53%) | (10.27%) | (7.17%) | (6.86%) | (14.32%) | (10.29%) | (10.58%) | (16.25%) | (11.58%) | (11.51%) |

**Table 7** *(Continued)*

| Panel B : Regressions for FOHFs | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Risk Mesure | Without Strategy Dummy Variables | | | | | | With Strategy Dummy Variables | | | | | |
| | Univariate Regression | | | Multivariate Regression | | | Univariate Regression | | | Multivariate Regression | | |
| | Live | Dead | Combined | Live | Dead | Combined | Live | Dead | Combined | Live | Dead | Combined |
| SD | 0.0344 | 0.0212 | 0.0238 | 0.0354 | 0.0453 | 0.0446 | 0.0032 | 0.0141 | 0.0100 | 0.0001 | 0.0363 | 0.0299 |
| | (14.73%) | (10.53%) | (11.16%) | (18.13%) | (16.18%) | (14.61%) | (19.60%) | (17.32%) | (16.22%) | (23.34%) | (22.34%) | (19.47%) |
| SEMD | 0.0522 | 0.0265 | 0.0222 | 0.0535 | 0.0612 | 0.0514 | 0.0098 | 0.019 | 0.0055 | 0.0047 | 0.0463 | 0.0310 |
| | (15.63%) | (10.77%) | (11.56%) | (18.96%) | (16.27%) | (14.93%) | (20.47%) | (17.37%) | (16.57%) | (24.18%) | (22.30%) | (19.72%) |
| VaR_np | 0.0158 | -0.0260 | -0.0103 | 0.0131 | -0.0053 | 0.0036 | -0.0014 | -0.0364 | -0.0230 | -0.0040 | -0.0217 | -0.0117 |
| | (14.02%) | (8.83%) | (9.82%) | (17.35%) | (14.47%) | (13.01%) | (19.24%) | (15.99%) | (15.11%) | (22.96%) | (20.94%) | (18.20%) |
| VaR_cf | 0.0144 | 0.0015 | 0.0023 | 0.0125 | 0.0175 | 0.0153 | -0.0068 | -0.0081 | -0.0096 | -0.0107 | 0.0004 | -0.0006 |
| | (14.64%) | (8.72%) | (9.67%) | (18.07%) | (14.22%) | (13.03%) | (19.96%) | (15.78%) | (15.18%) | (23.73%) | (20.76%) | (18.34%) |
| ES_np | 0.0102 | -0.0003 | -0.0003 | 0.0056 | 0.0103 | 0.0087 | -0.0032 | -0.0057 | -0.0072 | -0.0081 | 0.0010 | -0.0002 |
| | (13.57%) | (9.54%) | (9.94%) | (17.06%) | (15.05%) | (13.42%) | (18.99%) | (16.22%) | (15.34%) | (22.86%) | (21.29%) | (18.58%) |
| ES_cf | 0.0049 | 0.0073 | 0.0008 | 0.0006 | 0.0099 | 0.0051 | -0.0051 | 0.0007 | -0.0034 | -0.0099 | 0.0023 | -0.0010 |
| | (11.43%) | (8.48%) | (8.33%) | (15.11%) | (13.78%) | (11.69%) | (17.79%) | (15.74%) | (14.65%) | (21.71%) | (20.66%) | (17.74%) |
| TR_np | 0.0132 | 0.0104 | 0.0067 | 0.0111 | 0.0188 | 0.0144 | 0.0013 | 0.0079 | 0.0025 | -0.0026 | 0.0135 | 0.0087 |
| | (14.10%) | (10.39%) | (10.68%) | (17.56%) | (15.81%) | (14.09%) | (19.29%) | (16.88%) | (15.96%) | (23.12%) | (21.89%) | (19.11%) |
| TR_cf | 0.0078 | 0.0127 | 0.0058 | 0.0053 | 0.0156 | 0.0097 | -0.0016 | 0.0087 | 0.0029 | -0.0053 | 0.0099 | 0.0049 |
| | (12.16%) | (9.49%) | (9.40%) | (15.80%) | (14.81%) | (12.67%) | (18.20%) | (16.55%) | (15.41%) | (22.10%) | (21.35%) | (18.38%) |

Compared with the results from the test at the portfolio level in Table 3 and Table 4, the cross-sectional regression results made it possible to distinguish risk measures in terms of their ability to describe the cross-sectional variation in expected returns of HFs. As can be seen in Panel A of Table 7, the semi-deviation, expected shortfall and tail risk measures represented greater levels of significance than the standard deviation in both the univariate and multivariate regressions for HFs. Particularly, the Cornish-Fisher expansion was marginally better than the nonparametric measures for both expected shortfall and tail risk. The results were consistent with those of Liang and Park (2007). The multiple regression coefficients (average $R^2$) of ES_cf and TR_cf with fund strategy dummy variables for combined HFs were 0.0209 (11.25%) and 0.0226 (11.51%), respectively. They were positive and significantly different from zero at the 5% and 10% level, respectively. By contrast, the coefficient on standard deviation from the same model was not significant.

Contrary to the results showing that semi-deviation, expected shortfall and tail risk were superior to the standard deviation, VaR failed to reveal as much explanatory power as standard deviation. Interestingly, the VaR_cf explained less cross-sectional variation than the VaR_np[20] in the multivariate model without strategy dummy variables. This was consistent with the results of VaR at the portfolio level in Table 4[21]. In addition, the inclusion of the strategy dummy variables in the regression models made it possible to compare the results for the standard deviation measure with the other risk measures, except for VaR. ES_cf and TR_cf retained their significance levels after the adjustment of strategy effects, while the other risk measures lost explanatory power due to inclusion of investment strategy dummy variables. The average $R^2$ increased after the inclusion of strategy dummy variables in all regression models of HFs. This showed that each investment strategy tended to provide explanatory power for expected returns.

When the FOHFs were examined separately, the results were found to be different from those of HFs. Unfortunately, none of the risk measures exhibited predictive ability for FOHF returns as shown in Panel B of Table 7. This was consistent with the results of FOHFs at the portfolio level in Table 4. Therefore, the risk and return characteristics of FOHFs were also found to be different from those of HFs when the eight risk measures were analysed at the individual level.

## Conclusions

The collapse of some high profile hedge funds such as the Long Term Capital Management (LTCM) in 1998, the Soros Fund in 2000 and two Bear Stearns Hedge Funds in 2007 has emphasised the importance of downside risk management in the hedge fund industry. Due to dynamic trading strategies, traditional risk management measures were not appropriate risk measures to be applied to HFs and FOHFs. In this study, the risk-return trade-off in HFs and FOHFs were investigated and compared by alternative risk measures such as semi-deviation, Value at Risk, expected shortfall and tail risk. Also these risk measures were compared with the standard deviation in terms of their ability to explain the cross-sectional variation in the HF and FOHF returns.

As presented in the empirical results at the portfolio and individual levels, the FOHFs did not show the generally accepted risk-return trade-off. These results could be explained by the following facts. Firstly, as FOHFs were diversified portfolios of HFs, the variations of

[20] This is different from the results of Liang and Park (2007) where VaR_cf showed more significance than VaR_np.

[21] For combined HFs, the p-value of testing average return differential between low VaR_np and high VaR_np portfolio (0.0287) is lower than that between low VaR_cf and high VaR_cf portfolios (0.1254).

risk among FOHF portfolios formed by ranking a risk measure would be much less than risk variations among HF portfolios. Secondly, FOHF investors were observed to achieve less return than HF investors due to the different fee structure between HFs and FOHFs. While a HF charges a management and incentive fee, a FOHF charges extra fees at the underlying HF level as well as management and incentive fees at the FOHF level. Lastly, the negative relationship between risk and return in dead FOHFs would considerably affect the risk-return trade-off in overall FOHFs. Therefore, it can be expected that FOHFs did not display the statistically significant positive relationship between risk and return under the circumstances numerated above.

When the HFs were examined separately, the live and the combined HFs presented monotonically increasing risk-return relationships across the portfolios based on the estimated risk measures. The results at the individual level for the live and the combined HFs showed that semi-deviation, expected shortfall and tail risk were superior to the standard deviation in terms of their ability to explain the cross-sectional variation in expected returns, while VaR did not reveal as much explanatory power as did standard deviation. The Cornish-Fisher expansion was slightly better than nonparametric measures for both expected shortfall and tail risk. Furthermore, ES_cf and TR_cf kept their significance level when the investment strategy effects were included in the models, while the other risk measures decreased their explanatory power after controlling strategy effects.

The fund characteristics such as size, age and liquidity displayed explanatory power in cross-sectional variation for both combined HF and FOHF returns. However, the directions of age and size effects on expected returns were found to be different between combined HFs and FOHFs. The risk measures explained HF and FOHF returns better than the fund characteristics such as age, size and liquidity. Also the inclusion of the investment strategy dummy variables in all regression models of HFs increased average $R^2$. This meant that each investment strategy tended to provide explanatory power for expected returns.

It can be concluded from the empirical results that the available data on HFs and FOHFs exhibited different risk-return trade-offs. The ES_cf or TR_cf could be an appropriate risk measure for HF return. While appropriate alternative risk measures for the HFs could be found, it was difficult to determine the risk measures that best captured the cross-sectional variation in FOHF returns. Therefore, FOHF investors should apply different investment strategies from those adopted when investing in HFs. Also they should be more cautious about investment in FOHFs than that in HFs in terms of the risk-return relationship.

## References

Ackermann, C, McEnally, R & Ravenscraft D 1999, ‘The performance of hedge funds: Risk, return, and incentives’, *Journal of Finance,* vol.54, pp833-874.

Agarwal, V & Naik N 2004, ‘Risks and portfolio decisions involving hedge funds’, *Review of Financial Studies,* vol.17, pp63-98.

Amenc, N, Giraud, J, Martellini, L & Vaissie, M 2004, ‘Taking a close look at the European fund of hedge funds industry’, *Journal of Alternative Investment,* vol.7, pp59-69.

Amin, G S & Kat, H M 2003, ‘Welcome to the dark side: Hedge fund attrition and survivorship bias over the period 1994-2001’, *The Journal of Alternative Investments*, vol.6, pp57-73.

Ammann, M & Moerth, P 2005, ‘Impact of fund size on hedge fund performance’, *Journal of Asset Management*, vol.6, pp219-238.

Aragon, G 2007, ‘Share restriction and asset pricing: Evidence from the hedge fund industry’, *Journal of Financial Economics*, vol.83, pp33-58.

Asness, G, Krail, R & Lie, J 2001, 'Do hedge funds hedge?', *Journal of Portfolio Management*, vol.28, pp6-19.
Bali, T G, Gokcan, S & Liang, B 2007, 'Value at risk and the cross-section of hedge fund returns', *Journal of Banking and Finance*, vol.31, pp1135-1166.
Brown, S J, Goetzmann, W N & Ibbotson, R 1999, 'Offshore hedge funds: Survival and performance', *Journal of Business,* vol.72, pp91-117.
Brown, S J, Goetzmann, W N & Liang, B 2004, 'Fees on fees in fund of funds', *Journal of Investment Management,* vol.2, pp39-56.
Fama, E & French, K 1992, 'The cross-section of expected stock returns', *Journal of Finance,* vol.47, pp427-465.
Fama, E & MacBeth, J 1973, 'Risk, return and equilibrium: Empirical tests', *Journal of Political Economy,* vol.81, pp607-636.
Fung, W & Hsieh, D 1997, 'Empirical characteristics of dynamic trading strategies: The case of hedge funds', *Review of Finance Studies*, vol.10, pp275-302.
Hedge Fund Research Inc. 2010, 'HFR Industry Report'.
Hedges, R J 2003, 'Size vs performance in the hedge fund industry', *Journal of Financial Transformation*, vol. 10, pp14-17.
Herzberg, M M & Mozes, H A 2003, 'The persistence of hedge fund risk: Evidence and implications for investors', *Journal of Alternative Investments*, vol.6, pp22-42.
International Financial Services London 2009, 'Research of Hedge Fund'.
Liang, B 1999, 'On the performance of hedge funds', *Financial Analysts Journal*, vol.55, pp72-85.
Liang, B 2004, 'Alternative investments: CTAs, hedge funds and funds-of-funds', *Journal of Investment Management*, vol.2, pp76-93.
Liang, B & Park H 2007, 'Risk measures for hedge funds: A cross-sectional approach', *European Financial Management*, vol.13**,** pp317-354.
Lo, A 2001, 'Risk management for hedge funds: Introduction and overview', *Financial Analysts Journal*, vol.57, pp16-33.
Malkiel, B G & Saha, A 2005, 'Hedge funds: Risk and return', *Financial Analysts journal*, vol.61, pp80-88.