Tail Risk and the Returns of Fund of Hedge Funds

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JEL Classification: G01; G11; G15; G23

Key words: Hedge fund, Fund of hedge fund, tail risk, return, alpha

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Abstract

We examine the tail risk exposure of Fund of Hedge Funds (FOHFs) from 1995 to 2010. We show that most of the hedge funds and FOHFS have significant tail risk exposure during the sample period. On average, the tail risk exposure of FOHF is at a similar level to the normal hedge fund. Our research provides direct evidence that FOHFs cannot effectively diversify tail risk. In addition, we find that younger funds charging higher management fees, requiring shorter lockup periods and using leverages tend to have higher exposures to tail risk events. Moreover, we document an insignificant return of the portfolio taking short position on the lowest tail beta FOHFs and long position on the highest tail beta FOHFs. This leads to the view that the FOHFs writing tail risk insurances do not receive enough compensation for their extra loading on tail risk.

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1 Background

A Fund of Hedge Fund (FOHF) is a fund that holds a diversified portfolio of hedge funds. FOHFs provide opportunities for investors to get desired exposure to the hedge fund industry and, at the same time, reduce the risk associated with individual hedge fund investment through diversification. In the last decades, FOHFs have received increased popularity in the financial markets with total value of Asset under Management (AUM) reaching $533 billion by the first quarter of 2012. This accounted for about 25% of the total investment received by the hedge fund industry (Schizas, 2012).

FOHFs are believed to deliver diversification benefits to investors. However, the recent financial crisis has drawn doubts on the capability of FOHFs in risk diversification. Tail risk can be defined as the investment outcome that deviates from the expected performance due to the occurrence of extreme events. It is a common practice to use standard normal distribution to represent the foreseen investment outcome. And the “tails” are actually the part of the lower ends of the bell shape that represent the returns associated with extremely low chances of occurrence. However, investors with long enough investment horizons may face such left tail events and incur large losses. In addition, the distribution of the payoffs of a financial asset usually does not perfectly follow normal distribution, which means there are perhaps some tail events not captured by the assumed normal distribution. Financial assets with hidden tail risk are very likely to be overpriced by investors using expectations calculation and thus eventually pose unendurable losses. Based on the recent study of Dai and Shawky (2013), 2008 crisis (GFC) has caused severe deteriorations in returns of FOHFs. Additionally, the authors also found the large number of fund holdings didn't prevent the poor performance.

Although there is limited research on the direct relationship between tail risk and FOHFs' return, it has been found that ordinary hedge fund returns tend to "co-move" under negative market shocks. Significant contagions among hedge fund returns were observed under bear market conditions (Agarwal and Naik 2000a, Boyson et al. 2008). Given the fact that hedge fund would "hedge" themselves from suffering from bad market conditions, the deterioration of both hedge fund and FOHF returns during bear market seems to be a puzzle. Thus, the study on the impact of tail risk to the performance of hedge funds and FOHFs will provide important implications to investors and regulators. In particular, we are interested in answering the following questions.

Question 1: To what extent, does the tail risk exposure explain the return of FOHFs?

Question 2: To what extent, is the tail risk exposures of FOHFs differ from ordinary hedge funds?

Question 3: To what extent is the tail risk exposure explained by a fund's characteristics?

Question 4: Can tail risk exposure explain the cross sectional differences in FOHFs return?

In our research, we constructed a tail risk estimator using the cross-sectional stock daily returns as suggested by Jiang and Kelly (2012). We examined the tail risk exposure of hedge funds and FOHFs controlling for Fung and Hsieh (2007) eight factors (FH eight factors hereon). We found the impact of our tail risk measurement only becomes insignificant when there is an emerging market factor in the model. In addition, we found younger funds which charges higher management fees and incentive fees, uses high watermark and requires longer advance notice days tend to expose more to tail risk. We have tested whether the tail risk exposure helps to predict future performance. We found that the FOHFs with high level tail risk exposure and the FOHFs with low level tail risk exposure generate lower returns than other FOHFs with moderate tail risk exposure. Such phenomenon cannot be observed in the same analysis using our hedge fund sample. It seems that the excess returns from taking on extra tail risk have been traded-off by the losses caused by tail event shocks.

Our research contributes to the existing literature in the following ways. Firstly, to our knowledge, our research is among the first to investigate the direct relation between tail risk and FOHFs returns. We presented a comparative research by separating our sample into FOHFs and other ordinary hedge funds. We found that both samples have similar tail risk exposure which means FOHFs on average cannot diversify tail risk. Additionally, we documented a trade-off effect between tail risk exposure and the excess return of FOHFs with tail-risky investments. We found FOHFs with high level tail risk exposure are not rewarded by higher excess return. As such, the FOHFs following a clear strategy in tail risk exposure (either as insurer or hedger) will underperform other FOHFs.

The paper is organized as follows. We review the literature on tail risk measurements and hedge fund performance in the first section. Section two discusses the research methodology and the data to be used. We introduce the approach of estimating tail risk measurement as well as other models in section three. The test results are presented and analyzed in section four. We conclude the paper in section five.

2 Literature Review

Previous studies have established several benefits of investing in FOHFs. For example, Ang et al. (2008) proposed that the exposure to different investment styles through investing in FOHF comes with due diligence in fund selection and oversights in portfolio management, which helps to reduce the cost for unskilled investors. Brands and Gallagher (2005) found that in a mean-variance structure, FOHFs provide enhanced performance as the number of funds in the portfolio increases. Such diversification benefit has also been documented in Amo, et al. (2007).

However, Brown et al. (2011) raised a puzzle in FOHFs returns. They documented a decreasing trend in FOHF returns with the rise in the number of underlying hedge funds in the portfolio. They suggested that FOHFs tend to over diversify their portfolio and be more exposed to left-tail risk. The argument was supported by their finding that the magnitude of FOHFs' negative skewness is an increasing function of the number of funds in FOHFs portfolios.

There are more studies on the impact of 2008 Global Financial Crisis that provide relevant information on the impact of tail risk event on the returns of FOHFs. Schizas (2012) compares the performance of FOHFs before, during and after the crisis (from 1999 to 2011) and finds substantial deterioration in the performance of FOHFs. The correlation between FOHFs returns and stock markets has increased after the crisis. In another comparative study, Edelman et al. (2012) documents a decline in the ability of FOHF managers to gain excess return. The average alpha (5.28% annually) generated before the crisis (2005–2007) has diminished in the subsequent period (2008–2011).

Our research follows the previous line of research in decomposing hedge fund returns into exposures to different market factors. Such effort has its root in Jensen (1967) where the performance of mutual funds is explained by the return to the market risk exposure and the return to fund managing skills. The initial attempt to decompose hedge fund returns into different risk exposures can be found in Fung and Hsieh (1997). Furthermore, Fung and Hsieh (2004) specified the risk exposures of different hedge fund styles and eventually proposed seven factors that influence the return of hedge funds. The seven factors include two equity market factors, two fix-income security market factors and three trend-following risk factors.

The seven-factor model was adopted in Fung et al. (2008) to analyze the returns of 1603 FOHFs over the time period from January 1995 to December 2004. The model was found to explain the return of FOHFs. Furthermore, Fung et al. (2008) reported FOHFs time varying exposures to the seven factors and found vanishing alpha during market distress from 2000 to 2002.

The significant explanatory power of factor models may suggest that FOHFs gain their returns mainly through taking exposures to market wide factors. This argument was tested by Edelman et al. (2012) who examined the performance of FOHFs during 2005 to 2010. They found FOHFs exhibited insignificant alpha generating ability during the sample period and the majority of FOHFs to be classified as beta-only producers. The emerging market factor was found to have significant explanatory power since 2005 which confirms the appropriateness of inclusion of this factor into the seven-factor model as suggested by Fung and Hsieh (2007).

It should be noted that hedge fund returns are not linearly correlated to risk factors. Instead, many hedge funds exhibit option-like payoffs (Fung and Hsieh 1997, Kat 2002 and Agwal and Naik, 2000b). This unique relation leads to the inclusion of option type risk factors in various factor models. For example, the three trend-following risk factors in Fung and Hsieh (2004) take the form of look-back straddles on different asset classes. In the work of Agwal and Naik (2004), option-based factors such as the at-the-money European call option on the S&P 500 composite index were included in the factor model.

Hedge funds' tail risk exposure has received attentions from researchers in more recent time. There is a growing body of evidence showing that hedge funds are more sensitive to the negative market movements as outlined by

Geman and Kharoubi (2003) and Brown and Spitzer (2006). Brown and Spitzer (2006) attributed this phenomenon to the contagion across hedge funds under liquidity shocks and market distresses. Agarwal and Naik (2004b) presented research focusing on the left-tail risk of hedge funds. They found the payoffs of many equity-oriented hedge funds resembled those from a short position of an equity index put option and suggested that such hedge funds usually lose in market downturns and suffer from significant left-tail risk.

In the latest research of Jiang and Kelly (2012), hedge funds are found to be persistently exposed to left-tail risk. They found a strong relation between tail risk and fund returns in both time series and cross-sectional regressions. On average, the value of an aggregated hedge fund portfolio loses 2.88% under a unit tail risk shock, represented by 1% change in their tail risk measure. Controlling for other fund characteristics, hedge funds with negative exposure to the tail risk are found to generate 6% higher returns than the funds with positive correlation to the tail risk measure.

Brown and Spitzer (2006) observed strong correlation between extreme losses of FOHFs and the extreme losses of the market. They suggested that the tail risk of ordinary hedge funds cannot be effectively diversified in a FOHF's portfolio. Brown et al. (2011) documented a decreasing trend in FOHFs returns with the rise in the number of underlying hedge funds in the portfolio. They suggested that FOHFs tend to over diversify their portfolio and be more exposed to left-tail risk. The argument was supported by their finding that the magnitude of FOHFs negative skewness is an increasing function of the number of funds in FOHFs portfolios. This further indicates that tail risk should be taken as a component of systematic risk when evaluating the return of a portfolio of hedge funds using multivariate models.

3 Research method and data description

3.1 Research methods

We follow five steps to examine the tail risk of FOHFs. In step one, we adopt the method in Jiang and Kelly (2012) to develop a tail risk factor using cross section stock returns. They suggested that the information about market-wide extremes can be distilled from the cross section of individual firms' returns. Following this assumption, they developed a common left-tail risk measure using monthly firm-level price crashes. Lower tail risk events are assumed to follow a power law, which in formula reads:

$$P\left(R_{i,t+1} < r \mid R_{i,t+1} < u_t \text{ and } \mathcal{F}_t\right) = \left(\frac{r}{u_t}\right)^{a_i \zeta_t}$$

Where u_t represent a predefined extreme negative threshold, $R_{i,t+1}$ is the return of asset i at time $t+1$and we have $r < u_t < 0$. The shape of tail risk distribution is decided by parameter $a_i\zeta_t$ and is named as tail exponent. Higher value of $a_i\zeta_t$ corresponds to fat tail which implies extreme losses. The second tail exponent ζ_t varies with a random information set $\mathcal{F}_t$ and is the only dynamic parameter in the setting. Therefore, market-wide extreme movements are captured by ζ_t and Kelly defined it as tail risk in returns. Kelly estimated the monthly tail exponent by applying Hill's (1975) power law estimator to the cross section of CRSP stocks and it takes the form:

$$\frac{1}{\zeta_t^{\mathrm{Hill}}} = -\frac{1}{K_t}\sum_{k=1}^{K_t} \ln \frac{R_{k,t}}{u_t}$$

Where $R_{k,t} = (P_{k,t} - P_{k,t-1})/P_{k,t-1}$ is the k^{th} daily arithmetic return that is lower than u_t during month t, K_t counts the number of such exceedences within month t. Following Jiang and Kelly (2012), I will standardise the estimated ζ_t^{Hill} as:

$$\mathrm{Tail}_t = \frac{\hat{\zeta}_t^{\mathrm{HIll}} - \widehat{E}[\hat{\zeta}_t^{\mathrm{HIll}}]}{\hat{\sigma}(\hat{\zeta}_t^{\mathrm{HIll}})},$$

where $\widehat{E}$ and $\hat{\sigma}$ denote the sample mean and standard deviation of monthly tail risk estimates. The significance of the tail risk measure was tested in Jiang and Kelly (2012) and they found the measure closely related to the tail risk perceived by investors in equity index options.

At step two, we formed both equally weighted and value weighted portfolios made up of selected fund universes. We calculated the average monthly returns of the portfolios and run regressions to obtain the exposures of the portfolio returns to our tail risk factor. In our research, we use FH seven factors as control variables. Furthermore, we include an emerging market factor to form FH eight factor model to reexamine the significance of tail risk exposures. FH eight factor model takes the following form:

$$R_t^k = \alpha_t^k + \sum_{i=1}^{8} \beta_i^k F_{i,t} + e_t^k$$

Where R_t^k is the excess return of the decile portfolio j at time t, α_t^k represents the excess return of the portfolio over the risk premium. β_i^k is the portfolio's risk exposure to the ith factor and e_t is the residual. The list below introduces the eight factors in the regression model.

F_1: $excess\ return\ on\ S\&P\ 500\ index$;

F_2: $small\ minus\ big\ factor, calculated\ using\ Russell\ 2000\ index\ monthly\ return -$ $S\&P\ 500\ monthly\ return$;

F_3: $bond\ market\ factor, monthly\ change\ in\ the\ 10\ year\ treasury\ bond\ yield$;

F_4: $credit\ spread\ factor, the\ monthly\ change\ in\ the\ Moody's\ Baa\ yield\ minus\ 10 -$ $year\ treasury\ bond\ yield$;

F_5: $Emerging\ market\ risk\ factor, the\ residual\ of\ MSCI\ Emerging\ Market\ Index\ to\ SP500$

F_6, F_7, F_8: $Trend\ following\ risk\ factors, measured\ by\ the\ monthly\ returns\ of\ portfolios$ $of\ look\ back\ stradle\ on\ bond, currency\ and\ commodity\ respectively.$

At step three, we test the explanatory powers of different FOHF's characteristics on the tail risk exposure using cross-sectional regressions. We will examine whether fund characteristics, such as the fund age, fee structure and restrictions on investors help to explain the cross sectional differences in tail risk exposure.

Research step four involves the construction of tail risk quantile portfolios following the approach of Jegadeesh and Titman (1993). Each month, five quantile portfolios of FOHFs are formed in the ascending order according to their tail risk beta in the prior 18 months. The tail risk betas are obtained by running regression on individual funds' monthly returns, market excess return (S&P500) and the tail risk factor. The portfolios are held during a period of t and liquated at the end of the holding period. We aggregate the monthly returns of the portfolios according to their tail risk quantile so that we generate five monthly return time series. For example, during month k, the lowest beta quantile portfolio will contain t portfolios constructed in month k-t+1 to k. At the end of month k, the portfolio constructed in month k-t+1 will be liquidated and replaced by the portfolio constructed in month k+1. We test whether the mean returns of the quantile portfolios are significantly different from zero. For holding periods other than a month, we use Newey-West standard errors to adjust for the impact of autocorrelation. Similar to Jiang and Kelly, we also test whether the mean return of a short-long portfolio, which short low tail risk beta portfolio and long high tail risk beta portfolio, is significantly different from zero.

3.2 Data description

To form tail risk estimator following Kelly's (2012) approach, we collect the daily price of the constituents of Thomason Reuters Global Equity Indices from 1 January 1995 to 31 December 2013. The number of stocks with valid data in each year varies between 6000 and 10 000.

Our hedge fund data is provided by Hedge Fund Research Inc. (HFR). The reporting period starts from January 1991 and ends on 28 February 2010. The period covers the major market shocks to the hedge fund industry including the collapse of Long Term Capital Management in 1998, the burst of the high-tech bubble in the early 2000s and the 2008 GFC. There are 14,968 hedge funds included in the data pool and 4,055 of them are classified as FOHFs. The whole sample includes both living funds and defunct funds. HFR further classify the FOHFs into four subcategories according to their investment strategies: Conservative, Diversified, Market Defensive and Strategic. In our preliminary fund performance analysis and tail risk exposure analysis, we include the funds reporting more than 24 month returns and reporting asset under management (AUM) denominated in US dollars only. This could lead to some bias towards the US domiciling funds.

Data quality has been a constant problem for hedge fund research as all information available is voluntarily disclosed by hedge funds. To account for survivorship bias, we combined the data of living hedge funds with the data of the hedge funds in the graveyard so that the sample covers both living and dead funds. To alleviate back-fill bias, we deleted the returns before the reporting dates for all funds. This practice is commonly adopted in hedge fund studies, such as Fung and Hsieh (1997 and 2001).

Although many studies questioned the quality of the hedge fund data provided by commercial data vendors, the recent study of Edelman et al. (2013) provided evidence on the reliability of such data. They proved that the reporting mega funds have many similarities with those non-reporting mega funds. They compared the performance of mega funds that chose not to report to commercial databases with the performance of reporting mega funds. They presented evidence that there is no significant difference between the average return and volatility of the two groups. Thus, they claim that the performance of non-reporting funds can be inferred using the available performance reporting funds. The findings of this study add some credit to the reliability of the data provided from commercial data vendors.

4 Empirical results

4.1 Preliminary FOHFs performance analysis

We form equally weighted portfolios according to different hedge funds' and FOHFs' investment styles. The average monthly return, return volatility, skewness and kurtosis of the portfolios are reported in Table 1.

[Insert Table 1]

In general, we find FOHFs on average has generated the lowest monthly return 0.506% among the main categories of hedge funds. Excluding FOHFs, an average hedge fund has generated 0.68% monthly return during the sample period, which is about 1.35 times of the monthly return of an average FOHF. Almost all of the hedge fund strategies have exhibited fat tails in their return distributions except Macro. Moreover, on average FOHF portfolio reported higher skewness and higher kurtosis comparing with the average hedge fund (excluding FOHFs) portfolio. It implies that FOHFs on average may not be able to diversify the tail risk in ordinary hedge funds. Within the categories of FOHF investment styles, Conservative FOHFs has reported the highest kurtosis and the highest skewness. HFR defines Conservative investment style as an investment in hedge funds pursuing conservative strategies such as Equity Market Neutral and Fixed Income Arbitrage. Intuitively, such investment strategy will generate persistent performance regardless of the market condition. However, our preliminary analysis indicates that such funds tend to generate extreme negative returns than their peers. The FOHFs following Market Defensive strategy has a close to normal distribution and the normality test doesn’t reject the null hypothesis that the returns come from a normally distributed population.

We redo the performance statistics on value weighted portfolios of different hedge funds and FOHFs investment styles and the results are summarized in

Table 2.

[Insert Table 2]

The results from value weighted portfolios do not substantially deviate from the results from equally weighted portfolios. According to Shapiro-Wilk normality test, all portfolios exhibit significant non-normality. However, the non-normality of the value weighted portfolios is featured with high kurtosis instead of negative skewness comparing with the distributional characteristics of equally weighted portfolios. In particular, both value weighted hedge fund portfolio and FOHF portfolio have positive skewness but high kurtosis on average. At strategy level, the negative skewness appears in “Event Driven” and “Relative Value” for hedge funds and “Conservative” and “Diversified” for FOHFs. The normality test was rejected at all cases in value weighted portfolios.

In summary, both hedge funds and FOHFs, on average, exhibit non-normality in their return distribution. In addition, the funds pursuing certain strategy, such as “Relative Value” strategy hedge funds and “Conservative” strategy FOHFs, are more prominent in tail losses.

4.2 The tail risk exposure of hedge fund and FOHFs portfolios

Our computed tail risk measurement time series is depicted in Figure 1 top panel. The tail risk factor is quite stationary where the influence of the previous tail event shock disappears quickly in the next period.

TheACF diagnostic chart are reported in Figure 1 bottom panel. In addition, we performed KPSS test and Dickey-Fuller test to examine the stationarity of the tail risk time series and the results are reported in Table 3.

[Insert Figure 1]

[Insert Table 3]

According to the ACF diagnostic chart, the lag one month impact of a tail risk shock disappears quickly to be insignificant. Moreover, both stationarity tests suggest that the time series is stationary. When fitting AR(1) process to the tail risk measurement, we obtain a model with coefficient of 0.224. Following the approach of Jiang and Kelly (2012), we use the innovations in this AR(1) process to proxy the tail event shocks, which we refer to as tail risk factor hereafter. The plot of our tail risk factor is similar to the tail risk measurement time series in Figure 1.

We report our regression analysis findings in Table 4 where FH seven factors are used as control variables. We run regressions on both equally weighted hedge fund portfolios and FOHF portfolios to compare their differences in tail risk exposure. Controlling for FH seven factors, we find all portfolios have negative exposure to the tail risk factor, which coincide with the intuitive reflection that the higher the exposure to tail risk event, the higher the loss to the hedge funds.

[Insert Table 4]

Both of the equally weighted hedge fund and FOHF portfolios have significant exposure to the tail risk factor and the influences of the tail risk shock to the two portfolios are similar (-0.266 and -0.253 respectively). The result verifies our observation from the comparison of skewness and kurtosis of the two portfolios, so that we suggest, on average, FOHFs cannot diversify the tail risk exposure of ordinary hedge funds.

With regard to the alpha of hedge funds and FOHFs, we find ordinary hedge funds are able to deliver significant alpha controlling for the impact of seven factors and the tail risk factor. In contrast, all FOHF portfolios fail to deliver significant alpha over the sample period.

We continue to test the tail risk exposure of value weighted portfolios. The results are reported in Table 5.

[Insert Table 5]

Interestingly, our tail risk factor becomes insignificant in most of the portfolio regression results except for the FOHF portfolios following Conservative and Market Defensive strategy and the hedge funds following Relative Value strategy. The diminishing significance could be a result of size bias caused by value weighted averaging.

We try to test the significance of the tail risk exposure with more controlling factors. We use FH eight factors to consider the additional impact of emerging market in another group of regressions. The results are not reported but controlling for the additional influence of emerging market, we found the significance of tail risk exposure disappear for most of the portfolios.

As the tail risk factor time series are derived from equity market return data, we suspect that the disappeared significance of tail risk factor could stem from the strong correlation between the factors. The correlation matrix between factors is reported in Table 6.

[Insert Table 6]

The result suggests that there is a strong relation between the tail risk factor and the risk premium of equity market (SP500). Recall that the emerging market factor is measured by the residual from the regression between SP500 index risk premium and MSCI Emerging Market index risk premium, the inclusion of this factor may further reduce the explanatory power of the tail risk factor.

Comparing the explanatory power of the models, we find both FH seven-factor model and FH eight-factor model work better to explain ordinary hedge fund returns. The adjusted R^2 remains above 0.7 for most of the hedge fund styles and average hedge funds excluding FOHFs, but it remains around 0.55 for most of the FOHF investment styles and the equally weighted average FOHFs.

4.3 Tail risk exposure and FOHFs characteristics

The next step of our research is to investigate the relation between FOHF characteristics and the tail risk exposure. We selected the funds which reported their returns on a net-of-all-fees basis and we excluded the funds without reported net assets, usage of leverage, management fees, incentive fees, redemption frequency and a lockup period. This gives us 1364 FOHFs in the sample. We obtain tail risk beta for each fund controlling for FH seven factors. The distribution of cross-sectional tail risk betas is plotted in Figure 2 and the summary statistics are reported in Table 7.

[Insert Table 7]

The distribution of the tail risk beta coefficients are negative skewed with a skewness of -0.727. Tail risk shocks lead to significant negative movements in the return of 699 FOHFs but only significantly benefit 21 FOHFs. Given this observation, one would strongly question the ability of FOHFs in tail risk diversification.

Thus, we reduce our sample to the 699 FOHFs with significant tail risk beta coefficients and perform a series of cross-sectional regression analysis. To simplify the analysis, we calculate the absolute values of all beta coefficients and use them as independent variables in the regressions. We classify the fund characteristics into four groups: Age/Size/Survivorship, Fee structure, Restrictions to investors and Leverage. We run cross-sectional regression for each group of characteristics on the tail risk beta. The return and volatility in the previous 24 months are used as control variables. The regression results are reported in Table 8. In our specification, the higher the independent variable, the higher the exposures to the tail risk. Therefore, the funds at younger age, charging higher management, requiring shorter holding period and employ leverages tend to take more loadings on tail risk. The results have their intuitional rationales.

Usually, younger funds may face difficulties in attracting capital, so they have to gamble on tail risk event in order to improve their tracking records. The FOHFs charging higher management fees have incentives to take higher tail risk exposure in order to deliver the same net returns to the investors. The FOHFs requiring shorter lockup periods are more likely to liquidate their positions at a loss in market turmoils in order to meet urgent redemption requirements. At last, leverage will amplify the tail event shocks so that the FOHFs using leverages will incur higher losses in a market downturn.

[Insert Table 8]

4.4 Tail risk in the cross section of FOHF returns

Following the process described in Section three, we construct tail risk beta sorted quantile portfolios and test their performance in the post formation holding period. The results are reported in Table 9.

[Insert Table 9]

FOHFs in lower quantile portfolios report lower tail risk beta in the pre-formation period, which means such funds are tail risk insurers to the ordinary hedge funds. On the other hand, the FOHFs in the higher quantile portfolios are suspected to be tail risk hedgers as they report high tail risk beta in the pre-formation period. We expect to find significant difference between the lowest tail beta portfolio and the highest beta portfolio in the subsequent holding period. Intuitively, FOHFs with lower tail risk beta (thus higher tail risk exposure) should report higher expected returns. Therefore, portfolios following long-short tail risk strategy should generate significant negative returns in various holding periods. However, our results suggest that such difference do not exist in the cross section returns of FOHFs. The return of the portfolio taking long position in the highest tail beta portfolio and short position in the lowest tail beta portfolio is not significantly different from zero, no matter we set the holding period to one month, a quarter or even a year. Our result is different to the findings of Jiang and Kelly (2012), where they find the tail risk beta help to differentiate the cross sectional returns of hedge funds. In order to verify that our finding is not a result of the misspecification in tail risk modeling, we redo the portfolio construction and Newey-West error adjusted t-tests using ordinary hedge fund data. In addition, using FOHF and hedge fund sample separately, we construct portfolios taking long position in the highest tail beta portfolio and short position in other four quantile portfolios and test the significance of the return over different holding periods. We name the quantile portfolios as P1 to P5 in the ascending order of their tail risk beta. Therefore, FOHFs in P1 have the lowest past tail risk beta and the highest tail risk exposure and P5 has the lowest tail risk exposure. The results are reported in Table 10.

[Insert Table 10]

The test results using our hedge fund sample mirrors the results of Jiang and Kelly (2012). The average return of the portfolio following short-long tail risk strategy is significantly different from zero during the holding period of a quarter, half a year and one year. This is in contrast to the insignificant returns of similar portfolios made up of FOHFs. Moreover, when comparing the excess returns of FOHF portfolios, we find that only portfolios taking short positions in the lowest tail risk beta FOHFs deliver insignificant excess returns. It seems that tail risk beta can still help to differentiate the cross sectional returns of FOHF while it only fails to differentiate the return of a pure tail risk insurer (P1) and a pure tail risk hedger (P5). This is to say, if a FOHF follows a clear strategy on tail risk (whether as a tail risk insurer or a tail risk hedger), it will underperform the other FOHFs with less clear strategy on tail risk. Our findings on the performance of FOHFs as tail risk insurers appear to be contradictory to the traditional risk premium wisdoms. It seems that such FOHFs do not receive enough premiums for their extra loadings on the tail risk exposure.

Research literature has documented increasing correlations between hedge fund returns and market wide factors in market turmoil. If a FOHF underestimate such correlation and writes insurance on tail risk for hedge funds, it will eventually suffer from a market wide tail risk shock. This could partially explain the low premium for the tail risk insuring FOHFs. However, to verify this conjecture, we need to investigate the change of dependence structure between FOFHs and market wide factors in different market states. We leave this open for the future research.

5 Conclusions

The objective of the research is to investigate the relation between FOHF returns and tail risk exposure. Following the approach of Jiang and Kelly (2012), we constructed our time series of tail risk factor and apply it to a sample of 4055 FOHFs. The major research findings are summarized below.

We find FOHFs on average do not diversify tail risk. Our preliminary data analysis indicates that the return distribution of an equally weighted FOHF portfolio has fat tail and higher kurtosis. We document significant impact of the tail risk factor on the return of FOHFs, controlling for FH seven factors. On average, a standard unit of tail risk shock can lead to 0.249% drop in the monthly excess return of FOHFs. A similar impact is documented in the regression of ordinary hedge fund returns.

In addition, we document some relation between FOHF characteristics and tail risk beta. It is found that younger funds charging higher management fees, requiring shorter lockup periods and using leverages tend to have higher exposures to tail risk events.

Moreover, we find that tail risk exposure can help to differentiate most of the cross sectional FOHF returns. However, we document insignificant return of the portfolio taking short position on the lowest tail beta FOHFs and long position on the highest tail beta FOHFs. This leads to the view that the FOHFs as tail risk insurers are not compensated for their extra loading on tail risk.

One possible approach to investigate this phenomenon is to evaluate and compare the risk exposure of tail risk insuring, tail risk neutral and tail risk hedging FOHFs. However, as pointed out in section 4.2, our tail risk factor has strong correlation with equity market factor and emerging market factor. As a result, the tail risk factor loses its explanatory power when controlling for FH eight factors. Meanwhile, the popular FH seven-factor or eight-factor model cannot explain the return of FOHFs as much as it works for ordinary hedge funds. This could be due to some unique exposures of FOHFs that are beyond the scope of the traditional factor models. It is suggested that further research should be carried out to examine the dependence structure between FOHFs and other market wide factor returns in different market states.

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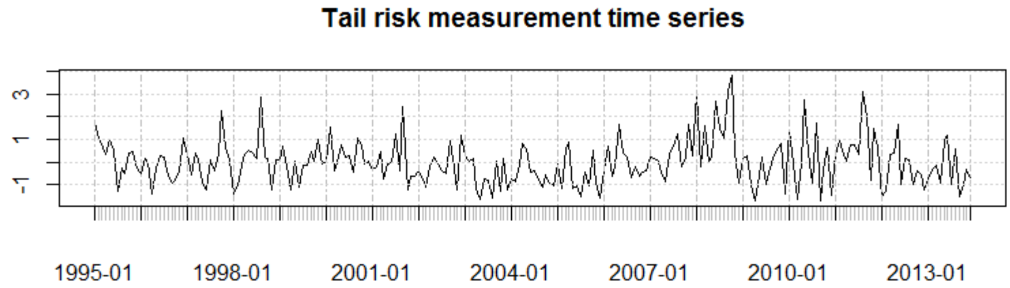
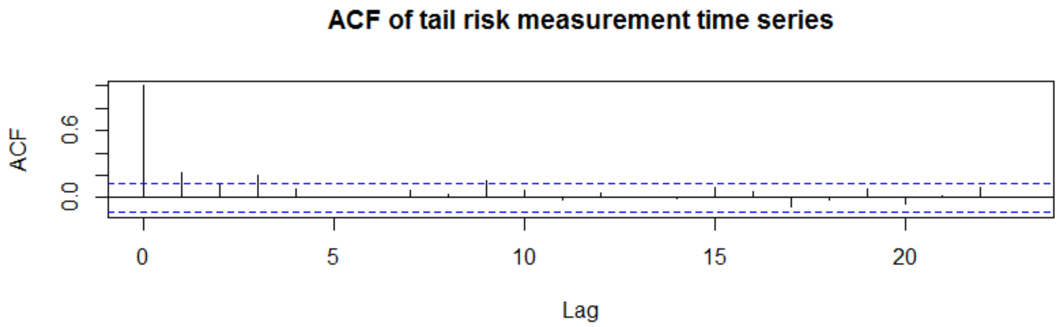
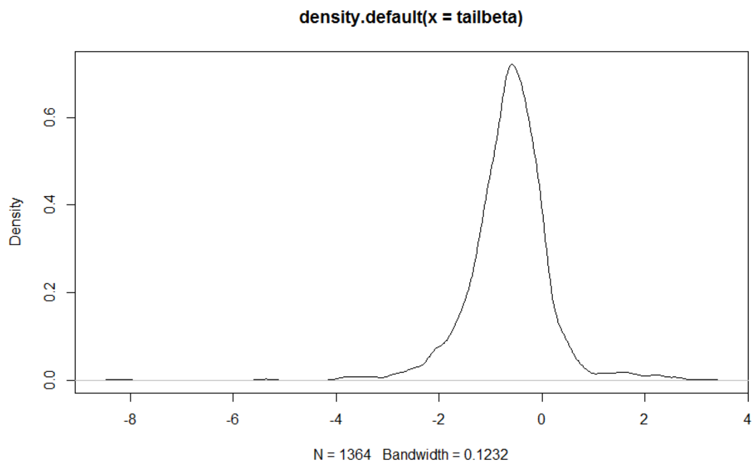
Figure1, Tail risk measurement time series and ACF diagnostic chart[a] (Jan 1995 to Dec 2013)





a. The tail risk measurement is derived using Hill's estimator which is discussed in Section 3.1. We use cross sectional daily returns of the constituents in Thomson Reuters Global Equity Index to derive the monthly tail risk measurement.

Figure 2 Distribution of cross-sectional tail risk betas[a]



a. The beta coefficients are obtained from the regression of each hedge fund's return to tail risk factor, controlling for FH seven factors.

Table 1 The performance of equally weighted[a] hedge fund, hedge fund style, FOHF and FOHF style portfolios[b]

		Count	mean	variance	skewness	kurtosis	Normality test[c]
Ordinary hedge funds portfolios	**HFs ex. FOHFs**	7113	0.680	4.281	-0.484	4.933	0.969***d
	Equity Hedge[e]	3523	0.716	8.782	-0.383	5.038	0.971***
	Event-Driven	748	0.737	3.259	-1.841	9.957	0.877***
	Macro	1471	0.636	3.770	0.316	3.021	0.993
	Relative Value	1235	0.618	1.949	-3.186	21.515	0.745***
Funds of hedge funds portfolios	**FOHFs**	2220	0.506	3.701	-0.687	6.582	0.934***
	Conservative	504	0.507	1.433	-2.619	13.779	0.785***
	Diversified	881	0.560	3.140	-0.729	6.547	0.937***
	Market Defensive	99	0.593	2.784	0.034	3.512	0.994
	Strategic	736	0.446	7.915	-0.355	5.509	0.951***

a. Each portfolio is constructed and rebalanced monthly. Every month, we calculate the arithmetic average return of all funds in the portfolio.
b. The time series span from 31 May 1996 to 28 February 2010.
c. We apply Shapiro-Wilk normality test on our sample. The null hypothesis of the test is that the sample come from a normally distributed population. If the p-value is lower than the chosen significant level, the null hypothesis should be rejected which suggests non-normality in distribution.
d. *** significant at 1% level, ** significant at 5%, * significant at 10%
e. Hedge fund and FOHF strategies are classified by HFR inc.

Table 2 The performance of value weighted[a] hedge fund, hedge fund style, FOHFs and FOHF style portfolios[b]

		Count	mean	variance	skewness	kurtosis	Normality test[c]
Ordinary hedge funds	HFs ex.FOHFs	7113	0.839	3.477	0.269	5.538	0.962***[d]
	Equity Hedge[e]	3523	0.866	7.678	0.367	6.656	0.947***
	Event Driven	748	0.950	3.235	-1.364	8.617	0.910***
	Macro	1471	0.836	4.642	0.417	3.231	0.986*
	Relative Value	1235	0.606	1.491	-2.574	15.151	0.790***
Funds of hedge funds	FOHFs	2220	0.657	7.053	0.033	6.042	0.913***
	Conservative	504	0.506	1.596	-2.692	13.681	0.768***
	Diversified	881	0.669	4.445	-0.214	6.278	0.937***
	Market Defensive	99	0.670	1.727	0.142	4.409	0.978***
	Strategic	736	0.604	17.946	0.204	5.660	0.928***

f. Each portfolio is constructed and rebalanced monthly. The weight of a particular fund in the portfolio is decided by its fund size relative to the total size of all funds in the same group.
g. The time series span from 31 May 1996 to 28 February 2010.
h. We apply Shapiro-Wilk normality test on our sample. The null hypothesis of the test is that the sample come from a normally distributed population. If the p-value is lower than the chosen significant level, the null hypothesis should be rejected which suggests non-normality in distribution.
i. *** significant at 1% level, ** significant at 5%, * significant at 10%
j. Hedge fund and FOHF strategy is classified by HFR inc.

Table 3, Stationarity test results[a]

Panel A: KPSS Test for Trend Stationarity		
KPSS Trend = 0.1435	Truncation lag parameter = 3	p-value = 0.05469
Alternative hypothesis: non trend stationary		
Panel B: Augmented Dickey-Fuller Test		
Dickey-Fuller = -4.6058	Lag order = 6	p-value = 0.01
Alternative hypothesis: stationary		

a. The two tests in Tables 2 are performed on the tail risk measurement time series from Jan 1995 to Nov 2013. The monthly measurements are obtained using Hill's estimator on the cross-sectional daily returns of the constituents in Thomson Reuters Global Equity Index.

Table 4 The tail risk exposure[a] of equally weighted hedge fund and FOHF portfolios, controlling for FH seven factors

	alpha	SP500	SMB	TBY	CSRD	PTFSBD	PTFSFX	PTFSCOM	Tail	Adj. R^2
Equity Hedge[b]	0.202 *[c]	0.422 ***	0.278 ***	-0.277	-1.578 **	-0.009	0.008	0.009	-0.236	0.741
Event-Driven	0.250 ***	0.184 ***	0.136 ***	-0.412	-2.467 ***	-0.022 ***	0.007	-0.001	-0.213 **	0.731
Macro	0.237 *	0.045	0.045	-1.760 ***	-0.817	0.021 **	0.034 ***	0.034 ***	-0.532 ***	0.354
Relative Value	0.164 ***	0.068 ***	0.031 *	-1.326 ***	-3.754 ***	-0.018 ***	-0.001	-0.002	-0.166 *	0.685
HF portoflio (exc.FOHFs)	**0.202 ** **	**0.269 *** **	**0.174 *** **	**-0.690 * **	**-1.847 *** **	**-0.006**	**0.011 ** **	**0.011**	**-0.266 ** **	**0.722**
FOHF_Conservative	0.058	0.055 ***	0.015	-0.646 **	-2.293 ***	-0.018 ***	0.005	0.002	-0.205 **	0.467
FOHF_Diversified	0.082	0.159 ***	0.117 ***	-0.739 *	-1.883 ***	-0.017 **	0.007	0.009	-0.261 *	0.504
FOHF_Market Defensive	0.186	-0.168 ***	-0.050	-1.704 ***	-2.114 **	-0.007	0.024 ***	0.019 **	-0.535 ***	0.253
FOHF_Strategic	-0.054	0.304 ***	0.224 ***	-0.604	-2.554 ***	-0.016	0.007	0.020 *	-0.312	0.574
FOHFs portfolio	**0.026**	**0.176 *** **	**0.131 *** **	**-0.830 * **	**-2.266 *** **	**-0.017 ** **	**0.007**	**0.011**	**-0.253 * **	**0.527**

a. SP500 is the spread between S&P's 500 and risk free interest rate; SMB is the difference between Russell2000 and S&P500 monthly return; TYB is the monthly change in the return of 10-year treasury bond yield; CSRD is the credit spread as the monthly change in Moody's Baa yield and 10-year treasury bond yield; PTFSBD, PTFSFX and PTFSCOM are the monthly returns of portfolios of look-back straddles on treasury bonds, foreign exchange and commodity. Tail is the tail risk factor which represent AR(1) innovation in the tail risk measurement time series.

b. The classification of hedge funds and FOHFs investment style is according to HFR. The definition of each category is provided in Appendix A.

c. *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table 5 The tail risk exposure[a] of value weighted hedge fund and FOHF portfolios, controlling for FH seven factors

	alpha	SP500	SMB	TBY	CSRD	PTFSBD	PTFSFX	PTFSCOM	Tail	Adj. R^2
Equity Hedge[b]	0.342 **[c]	0.357 ***	0.262 ***	-0.467	-0.789	-0.017	0.007	0.017	-0.191	0.583
Event-Driven	0.456 ***	0.152 ***	0.104 ***	-0.535	-2.132 ***	-0.027 ***	0.008	0.008	-0.197	0.498
Macro	0.421 ***	0.014	0.034	-2.328 ***	-1.194	0.013	0.028 ***	0.029 **	-0.272	0.194
Relative Value	0.169 **	0.018	0.005	-1.236 ***	-3.469 ***	-0.017 ***	-0.002	0.002	-0.158 *	0.550
HFs portfolio (ex.FOHFs)	0.359 ***	0.216 ***	0.152 ***	-0.944 **	-1.560 ***	-0.011	0.008	0.017 **	-0.082	0.519
FOHF_Conservative	0.060	0.050 **	0.011	-0.430	-2.262 ***	-0.018 ***	0.005	0.001	-0.236 **	0.429
FOHF_Diversified	0.172	0.227 ***	0.146 ***	-1.111 **	-1.724 **	-0.017 *	0.006	0.013	-0.062	0.442
FOHF_Market Defensive	0.278 ***	-0.008	-0.024	-1.215 ***	-1.713 ***	0.008	0.015 ***	0.015 **	-0.335 **	0.178
FOHF_Strategic	0.069	0.393 ***	0.084	-1.752	-2.361	-0.023	-0.002	0.055 **	-0.474	0.299
FOHFs portfolio	0.150	0.260 ***	0.075	-1.454 **	-1.894 *	-0.020	0.004	0.028 **	-0.213	0.332

a. SP500 is the spread between S&P's 500 and risk free interest rate; SMB is the difference between Russell2000 and S&P500 monthly return; TYB is the monthly change in the return of 10-year treasury bond yield; CSRD is the credit spread as the monthly change in Moody's Baa yield and 10-year treasury bond yield; EM is the residuals of the regression between the risk premium of MSCI Emerging Market Index and the risk premium of SP500; PTFSBD, PTFSFX and PTFSCOM are the monthly returns of portfolios of look-back straddles on treasury bonds, foreign exchange and commodity. Tail is the tail risk factor which represent AR(1) innovation in the tail risk measurement time series.

b. The classification of hedge funds and FOHFs investment style is according to HFR. The definition of each category is provided in Appendix A.

c. *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table 6, The correlation matrix of FH eight factors[a]

	SP500	SMB	TBY	CSRD	EM	PTFSBD	PTFSFX	PTFSCOM	Tail
SP500	1	0.022	0.153**	-0.416***	0.000	-0.143*	-0.196**	-0.165**	-0.597***
SMB	0.022	1	0.138*	-0.216***	0.355***	-0.090	0.008	-0.060	-0.161**
TBY	0.153**	0.138*	1	-0.524***	0.181**	-0.258***	-0.150*	-0.154**	-0.140*
CSRD	-0.416***	-0.216***	-0.524***	1	-0.308***	0.205***	0.326***	0.250***	0.450***
EMRES	0.000	0.355***	0.181***	-0.308***	1	-0.131*	-0.070	-0.055	-0.388***
PTFSBD	-0.143*	-0.090	-0.258***	0.205***	-0.131*	1	0.269***	0.233***	0.063
PTFSFX	-0.196**	0.008	-0.150*	0.326***	-0.070	0.269	1	0.366***	0.261***
PTFSCOM	-0.165**	-0.060	-0.154**	0.250***	-0.055	0.233	0.366***	1	0.188**
Tail	-0.597***	-0.161**	-0.140*	0.450***	-0.388***	0.063***	0.261***	0.188**	1

a. SP500 is the spread between S&P's 500 and risk free interest rate; SMB is the difference between Russell2000 and S&P500 monthly return; TYB is the monthly change in the return of 10-year treasury bond yield; CSRD is the credit spread as the monthly change in Moody's Baa yield and 10-year treasury bond yield; EM is the residuals of the regression between the risk premium of MSCI Emerging Market Index and the risk premium of SP500; PTFSBD, PTFSFX and PTFSCOM are the monthly returns of portfolios of look-back straddles on treasury bonds, foreign exchange and commodity. Tail is the tail risk factor which represent AR(1) innovation in the tail risk measurement time series.

b. The classification of hedge funds and FOHFs investment style is according to HFR. The definition of each category is provided in Appendix A.

c. *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table 7 Summary statistics of tail risk beta[a] coefficients

	count	% of total	maximum	minimum	average	skewness
Sig. negative beta[b]	699	51.25%	-0.255	-5.368	-1.068	1.607
Sig. positive beta	21	1.54%	3.153	0.333	1.266	0.032
Insig. beta	644	47.21%	2.634	-8.217	-0.238	0.585
Positive beta	175	12.83%				
Negative beta	1189	87.17%				
All beta	**1364**	**100%**	**3.153**	**-8.217**	**-0.64**	**-0.727**

a. The beta coefficients are obtained from the regression of each hedge fund's return to tail risk factor, controlling for FH seven factors.

b. The significant level is set to 5% so all significant negative beta coefficients have p value less than 0.05.

Table 8 FOHF characteristics[a] and tail risk beta

	(1)[b]	(2)	(3)	(4)	(5)
(Intercept)	-0.563***[c]	-0.140***	-0.396***	-0.053	-0.042
Age	-0.255***	-0.243***			
SIZE	-0.054*	-0.044			
SURVIV	0.103***	0.127***			
MNGFEE	0.255***		0.292***		
INCTFEE	0.002		0.009		
HWM	-0.062		0.003		
HRDRATE	0.104		0.013		
MININV	0.038			0.005	
ADVNTC	0.032			0.042	
LOCKUP	-0.085***			-0.083***	
LEV	0.207***				0.290***
X24mean	0.006	0.000	0.003	0.002	-0.005
X24var	0.772***	0.797***	0.755***	0.802***	0.786***
Adj. R^2	0.421	0.392	0.325	0.316	0.329

a. We run cross sectional regression to analyse the relation between FOHF characteristics and tail risk beta. The characteristics include age (Age), asset under management (SIZE), whether the fund is liquated, non-reporting or continuing (SURVIV), management fee (MNGFEE), incentive fee (INCTFEE), whether the fund sets a high watermark (HWM), whether the fund sets a hurdle rate (HRDRATE), minimum investment requirement (MININV), the days of advance notice period (ADVNTC), the months of lockup period (LOCKUP), and whether the fund uses leverage (LEV). We control for the impact of the previous 24 months mean return and volatility (X24mean and X24var).

b. We run regression on overall characteristics (1) and on individual groups of characteristics regarding fund size and age (2), fee structure (3), restrictions to investors (4) and leverage (5).

c. *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table 9, Tail risk exposure and the cross section FOHF return[a]

	Low Tail Beta	2	3	4	High Tail Beta	High-Low
Post Ranking Tail Risk Beta[b]	-1.199***	-0.637***	-0.565***	-0.408**	-0.226	0.972***
			Holding period: 12 Months			
Average Excess Return	0.409	0.476*	0.422*	0.383	0.122	-0.287
Alpha	0.427*	0.490**	0.436**	0.399**	0.139	-0.288**
			Holding period: 6 Months			
Average Excess Return	0.397	0.456*	0.441*	0.373	0.129	-0.269
Alpha	0.415*	0.469***	0.454***	0.389**	0.146	-0.269*
			Holding period: 3 Months			
Average Excess Return	0.399	0.444*	0.427*	0.378*	0.144	-0.255
Alpha	0.416*	0.457***	0.441***	0.394**	0.161	-0.255*
			Holding period: 1 Month			
Average Excess Return	0.382*	0.470***	0.439***	0.356**	0.142	-0.240
Alpha	0.397**	0.482***	0.452***	0.373***	0.159	-0.239*
	Low Tail Beta	2	3	4	High Tail Beta	High-Low

a. The table reports the average excess return and alpha of tail risk beta ranked portfolios with various holding periods. Beta coefficient and alpha are obtained from the regression of portfolio monthly returns on S&P 500 monthly excess return and tail risk factor. Figures in the brackets are the p-values of two-tailed t-tests. We use Newey-West standard error in the t-tests of the portfolios with holding periods longer than a month.

b. The reported beta coefficients are obtained from portfolios with one month holding period

Table 10, The excess returns of long-short tail risk hedge fund and FOHF portfolios[a]

		P5-P1	P5-P2	P5-P3	P5-P4
Hedge funds	Holding period: 3 months				
	Average excess return[b]	-0.696	-0.422	-0.343	-0.221
		(0.039)	(0.032)	(0.066)	(0.153)
	Holding period: 6 months				
	Average excess return	-0.676	-0.423	-0.340	-0.218
		(0.045)	(0.029)	(0.065)	(0.137)
	Holding period: 12 months				
	Average excess return	-0.630	-0.369	-0.305	-0.208
		(0.043)	(0.069)	(0.121)	(0.185)
FOHFs	Holding period: 3 months				
	Average excess return	-0.255	-0.300	-0.283	-0.234
		(0.192)	(0.055)	(0.035)	(0.048)
	Holding period: 6 months				
	Average excess return	-0.269	-0.328	-0.312	-0.244
		(0.171)	(0.022)	(0.015)	(0.030)
	Holding period: 12 months				
	Average excess return	-0.287	-0.354	-0.300	-0.260
		(0.111)	(0.016)	(0.024)	(0.023)

a. The table reports the average excess return of the portfolios constructed using the following strategy. During the holding period, the portfolio takes long position in the highest tail risk beta fund portfolio and shorts one of the lower tail risk beta portfolio. We rank and break the sample hedge funds into five portfolios (P1 to P5) in the ascending order of tail risk betas.

b. Beta coefficient and alpha are obtained from the regression of portfolio monthly returns on S&P 500 monthly excess return and tail risk factor. Figures in the brackets are the p-values of two-tailed t-tests. We use Newey-West standard error in the t-tests of the portfolios with holding periods longer than a month.