Tail Risk in Funds of Hedge Funds

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Statement of Originality

This is to certify that, to the best of my knowledge, the content of this thesis is my own work. This thesis has not been submitted for any degree or other purposes.

I certify that the intellectual content of this thesis is the product of my own work and that all the assistance received in preparing this thesis and sources have been acknowledged.

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Table of Contents

List of Figures

List of Tables

Abstract

Funds of hedge funds (FOFs) are portfolios of investment in hedge funds. Marketed to retail investors who are otherwise unable to access hedge fund investments, FOFs are normally depicted as well-diversified investment vehicles that benefit investors with their due-diligence selection process.

However, some earlier research has suggested that FOFs work like disaster insurance writers (Stulz, 2007; Agarwal and Naik, 2004). The implication is that they gain stable premium income during normal times but lose dramatically when the insured event occurs. The primary objective of this dissertation is to study the tail risk exposures of FOFs. Compared with hedge funds, which are exposed to tail risk mainly through dynamic trading, large leverage, and holdings of tail-risk-sensitive or illiquid assets (Agarwal et al., 2015), FOFs are obviously exposed to tail risk for different reasons. After conducting a hedge fund tail risk measurement (HFTR), I found that HFTR significantly explains the returns of FOFs. Moreover, HFTR substantially enhances the adjusted R-square of Fung and Hsieh's (2004a) seven-factor model. Despite FOFs being ostensibly more diversified portfolios, they have even higher exposure to tail risk compared to hedge funds. Moreover, FOFs with short histories, higher management fees and leverage, and shorter lockup periods are more sensitive to tail risk. I further documented a strong return-predictive power in FOFs' tail risk exposures. In particular, I found that the possible losses to one unit of tail risk exposure in a bearish market are double the possible gains in a bullish market. This non-linear payoff structure is a testimony to the claim that FOFs write crash insurance for hedge funds.

Chapter 1: Introduction

1.1 Motivation and research objective

Hedge funds are private investment vehicles that use dynamic trading strategies to pursue absolute returns. Compared with mutual funds, hedge funds are not heavily regulated and remain less transparent. In addition, hedge funds are less correlated to the other asset classes (Liang 1999) so that investors may further diversify their portfolio risk by adding hedge funds to their investment universe. However, hedge funds are generally not open to ordinary individual investors, and many hedge funds do not accept new capital injection. Moreover, information about hedge funds is not readily available to the public, which sets an investment barrier for smaller investors who do not have the necessary expertise on fund selection. Funds of hedge funds (FOFs) provide a good solution to the above-mentioned problems by offering a portfolio of hedge funds. A FOF invests heavily in the hedge fund market and holds diversified hedge fund portfolios. Ang, Rhodes-Kropf, and Zhao (2008) pointed out that unskilled investors benefit from investing in FOFs because the due diligence and oversight performed by FOFs help to reduce the due diligence and monitoring costs. As a result, FOFs have become more and more important in the financial markets. According to Schizas (2012), the total value of assets under management (AUM) of FOFs reached US$533 billion in 2012, accounting for about 25% of the total market value of the hedge fund industry.

The strong growth of FOFs has been driven by investor belief that a hedge fund portfolio will diversify the idiosyncratic risk of individual hedge funds and finally deliver better risk-adjusted returns. However, the recent performance of FOFs provides no support for such an expectation. Based on the mean return and the Sharpe ratio, quite a few studies have documented underperformance of FOFs compared with hedge funds (e.g., Brown and Goetzmann 2003; Beckers, Curds and Weinberger 2007). Furthermore, the entire FOF sector has been heavily shocked by the 2007-2008 global financial crisis (GFC). According to Schizas (2012), the monthly return of FOFs has decreased from 0.66% to 0.27% and remained at this low level in the aftermath of the GFC. According to modern portfolio theory, combining loosely correlated assets in a portfolio can generate a diversification effect so that one can achieve higher risk-adjusted return. The underperformance of FOFs seems to be a living contradiction of diversification theory.

It stands to reason that the second-layer fees paid to FOF managers, in addition to the fees charged by the individual hedge fund managers, may cause the return of FOFs to be consistently lower than a homemade hedge fund portfolio. Some pioneering studies, such as Brown, Gregoriou, and Liang (2004) and Ang, Rhodes-Kropf, and Zhao (2008), claim that fees on fees have trimmed the diversification benefits. However, even after adjusting for the influence of second-layer fees, the performance of FOFs is still inferior to average hedge funds in terms of mean return[1] as well as volatility.[2] In addition, it is hard to use a double-layer fee structure to justify the even worse performance of FOFs during market turmoil. Since the late 1990s, more and more

[1] According to the Morningstar database, the average monthly risk-adjusted return (Sharpe ratio) of FOFs from 1992 to 2012 is 0.192%, which is substantially lower than the risk-adjusted return of other hedge fund strategies (1.02%).
[2] The standard deviation of FOFs' monthly return from 1992 to 2012 is 2.025%, which is marginally higher than the standard deviation of the monthly return of other hedge fund strategies (2.016%). The standard deviation of FOFs' monthly return increases to 2.201% after adjusting for the extra fee charged by FOFs.

scholars have advocated the rethinking of FOF returns beyond the mean-variance framework assuming a Gaussian distribution for the following reasons.

First, hedge fund returns do not follow a normal distribution and usually have negative skewness and excess kurtosis. Most hedge fund managers define their objectives in terms of absolute return irrespective of market conditions. Reflected in trading strategies, hedge fund managers tend to avoid tracking the performance of a predefined index but use dynamic tactics to take advantage of market deficiencies, momentum, or other opportunities arising from market anomalies. Adding the fact that many hedge funds use highly leveraged positions, it is reasonable to expect the return distribution of a hedge fund to depart greatly from normality.

Furthermore, the dependence between hedge fund returns tends to be more complex than one might expect under modern portfolio theory. Diversification is closely related to the central limit theorem, which states that the mean of a large number of independent distributions tends to follow a normal distribution. As such, idiosyncratic returns of a single asset will be smoothed out in a well-diversified portfolio, leaving the portfolio return normally distributed with reduced variance. Diversification has a stronger effect when the individual assets are loosely correlated, but this is clearly untrue for hedge funds. As previously explained, hedge fund returns are highly abnormal, which means that the correlation in higher moments cannot be ignored when constructing an FOF portfolio. Moreover, researchers have observed significant contagions among hedge fund returns in bear markets (Agarwal and Naik 2000a; Boyson, Stahel and Stulz 2010). Hence, combining loosely correlated hedge funds may reduce variance but at the same time increase the probability of extreme losses, represented by lower skewness and higher kurtosis.

Last, although individual hedge funds may be less correlated with other asset classes, portfolios of hedge funds do not deliver such benefits (Kat 2002). In other words, the correlation between FOFs and traditional assets such as equity and debts is higher compared with individual hedge funds. As a result, FOFs should be more sensitive to the extreme downturns in the other markets and consequently deliver large losses under extreme market shocks.

In light of the above-mentioned reasons, we strongly believe the tail risk in hedge funds constitutes a non-diversifiable risk for FOFs. By definition, tail risk is the investment outcome that deviates from expected performance because of extreme events. Modern portfolio theory assumes that asset returns follow a bell-shaped normal distribution. The left tail of the bell shape represents the losses with rare chances of occurrence. In the long run, investors may incur large losses because of such left-tail events. In addition, if asset returns are non-normally distributed with fat left tails, modern portfolio theory will fail to capture the tail events. As a result, investors relying on the mean-variance framework tend to overprice a financial asset with a fat-tailed return distribution and eventually suffer unendurable losses. Many studies have found evidence to confirm the above description. For example, Agarwal and Naik (2004) found that a wide range of hedge fund strategies exhibited payoffs similar to that of writing a put option on an equity index. They suggested that such strategies usually incur large losses in market downturns. In addition, Brown and Spitzer (2006) revealed that market-neutral hedge funds become more sensitive to the substantial downside market movements.

Holding portfolios of hedge funds, FOFs nevertheless will be affected by the tail risk in the hedge fund industry. In the existing literature, the tail risk in ordinary hedge funds has drawn intensive interest, but researchers have largely ignored FOFs as a very special class of hedge funds that may have unique exposure to tail risk. This dissertation aims at filling this void in the literature with an investigation into the tail risk exposure of FOFs.

The primary objective of this dissertation is to investigate the relationship between hedge fund tail risk and the returns of FOFs. I follow Stulz (2007) in suggesting that FOFs write disaster insurance so that they earn stable premium income during normal times but lose dramatically when the insured event comes about. In our opinion, if the tail risk in hedge funds is undiversifiable, it should determine the expected returns of FOFs, the same as the other systematic risk factors. To test this proposition, I developed a measurement that directly associates with the tail risk in the hedge fund industry over the sample period from January 1995 to December 2012, named the "hedge fund tail risk factor" (HFTR). This approach follows the spirit of Kelly and Jiang (2014), who used cross-sectional equity returns and generated a tail risk factor that captures the systematic tail risk shocks in the equity market.

The second objective of this dissertation is to study the differences between hedge funds and FOFs with regard to tail risk. Compared with hedge funds – which are exposed to tail risk mainly through dynamic trading, large leverage, and holdings of tail risk-sensitive assets (Agarwal, Daniel and Naik 2015) or illiquid positions – FOFs could be exposed to tail risk for different reasons. For example, during market turmoil, the contagion among hedge funds may cause tail risk to aggregate in FOFs. Furthermore, FOFs gain direct risk exposure to the hedge fund industry instead of the other assets. Holding a long-only position in hedge funds, FOF managers lack the tail risk hedging tools that are usually available to hedge fund managers. For comparison purposes, I investigated the exposure of hedge funds to HFTR on both an aggregated- and individual-fund basis. Moreover, I investigated the relation between tail risk exposure and fund characteristics and documented what types of FOFs and hedge funds are more sensitive to tail risk shocks in the hedge fund industry.

Last, I am interested in studying the return predictive power of FOFs tail risk exposure – or, in other words, whether the current tail risk exposure of a FOF can predict its return in the next period. In practice, FOF managers can hardly adjust their holdings when the market turns sharply weaker because of the many restrictions set by hedge funds on redemptions. As a result, tail risk-sensitive hedge funds may remain in a FOF's portfolio after a tail risk event has occurred. Holding illiquid hedge fund portfolios, FOFs tend to be very sensitive to tail risk shocks during market turmoil. As such, the tail risk exposure of FOFs may possess certain predictive powers regarding their future returns, at least on a short-term horizon during a bearish period.

The value of the studies in this thesis lies in the following aspects. Theoretically, the research is among the first to link tail risk to the returns of FOFs as a systematic risk factor. As a result, I proved that the tail risk of hedge funds cannot be eliminated by diversification. This problem has been raised in the previous literature but has not been formally tested so far. Moreover, I contributed to the literature with HFTR, which captures systematic tail risk in the hedge fund industry. Adding HFTR to Fung and Hsieh's (2004a) seven-factor model, I have documented prominent improvements in the model's explanatory power at both the individual-fund and aggregated-portfolio levels. Based on HFTR, I found that FOFs are more sensitive to tail risk shocks in the hedge fund industry than hedge funds. In addition, I have found that HFTR possesses strong state-dependent predictive power. The results of this thesis highlight the importance of practitioners understanding tail risk in FOFs. A FOF investor should assess the hedge fund market state carefully, as randomly allocating capital to a FOF with significant negative HFTR exposure may lead to tremendous loss if the market state tends to be unfavourable in the next one to three months.

1.2 Structure and content of the thesis

This thesis is structured as follows.

Chapter 2: Literature review

This chapter reviews the relevant literature on hedge funds and FOFs, with a special focus on tail risk in the hedge fund industry. First, I present a general summary of studies on the performance of hedge funds and FOFs. Above all, studies on the return distribution of hedge funds and FOFs are introduced. Next, some important literature on modelling hedge fund and FOFs returns is summarised. This section addresses the following three aspects: 1) hedge fund and FOF risk exposure and factor models; 2) tail risk in hedge funds and FOFs; and 3) predicting hedge funds and FOF returns. Last, I review the literature on hedge fund data bias.

Chapter 3: Data and methodology

The first section of Chapter 3 introduces the data used in the thesis. In particular, I discuss the descriptive statistics of the data and introduce the processes that have been followed to moderate hedge fund data bias. The second section introduces the methodology, which is categorised according to the three studies in the thesis.

Chapter 4: Managerial differences between hedge funds and funds of funds

In the first study, I compared FOFs with hedge funds with respect to managerial characteristics. I performed comparison analysis on two sets of hedge funds and FOF samples and found that a large number of tail risk-sensitive FOFs

- Do not accept additional investments,
- Tend to have lower average fund size and net assets,
- Require longer notice in advance days and redemption frequency,
- Charge lower management fees and incentive fees,
- Tend to use less leverage and prefer bank credit to margin borrowing when taking leverage, and
- Turn over total assets fewer times in a year.

The results confirm the distinction between FOFs and hedge funds with respect to managerial arrangements. Furthermore, I show some possible links between such distinctions and the tail risk aggregation in FOF portfolios. In particular, the above-mentioned fund attributes relate to different areas of fund management, including investment capacity, liquidity restrictions, reward schemes, and fund leverage. The cross-sectional regression analysis further confirmed that the tail risk exposure of FOFs is significantly related to reward schemes and liquidity restrictions such as advance notice days and redemption frequency. In the existing literature, researchers tend to attribute the tail risk aggregation effect in FOF portfolios to a specific channel. Our findings, however, indicate a more complex tail risk aggregation dynamic.

Chapter 5 – Tail risk in funds of funds

The second study investigated the tail risk of FOFs relative to hedge funds. Following Kelly and Jiang (2014), I constructed the hedge fund tail risk factor (HFTR) using monthly returns of 7,782 hedge funds. I examined the tail risk exposures at the individual-fund level as well as the strategy level by comparing FOFs and hedge funds. I performed a range of regressions to test the significance of HFTR in explaining the returns of FOFs. The regressions were performed on various bases, including equally weighted portfolios, value-weighted portfolios, and individual FOFs. In addition, I varied the regression window and added more controlling factors to verify the robustness. Moreover, I examined whether tail risk exposure determines differences in cross-sectional returns using decile portfolio sorting.

The regression results using HFTR provide strong evidence against the tail risk management ability of FOF managers. At the individual FOF level, I found that the majority of our sample FOFs (83.79% of 4,275 FOFs) had significant negative exposure to HFTR during the sample period. At the portfolio level, all FOF portfolios exhibited significant negative exposure to this factor.

In addition, I performed cross-sectional regression using HFTR beta as a dependent variable and fund managerial characteristics as independent variables. I documented some relationships between fund characteristics and tail risk exposure. I found that tail risk-sensitive hedge funds and FOFs share some characteristics, such as younger age, higher management fees, and closure to new capital. There are also unique characteristics that explain the cross-sectional HFTR beta variations in FOFs. For example, HFTR-sensitive FOFs trade more actively in a year and use higher-water marking performance evaluation.

Chapter 6 – Can tail risk exposure predict the return of a fund of funds under different market states?

In this chapter, I used two approaches to examine the predictive power of HFTR exposure. First, I performed the Fama–MacBeth regression (1973), using both ordinary least square regression and quantile regression to investigate the relation between the tail risk exposure of an FOF and its return one month, two months, and three months ahead. The results indicate that, controlling for Fung and Hsieh's (2004a) seven factors, HFTR beta significantly explains the FOFs' return in the next one month to three months regardless of market states. I documented similar explanatory powers for the tail risk betas calculated on the rolling windows of 12, 18, and 24 months. Second, I sorted FOFs according to their tail risk exposures and constructed tail risk-sensitive and insensitive portfolios. Controlling for market states, I found very significant differences between the portfolio returns assuming monthly, quarterly, semi-annual, and annual rebalancing frequency. In general, I found that the predictive power of HFTR beta was strong under different market states but neutralised over the whole sample period.

Chapter 7 – Conclusions

In this chapter, the major findings in Chapters 4, 5, and 6 are briefly summarised and some further comments provided. Finally, I introduced the limitations of the thesis and discussed the directions for future research.

Chapter 2: Literature review

2.1 An overview of hedge fund research[3]

Scholarly studies on hedge funds emerged in the late 1990s, accompanied by the rapid growth of the hedge fund industry. Given the limited availability of data, early hedge fund research concentrated on an introduction to the industry, hedge fund performance appraisal, and the evaluation of data quality.

The early work on hedge funds was led by Fung and Hsieh (1997a), whose research used a database containing 409 hedge funds and compared the performance of the hedge funds with that of 3,327 mutual funds. The research adopted Sharpe's factor models to study the return attributions of both hedge funds and mutual funds but found that the traditional asset factors in Sharpe's model can only explain a very small proportion of hedge fund returns. The authors thus argued that it is the dynamic trading strategy of hedge funds causing the low explanatory power of Sharpe's model, and they suggested including style factors to improve the model. Fung and Hsieh (1997a) also found that hedge funds are very sensitive to extreme market movements, which leads to the view that hedge fund returns exhibit option-like characteristics. Moreover, the authors raised the issue of survivorship bias[4] in commercial hedge fund databases. They claimed that survivorship bias may have mixed influence on the reported return, and the extent of the bias is related to different incentives to quit databases by hedge funds.

[3] This section was prepared by consulting the following summaries of hedge fund literature: Das et al. (2002); Agarwal and Naik (2005); and Agarwal et al. (2015).
[4] Survivorship bias is caused by the data vendors' practice of excluding defunct funds from their databases, which leaves only living funds in the databases. As a result, research based on such databases tends to overestimate the average performance of the hedge fund industry.

Some other early work on hedge funds includes that by Brown, Goetzmann, and Ibbotson (1999), Ackermann et al. (1999), and Liang (1999). These early studies generally relied on traditional performance evaluation techniques such as mean-variance, the Sharpe ratio, and Jensen's α to analyse the returns of hedge funds. Most of these studies agreed on the hedge fund managers' ability to deliver absolute returns or higher Sharpe ratio results relative to the mutual funds. Since the early 2000s, hedge fund research has expanded in the following strands: 1. modelling hedge fund and FOF risks and returns; 2. the specific characteristics of hedge funds and their influence on hedge fund performance; 3. the effect of hedge funds in the global market; and 4. the problem of hedge fund data bias.

Hedge funds' dynamic strategies have been further investigated by many, with researchers noting that hedge funds adopt dynamic trading strategies that may cause time-varying systematic risk exposures (see Fung and Hsieh 2001; Brown and Goetzmann 2003) as well as non-linear payoff structures (see Lo 2001; Agarwal and Naik 2004). Therefore, the traditional factor models such as the Fama–French (1993) three-factor or the Carhart (1997) four-factor model do not work well to explain the returns of hedge funds. Given the non-linearity in hedge fund returns, a group of researchers suggested adding option-type factors to enhance the existing factor models. For example, Fung and Hsieh (2001) used lookback straddles to explain the returns of trend-following hedge funds, and Fung and Hsieh (2004a) later proposed seven factors to explain the returns of hedge funds. Another multifactor model containing option-type factors can be found in Agarwal and Naik (2004). Furthermore, researchers have also found that hedge funds gain exposure to other macro risk factors such as funding risk (Dudley and Nimalendran 2011); liquidity risk (Sadka 2010); correlation risk

(Buraschi, Kosowski and Trojani 2014); and tail risk (Kelly and Jiang 2014)[5]. Most of the above-mentioned research tested the significance of the proposed factors after controlling for the common factors of Fung and Hsieh (2004a). In general, previous research has shown that systematic risk is a primary resource of return for hedge funds, so caution should be applied when assessing hedge fund managers' ability to deliver absolute returns.

FOFs have usually been studied as a strategy group of hedge funds in many of the above-mentioned papers. The early research has found that FOFs tend to underperform hedge funds (see, for example, Brown, Goetzmann and Liang 2004; Amin and Kat 2003). Brown, Goetzmann, and Liang (2004) suggested that the double-layer fee structure of FOFs may explain their underperformance. Ang, Rhodes-Knopf, and Zhao (2008) argued that many previous studies did not use proper benchmarks to assess the performance of FOFs. They claimed that FOFs deserve the fees on fees, should a proper benchmark be used. Agarwal and Naik (2005), Agarwal, Ruenzi, and Weigert (2016), and Getmansky, Lee, and Lo (2015) provided comprehensive reviews of hedge fund and FOF risk studies and return modelling literature.

Instead of explaining hedge fund returns using macro risk factors, another group of researchers have tried to develop linkages between fund-specific characteristics and fund performance. Several characteristics have drawn the interest of researchers, such as fund age and size (Frumkin and Vandegrift 2009; Jones 2007); manager experience (Li, Zhang and Zhao 2011; Bernhardt and Nosal 2013); manager incentive schemes (Goetzmann, Ingersoll and Ross 2003; Brown, Goetzmann and Liang 2004; Agarwal, Daniel and Naik 2009); redemption restrictions (Park and Whitt 2013; Ang and Bollen

[5] A more comprehensive review of these risk factors is presented in Section 2.4.3.

2010); and hedge fund leverage (Schneeweis et al., 2005; Ang, Gorovyy and van Inwegen 2011). Quite a few studies have tested the influence of hedge fund characteristics on the cross-sectional variation of hedge fund returns or risk exposures. It has also become a general procedure to control fund characteristics when performing cross-sectional regression on hedge fund performance measurements. For example, Schaub and Schmid (2013) investigated the relation between hedge fund liquidity risk exposure and share restrictions. In their cross-sectional regression analysis, nine fund attributes were used as control variables, and they found that redemption notice periods are the most important liquidity restriction for hedge funds gaining exposure to liquidity risk.

Hedge funds are subject to less regulation and fewer disclosure mandates compared with mutual funds. As a result, hedge funds can use excessive leverage and take sophisticated positions in the derivative markets. Their exact holdings and trading activities, however, usually remain secret. Hedge funds are often criticised by the public for being opportunistic and an important cause of market turmoil such as occurred during the 1997 Asian financial crisis and the 2007-2008 GFC. Some studies have shed light on this issue under the growing concern on the role of hedge funds in the financial system. Brown et al. (2000) studied the role of hedge funds in the 1997 Asian currency crisis but found no evidence that hedge funds were responsible for the crisis. In the study of Halstead, Hedge, and Linda (2005) on the influence of the collapse of LTCM, the researchers suggested that the hedge fund crisis had little contagious effect on firms without exposure to hedge fund activities. In contrast, several studies have found that hedge funds contribute to the systemic risk of financial markets in many ways. For example, Chan et al. (2006) documented growing systemic risk caused by hedge fund activities and suggested that the banking sector is exposed to such risk by facilitating hedge fund activities, i.e., by means of primary brokerage. Racicot and Théoret (2016) investigated the relation between hedge fund activities and macroeconomic risk. They found that hedge funds' strategies become more homogeneous during a crisis period. Coupled with deleveraging activities, hedge funds thus contribute to the increased systemic risk in the financial system.

Last, hedge fund researchers are often concerned about the quality of data from commercial data vendors because hedge funds report to the vendors on a purely voluntary basis. There is some data bias that may influence the studies of hedge funds, such as survivorship bias, backfill bias, and multi-period sampling bias. In addition, hedge fund managers have been found to misreport their returns (Bollen and Pool 2009) or tactically delay reporting poor returns (Aragon and Nanda forthcoming). The literature on hedge fund reporting will be introduced in greater detail in Chapter 3.

As a special investment style of hedge funds, the return and risk profile of FOFs also appears to be very different from the other hedge fund styles. Past studies on FOFs have raised some interesting questions that need further investigation such as the aggregation of hedge fund tail risk in FOFs. This thesis thus endeavours to contribute new evidence to the understanding of this issue.

The remainder of this chapter will introduce the relevant literature in four sections: Section 2.2 discusses the previous findings on the statistical characteristics of hedge fund return distributions; Section 2.3 introduces the previous studies on hedge fund return modelling, with an emphasis on hedge fund factor models; Section 2.4 summarises the literature on FOF performance relative to hedge funds and introduces the research on the diversification trap; and Section 2.5 presents a summary of the studies on tail risk or downside risk of hedge funds and FOFs.

2.2 Statistical properties of hedge fund returns

2.2.1 Fat tail and autocorrelation in hedge fund returns

Because of their short history and data limitations, hedge fund indices published by various data vendors were often used in hedge fund research in the early 2000s to proxy the returns of hedge funds. Brooks and Kat (2002) studied the statistical properties of 48 hedge fund indices constructed by different data vendors. In their research, hedge fund indices are categorised into eight groups according to the investment strategy. Their results show that the distribution of most indices is non-normal, except for the Macro and Long-Short Equity indices. A similar investigation was conducted by Geman and Kharoubi (2003). They used the monthly returns of 14 hedge fund style indices over seven years and found that most of them generated a higher return and lower volatility than equity market indices. Significant negative skewness was observed in 11 hedge fund styles, and all fund indices failed to pass the Jarque–Bera normality test. Eling (2006) studied Credit Suisse First Boston/Tremont (CSFB) hedge fund indices between 1994 and 2004 and found that most of them displayed negative skewness, excess positive kurtosis, and autocorrelation. Eling (2006) suggested that the asymmetric return distribution and fat tails are caused by hedge funds' investment in derivative instruments. Negative skewness and high levels of kurtosis in the return distributions of different hedge fund indices are also documented in various studies, such as that of Agarwal and Naik (2000a), Bergh and van Rensburg (2008), Ranaldo and Favre (2005), and Zakamouline and Koekebakker (2009).

Instead of using hedge fund indices, many hedge fund researchers choose to construct hedge fund portfolios, usually equally weighted portfolios, to proxy the returns of hedge funds following similar investment strategies. Fung and Hsieh (1997a) analysed five hedge fund investment styles and found that three of them exhibited high kurtosis in return distribution and displayed sensitivity to extreme market states. Kat and Lu (2002) studied the statistical properties of 2,183 hedge funds and documented significant average negative skewness and kurtosis in the sample. Getmansky, Lee, and Lo (2015) found that eight out of 12 hedge fund strategies displayed negative skewness, and 11 out of 12 strategies showed excessive high kurtosis in their return distribution during the period from 1994 to 2006. In addition, they uncovered that the categories with higher autocorrelation also exhibited a fat-tailed return distribution. The return autocorrelation problem in hedge fund returns was formally investigated by Getmansky, Lo, and Makarov (2004). The authors argued that the serial correlation in hedge fund returns may be attributed to a variety of reasons, but they concluded that illiquidity and smoothed returns are the primary reasons, according to the empirical results.

As a subclass of hedge funds, FOF returns were found to display negative skewness and excess kurtosis (Beckers, Curds and Weinberger 2007; Bollen and Whaley 2009). For example, Bollen (2011) investigated the cross-sectional return distributions of hedge funds and FOFs in three sample periods: 1994 to 2006, 2007, and 2008. He documented a thicker left tail in FOF distribution as compared to hedge funds. These observations suggest that FOFs have a higher chance of incurring extreme losses than that described by a normal distribution, thereby being an indicator of tail risk.

The implication of non-normally distributed and autocorrelated return to asset management is twofold. First, as argued by Kat (2002), when encountered with non-normality, the standard deviation cannot fully reveal the potential risk carried by a financial asset. Thus, the higher moments including, skewness and kurtosis, should be taken into account when assessing the riskiness of an investment. As standard deviation is a biased risk measurement given non-normally distributed returns, the Sharpe ratio – the universally accepted performance measure – also loses its power in the evaluation of hedge fund performance. According to Kat (2002), the Sharpe ratio can systematically overstate the true hedge fund performance. Second, the unique return patterns of hedge funds will add complexity to portfolio construction. Given the non-normality of hedge fund returns, if an investor has non-quadratic preferences, mean-variance tools may not be appropriate for portfolio construction. Fung and Hsieh (1997a) provided an illustration where an investor's major concern is the downside risk, but a traditional mean-variance approach may wrongly exclude hedge funds from the portfolio. Eling (2006) demonstrated that autocorrelation and a fat tail in hedge fund returns may distort the traditional performance measurements and result in over-allocation in the hedge fund sector when constructing portfolios.

2.2.2 Non-linear and dynamic risk exposures

Ackermann, McEnally, and Ravenscraft (1999) compared hedge funds with mutual funds using data from Hedge Fund Research, Inc. (HFR). They found that hedge funds generate a higher average return and Sharpe ratio than mutual funds. In addition, hedge funds were found to exhibit weak correlation with the selected market indices. Several other studies in the same period (see Liang 1999 and Fung and Hsieh 1999, among others) also suggested that hedge funds provide diversification benefits to a portfolio, given their weak correlations with the traditional asset classes.

In the late 1990s and early 2000s, the global financial market experienced several extreme events, such as the 1997 Asian market crisis, the 1998 Russian debt crisis and the dot-com crash in the US equity market. Many hedge funds exhibited strong correlation with the markets and suffered great losses in the market downturns. Agarwal and Naik (2004) argued that the traditional factor models such as CAPM and APT assume a linear relation between factors and returns, which is usually not the case for hedge funds. Using buy-and-hold and option-based factors, Agarwal and Naik (2004) found that many hedge fund strategies generate returns akin to writing a put option on the equity index. In addition, controlling for the option-based risk factors, hedge funds were found to be significantly exposed to Fama and French's (1993) size and value factors and Carhart's (1997) momentum factor.

The risk exposures of hedge funds are also dynamic. Bollen and Whaley (2009) studied the time-varying exposures of hedge funds and attempted to use optimal changepoint regression and the stochastic beta model to remedy the problem. The authors found that 40 per cent of the sample hedge funds displayed significant changes in risk factor loadings between 1994 and 2005. They thus concluded that the alphas from a constant parameter regression will be biased measures of abnormal returns. Patton and Ramadorai (2013) studied the dynamic hedge fund risk exposure using high-frequency variables[6], finding significant intra-month variation in hedge fund risk exposures, which suggests active exposure management at a high frequency.

The correlation between hedge fund return and the market is also state-dependent. In Fung and Hsieh (1997a), hedge fund returns are explained as a combination of the returns from style factors and those from exposure to Sharpe's asset class factors. The authors found that the correlations between style factors and asset class returns are uncorrelated most of the time but become correlated during extreme moves or tail

[6] Most existing hedge fund studies use monthly reported hedge fund returns. Patton and Ramadorai (2013) used a daily factor model to resemble the monthly returns of hedge funds to capture the exposure change on a daily basis.

events. Guesmi, et al. (2015) investigated the correlations between hedge fund strategy indices and other asset classes (i.e., stocks and bonds) during bull and bear markets. Using the Dynamic Conditional Correlation GARCH model, they documented significant correlations between hedge funds and the stock market, particularly during the 2007–2008 GFC.

One possible explanation of the state-dependent risk exposure is that hedge fund managers may actively change their exposures following the market conditions and produce procyclical portfolio betas. Racicot and Théoret (2013) studied this problem using conditional modelling, Kalman filtering of hedge funds' absolute returns, and systematic risk exposures. The authors found that hedge fund betas react to cyclical change in the macroeconomic variables. In Racicot and Théoret (2014), hedge fund managers were found to modify portfolio betas, according to the volatility of financial markets, but the strategies' alphas and betas co-moved less strongly in the subprime crisis compared with previous crises. The results thus indicate a maturation process in the hedge fund sector.

In summary, existing literature has found that hedge fund returns are non-normally distributed, with negative skewness and excessive high kurtosis. There is autocorrelation in hedge fund reported returns, mainly because of an illiquid portfolio or the return smoothing of hedge fund managers. Hedge funds have a loose correlation with traditional markets, but the correlation may increase during extreme market events.

Compared with other hedge fund strategies, FOFs are more correlated with the traditional asset classes. Kat and Lu (2002) investigated the correlation between hedge funds and market indices in terms of return, standard deviation, skewness, and kurtosis and found that FOFs exhibit the highest correlation to market indices in the higher moments. Ennis and Sebastian (2003) calculated the Effective Style Mix (ESM)[7] benchmark for the HFR FOF index and analysed the performance of the FOF index from 1994 to 2003. The authors documented two characteristics of the FOF index. First, they found that the index behaved the same as a portfolio with 44 per cent of its holdings directed towards various asset classes. Second, they uncovered intertemporal variation in the index's risk exposures. Interestingly, even though risk factor exposures vary markedly over time, the FOF index's correlation with markets remained consistently around 60 per cent during the whole.

[7] ESM is calculated by mixing market indices in proportion to form a benchmark with the highest possible degree of correlation with a particular return series (Ennis and Sebastian, 2003).

2.3 Modelling hedge fund and fund of hedge fund returns

Linear factor models are widely adopted in the hedge fund performance attribution literature. A general factor model can be represented by

$$\boldsymbol{R_{i,t} = \alpha_i + \beta_{i,1}F_{1,t} + \cdots + \beta_{i,n}F_{n,t} + \epsilon_{i,t}} \qquad (2.\ 1)$$

where $R_{i,t}$ is the return of fund i in the tth period and $\{F_{k,t}\}$ are "the explanatory variables such as an equity or bond index, or the returns of well-defined strategies such as mean-reversion, momentum, and trend-following strategies" (Getmansky, Lee and Lo 2015, p.41). The inability of traditional factor models such as CAPM to explain the returns of hedge funds can be attributed to two reasons. First, factor models normally assume a linear relationship between a dependent variable and factors, which is not realistic in the situation of hedge funds. As mentioned in Section 2.2.2, hedge funds adopt dynamic trading strategies to remain market neutral and trade derivative contracts with payoff non-linearly correlated with the traditional markets. As a result, hedge fund returns are usually not linearly correlated with equity and bond returns. Second, the significant unexplained residuals, such as those in Liang (1999), may contain unidentified systematic factors that are significantly correlated with hedge fund returns. In the hedge fund literature, a considerable number of studies have been performed to enhance the explanatory power of factor models by tackling the above two problems.

2.3.1 Early attempts

The mainstream literature on the risk–return relationship of hedge funds attributes hedge fund returns to the rewards from taking exposures to systematic risk factors and unexplained returns to managers' skills or fund-specific factors. Such efforts have their roots in Jensen (1967) as well as the Sharpe (1992) asset class factor model. Liang (1999) regressed the returns of hedge fund strategy groups on four benchmarks, including Standard & Poor's 500 (S&P500) index, Eurodollars, U.S. bond returns, and emerging markets. He noted that the factor loadings of hedge funds on the benchmarks are scattered, and the unexplained returns are statistically significant in many hedge fund groups. Fung and Hsieh (1997a, 1997b) adopted principal component analysis (PCA) and a factor analysis approach to distil style factors from a pool of hedge fund returns. This found higher explanatory power by adding the new style factors to the Sharpe asset class factor model.

2.3.2 Factors measuring non-linearity in hedge fund returns

Recognising the difficulty in using traditional asset class factor models to explain the option-like returns of hedge funds, Fung and Hsieh (2001) proposed studying non-linear hedge fund payoffs using trend-following hedge funds as an example. The authors found that lookback straddle[8] returns are similar to the returns of trend-following hedge funds. They also documented that the returns of trend-following funds can be significantly explained by a combination of lookback straddles on currencies, commodities, and debt securities. The authors thus concluded that trend-following funds are exposed to risk that cannot be observed in a linear-factor model.

Based on their findings in 2001, Fung and Hsieh (2004a) studied the risk exposures of different hedge fund styles, following a top-down approach, and eventually proposed seven factors that can explain the returns of hedge funds: two equity market factors, two debt security market factors, and three trend-following risk factors. The seven-factor model was found to explain the returns of a variety of hedge fund and FOF

[8] In theory, a lookback straddle is made up of a lookback call option and a lookback put option, which allows the holder rights to buy or sell at the most favourable prices observed in a past period.

indices significantly. The authors, however, highlighted that the seven-factor model is not flawless. For example, the explanatory power of the model will decrease when applied to a single hedge fund or a particular hedge fund style. The seven-factor model received an update in Edelman et al. (2012). This study found that the emerging market factor has significant power to explain FOF returns and should be added to the seven-factor model to form an eight-factor model. The eight-factor model was then used to analyse the performance of FOFs from 2005 to 2010, and finding that FOFs tend to generate insignificant alphas, the authors suggested classifying the majority of FOFs as beta-only producers.

In the same year as the publication of Fung and Hsieh's (2004a) seven-factor model, Agarwal and Naik (2004) published their research findings on modelling hedge fund returns. Instead of using lookback straddles to represent the option-like returns of hedge funds, Agarwal and Naik (2004) constructed four option-based factors[9] to approximate the non-linear hedge fund returns and used them in a multifactor model to investigate the common risk exposures of different hedge fund indices. It was found that many hedge fund indices gain significant negative exposure to the put option factors; in other words, they display the same payoff structure as writing a put option on the S&P500 index.

Multifactor models have several limitations, and one is called non-investability (Getmansky, Lee and Lo 2015). In general, investors cannot rely on these models to replicate the indicated hedge fund, as many factors are not marketable, such as the lookback straddles in the Fung and Hsieh (2004a) seven-factor mode. Agarwal, Bakshi,

[9] The four factors of Agarwal and Naik (2004) are constructed by assuming the monthly holding of at the money call options, out the money call options, at the money put options, and out the money put options on the S&P500. The model does not assume a long/short position in the options but leaves it to be decided by the sign of the regression coefficients.

and Huji (2009) attempted to tackle this problem by constructing investable factors for higher moments (volatility, skewness, and kurtosis) of equity risk, and they showed that the returns of equity-oriented hedge funds are significantly exposed to these higher moment factors.

2.3.3 The other factors that may explain hedge fund returns

Besides using various techniques to approximate non-linearity in hedge fund returns, researchers have also tried to identify the factors that may be tightly correlated with hedge funds but have not been identified in the traditional asset-based factor model.

Bali, Brown, and Caglayan (2014) pointed out that hedge fund returns can be influenced by changes in macroeconomic factors such as inflation and unemployment. This is because many of them pursue investment opportunities by varying exposure to leading economic factors. To test this proposition, the authors constructed macroeconomic risk measurements using the conditional standard deviation of some economic indicators such as default spread, aggregated dividend yield, and the US inflation rate. Using quintile portfolio sorting and a conditional asset pricing model with macroeconomic risk, Bali, Brown, and Caglayan (2014) found that macroeconomic uncertainties can explain the variation in cross-sectional hedge fund returns. Thus, the authors concluded that macroeconomic risk has a stronger influence on cross-sectional dispersion in hedge fund returns compared to the standard measures of risk.

Buraschi, Kosowski, and Trojani (2014) analysed the relation between correlation risk and cross-sectional hedge fund returns. The authors defined correlation risk as “an unexpected change in the correlation of the returns between different assets or asset classes” (Buraschi, Kosowski and Trojani 2014, p.581). In this study, correlation risk was measured by the swap price of the average S&P500-realised correlation. Using the Fung and Hsieh seven-factor model as the base model, the authors tested the correlation risk exposures of a range of hedge fund strategies. FOFs were found to have a significant negative exposure to the correlation risk factor. Moreover, hedge funds were found to be rewarded by taking higher exposures to the correlation risk factor. However, such funds exhibit larger drawdowns when market correlation tightens during an economic crisis.

Sadka (2010) investigated the influence of liquidity risk on the cross-sectional variation in hedge funds returns. Liquidity risk was measured by the covariance of fund returns with the unexpected shocks' aggregated liquidity. This paper showed that funds with significant exposure to liquidity risk outperform the low-loading funds by about 6 per cent annually. The question of whether liquidity risk is priced in hedge fund returns was also investigated in Brandon and Wang (2013). The authors suggested that a large portion of the previously observed manager skill should be attributed to the liquidity risk premium; in other words, liquidity is a priced systematic factor in hedge fund returns.

In addition to the above-mentioned studies, research has also been undertaken to find other factors that may significantly explain the cross-sectional variation in hedge fund returns. Bali, Brown, and Caglayan (2012) studied systematic risk in cross-sectional hedge fund returns; Agarwal, Arisoy, and Naik (2016) examined the influence of uncertainty about aggregate volatility (referred to as the aggregate volatility factor) on hedge fund returns; and Ilerisoy, Sa-Aadu, and Tiwari (2014) investigated the relation between funding liquidity risk and hedge fund performance.

2.3.4 Predicting hedge fund returns

One of the purposes of modelling hedge fund returns is to forecast hedge fund performance. Many previous studies have found that hedge fund performance persists over various time horizons. For example, Agarwal and Naik (2000a) and Bares Gibson and Gyger (2003) documented short-term performance persistence from one to three months. Edwards and Caglayan (2001) and Jagnnathan, Malakhov, and Novikov (2010) found strong evidence of performance persistence on longer horizons from one to three years.

Most of the above-mentioned studies attributed performance persistence to manager skills, but Glode and Green (2011) argued that it might be the ability to maintain one's proprietary strategy that leads to persisting performance. The authors suggested that good performance is the result of an innovative trading strategy or emerging sector instead of the skill of a manager. Thus, informed initial investors will partner with the incumbent manager and be reluctant to leave, which causes performance persistence. However, the profitability of the strategy may disappear when information spills over and other competitors join the same strategy market. Eling (2009) pointed out that short-term performance persistence could also be caused by data bias and return smoothing.

The main takeaway from the above-mentioned hedge fund performance literature is that there may be some hedge funds that can consistently outperform or underperform others, but the duration of the persistence varies when different methods, databases, market states, or sample periods are used. As a result, we cannot rely only on past returns to forecast the returns in the next period. For instance, Boyson (2008) documented no performance persistence when focusing only on past returns, but she found that persistence is partially influenced by manager tenure and hedge fund style.

It thus becomes crucial to find some appropriate filters, with a degree of reliability, to assist in hedge fund selection, and much of the hedge fund performance predictability research is aimed at this.

A group of studies used hedge fund-specific characteristics as filters combined with some performance indicators to predict future performance. Edwards and Caglayan (2001) suggested that hedge funds paying higher incentive fees may motivate better performance and produce predictability in hedge fund returns. Cremers and Petajisto (2009) found that actively managed portfolios, measured by their active share indicator, deliver superior performance ex-ante. Fund flows were also shown to predict future performance (Agarwal, Daniel and Naik 2007; Fung et al., 2008; Ding et al., 2007).

In contrast, many researchers use risk measurements, i.e., loadings on risk factors, as predictors of future performance. Avramov et al. (2011) proposed incorporating predictability in managerial skills when constructing optimal portfolios of hedge funds. The authors found that macroeconomic variables, such as the default spread and VIX, have strong return-predictive power. In addition, the simulated portfolio, following the suggested strategy, outperformed ex-post the other competing strategies. Further to this study, Avramov, Barras, and Kosowski (2013) conducted a more comprehensive analysis on hedge fund return predictability. They found that a large proportion of hedge funds are predictable using a single predictor strategy, where predictors are mainly macroeconomic variable. Further, if a combined forecast strategy is followed, the portfolio can deliver superior performance.

Bali, Brown, and Caglayan (2011) investigated whether hedge fund betas possess predictive power regarding the returns in the next period. Using a wide range of financial and macroeconomic risk factors in a multifactor model, the authors found that hedge fund returns are sensitive to changes in the default premium and inflation rate. The two factors are proven to possess predictive power using Fama–MacBeth (1973) regression and decile portfolio sorting, and the results remained robust during various sample periods and using alternative measurements.

To sum up, a growing body of literature has shown that hedge funds have significant exposure to a variety of systematic risk factors. Therefore, hedge fund returns can be effectively explained by a multifactor model that incorporates the traditional equity and debt factors as well as the other factors that reflect the unique risk-return profile of hedge funds.

2.4 The performance, diversification puzzle, and tail risk of funds of hedge funds

FOFs benefit investors in a variety of ways. For example, Brand and Gallagher (2005) documented diversification benefits in FOF portfolios in a mean-variance setting. Ang, Rhodes-Kropf, and Zhao (2008) found that unskilled investors receive cost savings because FOFs perform due diligence in fund selection. Darolles and Vaissié (2012) found evidence that FOFs add value mainly from strategic asset allocation, which accounts for 68 per cent of the variability and 45 per cent of the level of return of FOFs. The authors thus suggested that the value added by FOFs across market regimes outweighs the costs of the double fee structure. Aiken, Clifford, and Ellis (2015) showed that FOFs make skilful termination decisions after they invest in a hedge fund. Above all these benefits, arguably, the greatest one is the ability of FOFs to deliver better risk-adjusted performance via diversification.

2.4.1 The performance of FOFs

Although it is expected that FOFs provide better risk-adjusted performance than an ordinary hedge fund, there is growing evidence from academic literature suggesting that this expectation may not be realistic. The performance of FOFs between 1994 and 1999 is examined by Brown Goetzmann and Liang (2004), who found that FOFs offer more consistent, lower risk-adjusted returns than hedge funds. Gregoriou et al. (2007) found that FOFs underperformed hedge funds in the bullish market from 1995 to 1999 and underperformed non-directional hedge funds in the period from 1995 to 2002, irrespective of the market conditions. Moreover, they found that simple, equal-weighted portfolios of no more than four hedge funds dominate the performance of the best FOFs, and they claimed that the second layer of fees trims down the performance of FOFs. As suggested by Brown Goetzmann and Liang (2004), the more diversified portfolio an FOF holds, the more likely it is that the investors have to pay an incentive fee to the underlying hedge fund managers even if the FOF delivers poor overall performance. Ammann and Moerth (2008) found a positive relation between fund size and performance, but they claimed that FOFs failed to generate significant alpha over a 120-month period.

Table 1 summarises some selected empirical results of FOF performance. Across all the selected studies, FOFs generated lower returns than other hedge funds but, in contrast, deliver lower volatility. Based on the return and standard deviation measures, I calculated the coefficient of variation to represent the risk-adjusted return. I found that, overall, FOFs generated lower risk-adjusted returns in seven out of nine studies. In addition, the returns of FOFs were found to be non-normally distributed. Most research has found negative skewness and high-level kurtosis in the return distribution of FOFs.

Table 2.1 The performance of funds of hedge funds (FOFs) and hedge funds in different empirical research

This table summarises the performance of FOFs and hedge funds in a variety of empirical studies. Four performance measurements are summarised: return, standard deviation, skewness, and kurtosis. Moreover, the author manually calculated the coefficient of variance (CV) following $CV = return/std.dev$ as a simple measure of risk-adjusted return.

		Return	Std. dev	CV	Skewness	Kurtosis	Time span
Brown Goetzmann and Liang (2004)	FOFs	0.86[***a]	3.91[***]	0.22	-0.31[***]	4.06	1989–2000
	HFs	1.38	5.74	0.24	-0.13	3.79	
Beckers et al. (2007)	FOFs	10.28	6.13	1.67	n.a.	n.a.	1991–2005
	HFs	12.95	11.48	1.23			
Brooks and Kat (2001)	FOFs	1.25	2.32	0.54	0.03	2.32	1995–2001
	HFs	1.42	2.35	0.6	-0.26	2.13	
Malkiel and Saha (2005)	FOFs	7.02	7.44	0.94	-0.14	6.31	1995–2003
	HFs	8.82	9.21	0.96	-0.25	5.51	
Ranaldo and Favre (2005)	FOFs	0.9	1.7	0.53	-0.3	3.7	1990–2002
	HFs	1.2	-2.1	0.57	-0.7	2.6	
Diez De Los Rios and Garcia (2011)	FOFs	6.69	6.21	1.08	-0.19	3.08	1996–2004
	HFs	8.5	6.88	1.23	-0.23	2.44	
Gregoriou et al. (2007)	FOFs	0.81	2.87	0.28	-0.38	8.2	1995–2002
	HFs	1.08	5.28	0.2	-0.16	7.29	
Avramov et al. (2009)	FOFs	2.2	7.3	0.3	-0.09	3.4	1994–2008
	HFs	4.7	9.4	0.5	-0.06	3.5	
Capocci Corhay and Hubner (2005)	FOFs	0.72	1.77	0.4	-0.11	3.34	1994–2002
	HFs	1.08	2.28	0.47	-0.26	2.77	

2.4.2 The diversification puzzle of FOFs

Under the mean-variance framework (Markowitz 1952), the diversification effect takes place by combining loosely correlated assets to eliminate the unsystematic risk of individual assets. However, the mean-variance framework assumes that portfolio returns are normally distributed, yet this has been proved untrue in the hedge fund portfolios. According to Low, Faff, and Aas (2016), asymmetries within the joint distribution of asset returns, such as the skewness of individual assets or the asymmetric dependence between individual asset returns, are the major concerns when constructing portfolios under the mean-variance framework. These statistical properties, as discussed in the previous section, are typical in hedge fund and FOF returns.

In FOF literature, there is limited evidence in favour of the diversification benefits of FOFs (Brands and Gallagher 2005; Amo, Harasty and Hillion 2007). Instead, mounting studies show strong contradictory evidence of FOF diversification, especially when the higher moments of portfolios are considered. Amin and Kat (2002) examined the relationship between underlying fund numbers and the diversification effect of FOF portfolios. They constructed random, equally weighted hedge fund portfolios with a varying number of underlying hedge funds, from 1 to 20, and calculated the statistical characteristics of the portfolios. They found that, by increasing the number of underlying hedge funds, the standard deviation and the skewness of the portfolios tend to decrease, whereas correlations between the portfolios and equity markets increase. This means that, for an investor with a low tolerance to extreme losses and high market correlation, investing in a single hedge fund would be a better choice than investing in an FOF. Lhabitant and Learned (2002) performed a similar study on the optimal number of underlying funds to achieve diversification. By constructing naïve equally weighted random portfolios, they found that diversification reduces variance at the cost of lower skewness, higher kurtosis, and stronger correlation with equity markets. Lhabitant and Learned (2002), however, noted that the unfavourable changes in the higher moments may be caused by the naïve portfolio construction approach.

In the most recent study of Joenväärä and Scherer (2016), the authors used a data set containing holding information of 127 FOFs. Assuming frictional diversification costs (such as due diligence and monitoring costs per extra underlying fund), they found a positive log-linear relation between the number of underlying funds in an FOF and the corresponding AUM of the FOF. Joenväärä and Scherer (2016, p. 2) thus argued that diversification in FOF is not a free lunch: *"over-diversification is as detrimental to performance as under-performance"*.

Brown, Gregoriou, and Pascalau (2012) found that FOFs with higher numbers of underlying hedge funds are more exposed to left-tail risk. The author defined this observation as a diversification puzzle. The authors thus proposed that FOFs tend to over-diversify their positions, leading to excessive left-tail risk. Allen et al. (2014) studied FOF diversification by simulating FOF portfolios using a variety of optimisation techniques, including the Markowitz mean-variance, naïve diversification, and optimisation with draw-down strategies. They found that Markowitz portfolios, which match the characteristics of hedge fund indices well, outperform the other portfolios on the Sharpe ratio and a series of downside risk measurements. Allen et al. (2014) noted that the various draw-down strategies are unable to dominate the Markowitz mean-variance portfolio in relation to controlling portfolio drawdowns. This evidence strongly supports the proposition of Brown, Gregoriou, and Pascalau (2012) that tail risk in hedge funds is not diversifiable.

2.4.3 Why is tail risk relevant to funds of hedge funds?

As introduced in the last section, FOFs seem to exhibit an inability to diversify the extreme losses of underlying hedge funds. This diversification puzzle may find its roots in the general asset pricing theory with regard to the aggregation of tail risk. Ibragimov and Walden (2007) proved that, as long as the risks are concentrated on a sufficiently large interval, diversification may increase value at risk (VaR) irrespective of whether the distribution support is bounded or unbounded. Based on this theoretical framework, Ibragimov, Jaffee, and Walden (2009) modelled catastrophic risk and found that the value of diversification decreases dramatically or in some cases becomes negative when the underlying asset distributions are heavy-tailed. Ibragimov, Jaffee, and Walden (2009) named this phenomenon a "diversification trap". As a conclusion, the authors suggested that the heavier the tails are, the less reliable standard mean-variance analysis is, based on the normal distribution assumption. FOFs may be a living example that supports the diversification trap theory.

Hedge funds are found to have non-linear payoff structures and exhibit strong tail dependence in the traditional asset classes (Fung and Hsieh 1997b; Amin and Kat 2003; Agarwal and Naik 2004). They are also very sensitive to market downturns, as pointed out by Geman and Kharoubi (2003), Brown and Spitzer (2006), and Guesmi et al. (2015). Boyson, Stahel, and Stulz (2010) further provided evidence on the contagion of worst returns across the hedge fund industry. These characteristics exactly fulfil the condition of Ibragimov, Jalfee, and Walden (2009) to form a diversification trap in the portfolios of FOFs. In fact, Brown and Spitzer (2006) found that the extreme losses of FOFs are significantly correlated to the extreme losses of the market. They suggested that an FOF portfolio cannot effectively diversify the tail risk of ordinary hedge funds.

Ignoring tail risk may result in detrimental consequences when constructing an FOF portfolio. Agarwal and Naik (2004) compared a portfolio constructed under a mean-variance framework (ignoring tail risk) with another portfolio constructed under the mean-conditional VaR framework. They found that ignoring tail risk may result in excessive asset allocation to hedge funds and significant losses during large market downturns. This opinion is also held by Brown, Gregoriou, and Pascalau (2012), who found that the higher moments of simulated hedge fund portfolios become more outstanding with more underlying funds being added (see the discussion in Section 2.3.2).

2.4.4 Modelling the tail risk of hedge funds

According to the existing evidence, the tail risk of hedge funds cannot be eliminated by diversification. It thus follows that tail risk could be a systematic risk that should be priced in the returns of hedge funds[10]. Ideally, we should have a tail risk factor that may explain the variation in the returns of hedge funds and capture the tail risk shocks to the hedge fund industry. This topic remains a focal point in hedge fund research in recent years, for example in the work of Jiang and Kelly (2012) as well as that of Agarwal, Ruenzi, and Weigert (2016).

Kelly and Jiang (2014) assumed that the tail risk of individual firms follows a power law but is influenced by market tail risk. The magnitude of market tail risk thus can be estimated by using the Hill estimator from the cross-sectional asset returns. This tail risk factor was utilised in Jiang and Kelly (2012) to study the tail risk exposures of hedge funds. They found that the tail risk factor can significantly explain fund returns

[10] The findings in Bali, Gokcan, and Liang (2007), as well as those in Liang and Park (2007), provide evidence on the significant relation between downside risk and the cross-section of hedge fund returns.

in both time series and cross-sectional regressions. They found that a unit tail risk shock may lead to a 2.88 per cent decrease in the value of an aggregated hedge fund portfolio.

Agarwal, Ruenzi, and Weigert (2016) developed a tail risk factor by employing the tail sensitivity of hedge funds to equity market tail returns. This non-parametric tail risk factor contains information of equity market tail risk shocks as well as the sensitivity of cross-sectional hedge funds to the market tail risk shocks. Similar to that of Jiang and Kelly (2012), this research documented a robust explanatory power of market tail risk. Furthermore, using funds' quarterly holding information from 13F filing, Agarwal, Ruenzi, and Weigert (2016) found that the tail risk exposure of hedge funds mainly stems from their holdings of tail risk-sensitive stocks and options.

Chapter 3: Data and methodology

3.1 Introduction

This chapter describes the data and methodology used in this thesis. Hedge funds are not subject to an information disclosure mandate in most jurisdictions, but many hedge funds voluntarily report their performance to commercial data vendors. Hedge fund researchers have identified some data bias in hedge fund return data and studied how such bias may distort hedge fund reported performance.

The first part of this chapter introduces the major forms of hedge fund data bias, including survivorship bias, self-selection, and backfill bias as well as the autocorrelation problem with returns. The relevant literature is also reviewed in this section. The second part of the chapter discusses the sample data used in this research. I will introduce the steps taken to alleviate potential data bias. I find the combined survivorship bias and backfill bias to be around 3.09 per cent p.a. in the hedge fund sample and 1.03 per cent p.a. in the FOF sample. In the meantime, the autocorrelation of reported returns caused severe understatement of the standard deviation by around 0.45 per cent in the monthly returns of both the FOF and hedge fund samples. The third part of this chapter discusses the relevant methodology adopted in this thesis. I will introduce some important downside risk measurements, including the Kelly and Jiang (2014) tail risk factor, the Fung and Hsieh (2004a) seven-factor model, and other techniques used in the remainder of this thesis.

3.2 Hedge fund data bias

3.2.1 Survivorship bias

Survivorship bias occurs when data vendors delist the information of any fund that becomes defunct or otherwise stops reporting. There are various reasons for a hedge fund to discontinue information disclosure. For instance, a hedge fund may close down because it no longer has the capacity to profit from its strategy or it is forced to liquidate because of poor performance. This will result in a favourable bias in the average returns from the funds remaining in the sample, also known as "extinction bias" (Getmansky, Lee and Lo 2015). However, a hedge fund may stop reporting because it lacks ambition for new capital, especially when it receives abundant investments attracted by its past superior performance (Ackermann, McEnally and Ravenscraft 1999). Conceivably, delisting for this reason may cause an unfavourable bias in the average returns. In some circumstances, the delisting decision is made by a data vendor to avoid the liabilities of misreporting (Fung and Hsieh 1997a). The influence of this type of survivorship bias is not obvious, as it can happen to both underperforming and outperforming funds.

Brown, Goetzmann, and Ibbotson (1999) studied survivorship bias in the US Offshore Funds Directory from 1990 to 1997. They found that survivorship bias could be around 3 per cent p.a., as measured by the difference between the mean return of the whole sample index and the surviving fund index. A few similar studies estimated the survivorship bias in commercial hedge fund databases such as TASS and HFR, and the results varied depending on the sample period and the estimation method. For example, Barry (2003) documented a 3.8 per cent survivorship bias in the TASS database from 1994 to 2001, while Agarwal and Jorion (2010) measured a 5.23 per cent survivorship bias in the same database during the same period.

More convincing evidence was contributed by Aiken, Clifford, and Ellis (2013), in whose study a sample of hedge funds that had discontinued reporting to data vendors was formed. It was found that the average post-delisting performance of these “dead” funds is non-trivially bad, which means that the de-listing of these hedge funds resulted in a positive bias in the commercial databases. In addition, by comparing the distributions of the database sample and the non-reporting sample, the authors found that the most extreme disparity was at the left tails of the distributions; in other words, some of the worst-performing funds choose not to report to a commercial database.

3.2.2 Self-selection bias

Hedge fund managers usually have great autonomy when making a decision on external reporting, such as the timing of reporting, the databases to report to, and the frequency of reporting. Given such wide flexibility, managers can deliberately manage reporting at any stage of the fund life cycle for an optimal marketing effect, but at the same time, this practice will cause self-selection bias in the commercial databases.

Bollen (2011) found that the cross-sectional hedge fund return distributions are consistently discontinued at zero in the three sample periods, whereas FOF distribution lost discontinuity in the first nine months of 2008. According to Fung and Hsieh (2002), FOF returns are less biased because they contain information on both database and non-database funds. Therefore, Bollen (2011) suggested that the discontinuity in return distribution is mainly caused by the action of hedge fund managers to avoid reporting losses.

The existing literature so far shows no firm agreement on the exact influence of self-reporting bias. Aiken, Clifford, and Ellis (2013) compared a range of performance indicators between a sample of 1,445 non-database hedge funds and a sample of database funds. They found that the seven-factor alpha of non-database hedge funds is insignificant from zero and lower than the alpha of database hedge funds by 105bps/quarter. Agarwal, Fos, and Jiang (2013) performed a similar comparison using 13F filing information but found no significant differences between reporting and non-reporting hedge funds in their mean return.

Another self-selection related bias is called backfill bias. It occurs when a hedge fund waits to join a database until it has generated a good performance. The past performance between the fund inception date and the start of reporting date is thus backfilled and causes a positive bias in the average return. The presence of backfill bias has been recognised in early hedge fund studies, but the estimation varies a great deal across different sample periods. Taking the Lipper TASS database as an example, Fung and Hsieh (2000) documented a backfill bias of 1.4 per cent p.a. from 1994 to 2000, yet Malkiel and Saha (2005) estimated a backfill bias of 7.31 per cent in the same database between 1994 and 2003. Ibbotson, Chen, and Zhu (2011) updated the estimation of backfill bias and recorded a 2.97 per cent backfill bias from 1995 to 2009.

3.2.3 Autocorrelation

As discussed in Section 2.2.2, hedge fund returns exhibit strong serial correlation. Getmansky, Lo, and Makarov (2004) explained the reported hedge fund returns as a moving average of unobserved economic returns and found their model to be robust when fitting to a sample of 908 hedge funds. The authors attributed the autocorrelation to two reasons: investment in illiquid assets and return-smoothing.

Compared with mutual funds and pension funds, which are subject to strict investment regulation, hedge funds have a better capacity to invest in illiquid assets such as distressed securities and small cap shares. As Agarwal, Mullally, and Naik (2015) described, such illiquid holdings may impede asset valuation because their market price is not readily available. Thus, hedge fund managers have to use the most recent security price as the market value of the illiquid assets, but this gives rise to a stale price bias in the hedge fund database. In contrast, fund managers may perform return smoothing on game performance indicators, and this may also lead to serial correlation in a return series (Spurgin 2001; Agarwal, Daniel and Naik 2011).

To sum up, hedge fund return information in a commercial database may be subject to a variety of bias that may distort the true risk-return relation in hedge funds. Although the reliability of the vendor hedge fund data remains questionable, some research provided evidence supporting the usefulness of such data. Edelman, Fung, and Hsieh (2013) found no significant difference between the performance of reporting mega hedge funds and non-reporting mega hedge funds. They further suggested that the reporting hedge fund performance can represent the performance of the non-reporting funds. In the next section, I will introduce details of how the above-mentioned data bias is processed.

3.3 Data

3.3.1 Hedge fund data

The hedge fund data used in this thesis is provided by Morningstar. The sample period starts in January 1995 and ends on 31 December 2012. The Morningstar hedge fund data contains 22,644 hedge funds with a combination of living funds and defunct funds. Morningstar further classifies the hedge funds and FOFs into different categories according to their investment strategies and major risk exposures. The full classification includes 39 categories, and the descriptions of the categories are listed in Appendix A. To ensure a sufficient number of funds in the hedge fund style analysis, I aggregated some of the categories. In addition, I have removed the funds providing fewer than 24 monthly returns to guarantee sufficient observations in the individual fund tests[11]. I dropped four funds that report constant returns in the whole sample period. As a result, 7,782 HFs and 4,275 FOFs remain in the sample. This sample size is about the same as in the Agarwal, Ruenzi, and Weigert (2016) study and larger than the sample size in another hedge fund tail risk paper by Jiang and Kelly (2012), which studied 6,252 hedge funds. The focus of this research is FOFs, which are known to report less biased information than the other hedge fund strategies (Fung et al., 2008; Edelman et al., 2012). I will also present some evidence in Section 3.3.1 to support this claim.

[11] This is a common practice adopted in a wide range of hedge fund research; see, for example, Liang and Park (2010), Bali, Brown, and Caglayan (2011), and Kelly and Jiang (2014). These studies reported no resulting sample selection bias.

3.3.1 Hedge fund data bias alleviation

As discussed in Section 3.2, hedge fund data may be subject to survivorship bias, self-selection bias, and autocorrelation issues. I adopted the following processes to alleviate possible data bias in the raw data set. To account for survivorship bias, I used a combined dataset containing both living and dead hedge funds. In addition, following the approach of Fung and Hsieh (1997b and 2001), I removed the returns before the database entry dates for all sample funds to alleviate backfill bias. To reduce the autocorrelation in fund returns, I fit an MA(2) process to each hedge fund and unsmooth the fund returns, following the approach of Getmansky, Lo, and Makarov (2004). In particular, the observed return series $\{R_t^O\}$ is expected to be a weighted average of the true return R^C over the most recent three periods:

$$R_t^O = \lambda_0 R_t^C + \lambda_1 R_{t-1}^C + \lambda_2 R_{t-2}^C \tag{3.1}$$

$$\lambda_l \epsilon [0,1], l = 0, 1,2 \tag{3.2}$$

$$\boldsymbol{\lambda_0 + \lambda_1 + \lambda_2 = 1} \tag{3.3}$$

The smoothing coefficients λ_l can be estimated using the maximum likelihood approach. The unsmoothed return R_t^C can be estimated through a recursive process using

$$R_t^C = \frac{R_t^O - \widehat{\lambda_1} R_{t-1}^C - \widehat{\lambda_2} R_{t-2}^C}{\widehat{\lambda_0}} \tag{3.4}$$

In Table 3.1, I display the summary statistics of both hedge funds and FOFs to show the effect of potential data bias on performance measurements. The Morningstar database reveals the status of a fund in three categories, dead, living, or merged, and the top panel in Table 3.1 reports the number of funds in each category. I find a higher proportion of FOFs that are defunct, having been either liquidated or merged, than of hedge funds. This observation is consistent with the most recent research findings that FOFs have been affected more severely by the 2007–2008 GFC than other hedge fund styles (Schizas 2012; Edelman et al., 2012).

Table 3.1 Morningstar hedge fund data bias summary

This table shows the performance statistics of Morningstar hedge fund data with the procedures of data bias alleviation. Three types of data bias are processed: survivorship bias, backfill bias, and autocorrelation bias. Panel A shows the information of raw data, Panel B shows the information of the data with alleviated backfill bias, and Panel C shows the information of the data with both backfill and autocorrelation bias having been alleviated. The difference between the combined mean and the mean of each dead, living, and merged category goes through a t-test for significance. The data sample period is from January 1995 to December 2012.

	Funds of funds (FOFs)				Hedge funds (HFs)			
	Dead[a]	Living	Merged	Combined	Dead	Living	Merged	Combined
Count	2764	1315	196	4275	4736	2910	140	7786
% of Total	64.7%	30.8%	4.6%	100.0%	60.8%	37.4%	1.8%	100.0%
Panel A: Performance of FOFs and HFs – raw data								
	FOFs				HFs			
	Dead	Living	Merged	Combined	Dead	Living	Merged	Combined
Mean	0.56^{***b}	0.69***	0.51	0.62	0.89***	1.16***	0.65***	1.00
Std. dev.	2.08	2.08	2.77	2.09	1.96	2.37	2.82	2.10
Skewness	-1.21	-0.86	-0.85	-1.11	-0.70	-0.34	-0.79	-0.59
Kurtosis	4.57	3.16	2.77	4.18	2.06	1.07	3.41	1.83
Sharpe ratio	0.15	0.22	0.10	0.18	0.33	0.39	0.14	0.36
Panel B: Performance of FOFs and HFs – data with alleviated backfill bias								
	FOFs				HFs			
	Dead	Living	Merged	Combined	Dead	Living	Merged	Combined
Mean	0.54***	0.69***	0.52	0.61	0.81***	1.09***	0.54	0.93
Std. dev.	2.08	2.08	2.84	2.09	1.97	2.40	3.09	2.12
Skewness	-1.23	-0.83	-0.76	-1.11	-0.75	-0.38	-0.52	-0.63
Kurtosis	4.65	3.11	2.65	4.19	2.32	1.23	2.96	2.01
Sharpe ratio	0.14	0.22	0.10	0.18	0.29	0.35	0.10	0.32
Panel C: Performance of FOFs and HFs – data with alleviated backfill bias and autocorrelation bias								
	FOFs				HFs			
	Dead	Living	Merged	Combined	Dead	Living	Merged	Combined
Mean	0.55***	0.70***	0.53	0.61	0.81***	1.09***	0.53	0.93
Std. dev.	2.58	2.51	3.44	2.56	2.37	2.84	3.66	2.55
Skewness	-0.92	-0.61	-0.51	-0.83	-0.64	-0.35	-0.46	-0.55
Kurtosis	2.98	1.85	1.54	2.65	1.55	0.67	2.36	1.27
Sharpe ratio	0.12	0.18	0.08	0.14	0.24	0.3	0.08	0.27

a. Morningstar defines three hedge fund statuses: Dead covers those that have been liquidated; living represents the extant funds at the last sample date; and merged comprises the funds that have merged into other funds.

b. The asterisk indicates the significance of the difference between each category's mean and the total mean, as indicated in Student's t-test. *** represents significance at the 1% level.

Panel A shows the summary information of the raw data. Comparing the mean return of dead funds with the total in both FOF and hedge fund samples, I find a clear indicator of survivorship bias. For instance, the mean return of dead hedge funds is 0.89 per cent monthly, which is 0.27 per cent lower than living hedge funds per month, or 3.65 per cent lower on the annual compounding basis. Aggregating the three types of hedge fund, the mean return of the total hedge funds is 1 per cent monthly, which is still significantly higher than that of dead hedge funds, according to the t-test result. The survivorship bias in FOFs is estimated to be 1.66 per cent on the annual compounding basis. In addition, both dead FOFs and hedge funds report lower skewness and higher kurtosis than their counterpart living funds, which indicates a survivorship bias in the return distribution as well.

Panel B presents the information with reduced backfill bias. The change in mean returns from Panel A to Panel B strongly supports the claim made by Fung and Hsieh (2002) that FOF return information is less biased than the other hedge fund strategies. To be exact, the mean returns of all FOF categories in Panel B remain almost the same as in Panel A, but those of the four hedge fund categories have consistently decreased. However, the differences in standard deviations between the two panels are not as remarkable as in the mean returns. It seems that backfill bias mainly occurs in the means but not in the higher moments. Overall, backfill bias leads to a positive bias of 1.01 per cent in the annualised return of my hedge fund sample after controlling for survivorship bias.

Last, the effect of autocorrelation in hedge fund return is reported in Panel C. By construction, the unsmoothing technique of Getmansky, Lo, and Markarov (2004) adjusts standard deviation upward while leaving mean returns unchanged, and Panel C figures strongly support this claim. Compared with the standard deviations in Panel

B, the standard deviations of total FOFs and total hedge funds receive a 0.47 per cent and 0.43 per cent increase, respectively, after autocorrelation is removed. The change in Sharpe ratios across all the categories coincides with the claim that hedge fund managers could manipulate the Sharpe ratio by return smoothing.

3.3.2 Descriptive statistics of the sample data

In this section, I will summarise the descriptive statistics of the sample data after processing for data bias. Table 3.2 shows the headcounts of the selected data points in the sample.

Table 3.2 Headcounts of Morningstar information variables (1995 to 2012)

This table reports the headcounts of selected Morningstar information variables of hedge funds and FOFs. For each variable, the number of reporting funds is recorded in the column titled "Count". Then the number is divided by the category total, 7,782 for hedge funds and 4,275 for FOFs, and the result is reported as a percentage in the column titled "% of HF/FOF total".

	Hedge funds (HFs)		**Funds of funds (FOFs)**	
	Count	% of HF total	Count	% of FOF total
Domicile	7782	100.0%	4275	100.0%
Fund legal structure	7782	100.0%	4275	100.0%
Management fees	6979	89.7%	3463	81.0%
Performance fees	6840	87.9%	3306	77.3%
Average net assets	6182	79.4%	3641	85.2%
High water mark	5809	74.6%	2585	60.5%
Redemption frequency	5092	65.4%	2589	60.6%
Advanced notice days	4620	59.4%	2331	54.5%
Lockup months	4272	54.9%	1684	39.4%
Uses leverage	2255	29.0%	1095	25.6%
Average leverage	1592	20.5%	506	11.8%

The information used by my study includes advance notice days, average leverage, fund size, lockup months, management fees, performance fees, average net assets, domicile, fund legal structure, and high water mark. For each information variable, the number of reporting funds is recorded in the column titled "Count". Then the number is divided by the category total, 7,782 for hedge funds and 4,275 for FOFs, and the result is reported as a percentage in the column titled "% of HF/FOF total".

The information in this table can be viewed as an indicator of data quality because a large sample is usually preferred. In contrast, this information also reflects the preference of hedge fund managers towards information disclosure. Although most of the information variables receive a significant amount of reporting from more than 50 per cent of the total hedge funds or FOFs, they display a structural difference in the distribution of headcounts across hedge fund styles. In particular, 100 per cent of the funds report their domicile and legal structure to Morningstar, and the vast majority (more than 70 per cent) of them report the information on manager incentive facilities, including management fees, performance fees, and high water mark. Redemption restriction information, such as redemption frequency, lockup months, and advance notice days, receive reporting from around 40-60 per cent of funds. Last, the leverage variable receives the lowest reporting: less than 30 per cent of the sample funds are willing to disclose such information to the database. The difference in reporting here reflects the attitude of hedge fund managers towards reporting: on one hand, managers would like to get public attention through the commercial data vendors, but on the other hand, they would like to remain secretive regarding their investment strategies. A comprehensive discussion of hedge fund and FOF managerial characteristics will be presented in Chapter 4.

Table 3.3 Descriptive statistics of the return information in the Morningstar hedge fund database

The hedge fund and FOF samples are grouped according to investment strategy, and the number of monthly returns reported by each fund in the strategy group is counted. The section "Statistics of the number of reported returns" describes the proportion of the group total that reports a particular number of returns, i.e., "<36" indicates reporting of less than 36 monthly returns. The section "Quantile summary of the number of reported returns" shows the distributional attributes of each strategy group. For instance, the figures in the 1st Q. column represent the number of returns reported by the fund ranked in the 25th percentile from the lowest in each strategy group. The sample contains only the funds with at least 12 monthly returns after processing for backfill bias.

Panel A: Descriptive statistics of hedge fund returns

Investment strategy		Statistics of the number of reported returns				Quantile summary of the number of reported returns					
	No. of funds	< 36	36 to 60	61 to 120	>120	Min.	1st Q.	Median	Mean	3rd Q.	Max.
Debt	969	34.9%	25.0%	26.0%	14.1%	12	29	50	63.13	88	216
Equity	4256	32.2%	22.9%	30.9%	14.0%	12	29	54	66.51	92	216
Event-driven	487	22.4%	19.3%	36.1%	22.2%	12	39	71	82.28	115	216
Multi-strategy	637	36.6%	26.5%	25.3%	11.6%	12	26	47	60.19	81	216
Systematic futures	700	29.7%	20.7%	27.7%	21.9%	12	33	58.5	77.48	107.2	216
Volatility	50	16.0%	46.0%	30.0%	8.0%	12	38.5	50	60.8	87.5	184
Macro	683	31.2%	21.7%	29.6%	17.6%	12	31	55	70.15	95.5	216
Hedge fund total	**7782**	**31.9%**	**23.1%**	**29.7%**	**15.3%**	**12**	**30**	**53**	**67.82**	**93**	**216**

Panel B: Descriptive statistics of FOF returns

Investment strategy		Statistics of the number of reported returns				Quantile summary of the number of reported returns					
	No. of funds	< 36	36 to 60	61 to 120	>120	Min.	1st Q.	Median	Mean	3rd Q.	Max.
Macro/systematic	360	24.7%	22.8%	39.2%	13.3%	12	36	62.5	71.24	89.25	216
Debt	208	33.2%	28.8%	28.4%	9.6%	12	32	46	59.63	81	209
Equity	1192	21.2%	22.1%	38.8%	17.8%	12	39	67	77.15	102.2	216
Event	210	17.1%	21.9%	47.6%	13.3%	12	45	70.5	75.79	96.75	216
Multi-strategy	2117	22.5%	26.3%	39.0%	12.3%	12	38	61	70.69	94	216
Relative value	188	21.8%	21.8%	41.0%	15.4%	12	39	67	74.06	95	214
FOF total	**4275**	**22.5%**	**24.5%**	**38.9%**	**14.0%**	**12**	**38**	**63**	**72.4**	**95**	**216**

Besides the information on hedge fund managerial attributes, I will also use fund return information intensively in this research. I will perform some cross-sectional regression analysis as well as time-series regressions at both the individual fund level and the portfolio level. In either case, the number of observations is a concern. Therefore, I counted the total number of monthly returns reported by each fund and present the statistics in Table 3.3. The hedge fund and FOF samples are grouped according to investment strategy, and the number of monthly returns reported by each fund in the strategy group is counted. The section "Statistics of the number of reported returns" describes the proportion of the group total that reports a particular number of returns; i.e., "<36" indicates reporting less than 36 monthly returns. The "Quantile summary of the number of reported returns" section shows the distributional attributes of each strategy group. For instance, the figures in the 1st Q. column represent the number of returns reported by the fund ranked in the 25th percentile from the lowest in each strategy group.

The Morningstar database recognises 39 hedge fund investment strategies, and FOFs are classified as a subset of multi-strategy hedge funds. FOFs are further classified into six strategy groups by Morningstar. For ease of analysis and explanation, I aggregate these strategies into eight broad categories: debt, equity, event-driven, multi-strategy (excluding FOFs), systematic futures, volatility, macro, and FOFs. I keep the original classification of FOFs unchanged. In the end, I have seven hedge fund strategy groups and six FOF strategy groups. The headcounts of these groups are displayed in the first column of Table 3.3. The largest strategy group in the hedge fund sample is equity, containing 4,256 hedge funds. The size of the other hedge fund strategy groups is similar: between 500 and 1000 except for volatility, which contains only 50 hedge funds. In FOFs, multi-strategy and equity are the two largest strategy groups, and the other groups contain only around 200 to 400 funds. A comprehensive analysis of hedge fund strategies is presented in Chapter 4.

As shown in the last row of Panel A, most of the hedge funds report more than 36 monthly returns, and around 50 per cent of them submit 36 to 60 monthly returns. According to the quantile summary, the median of the reporting distribution is 53 monthly returns. Specific to hedge fund strategy groups, event-driven hedge funds report the highest average number of returns measured by both mean and median, whereas multi-strategy hedge funds report the lowest average number of returns. Across all hedge fund groups, the lowest first quintile threshold is 29, which means that only 25 per cent of each strategy group report fewer than 29 monthly returns.

Compared with hedge funds, FOFs, on average, have a longer reporting history. Around 77.5 per cent of FOFs report more than 36 monthly returns, and more than half of FOFs report more than 60 returns. The median of FOF reporting months is 63, 10 months higher than hedge funds. Among the six FOF strategy groups, event and equity FOFs have the highest number of reporting months, as shown by the quantile summary. The lowest first quartile threshold is 32 monthly returns in the distribution of debt FOFs, while the same threshold for the other strategies is more than 36 monthly returns.

In summary, although the initial filtering and backfill bias adjustment have removed many samples or return observations from the original sample, the remaining sample is still large and contains a good number of observations. As shown by the quantile summary in Table 3.3, if we use 24 months as the standard regression window, we can keep the majority of the funds in each strategy group without losing too much information. It should be noted that a 24-month-window contains a relatively small number of observations, which may lead to noisy and unreliable results[12].

3.3.3 Other data

Throughout this research, I will also use equity data. The data includes the daily prices of the constituents of Thomson Reuters Global Equity Indices[13] from 1 January 1995 to 31 December 2013, the monthly time series of Fung and Hsieh's (2004a) seven factors[14], the monthly time series of the Fama–French–Cohart four factors[15], the monthly time series of Robert F. Stambaugh's liquidity factor[16], and the monthly return of the Chicago Board Options Exchange (CBOE) Volatility Index (VIX)[17].

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[12] For most of the tests in this thesis, I have performed robustness tests using a 36-month regression window and received similar results.
[13] The constituents' prices were downloaded from Datastream.
[14] I obtained Fung and Hsieh's (2001) seven factors from David A. Hsieh's Hedge Fund Data Library (https://faculty.fuqua.duke.edu/~dah7/HFData.htm).
[15] Risk-free interest rate and momentum factor data were downloaded from the Kenneth R. French Data Library (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).
[16] The liquidity factor series was provided on Robert F. Stambaugh's professional web page (http://finance.wharton.upenn.edu/~stambaug/).
[17] VIX data was obtained from Chicago Board Options Exchange (CBOE) website (http://www.cboe.com/micro/vix/historical.aspx).

3.4 Methodology

In this section, I will introduce the methodology adopted in Chapter 5 and Chapter 6.

3.4.1 Estimation of risk measures

I examined several risk measurements in the preliminary performance analysis. Four risk measures, standard deviation, semi-deviation, non-parametric VaR, and non-parametric expected shortfall, are used to analyse the historical performance of hedge funds and FOFs at both the individual fund level and the portfolio level.

3.4.1.1 Standard deviation (SD)

Standard deviation is widely used as a fundamental risk measurement. It describes the level of dispersion of a set of data values. Many performance indicators require standard deviation as an ingredient, such as the Sharpe ratio and Jensen's alpha. However, standard deviation loses its reliability when the data values are not normally distributed, which is exactly the case for hedge fund and FOF returns. Assuming a time series of monthly return $\{R_t\}$ $(t = 1,2, \ldots, T)$, the standard deviation of $\{R_t\}$ is estimated in the following way:

$$SD_t = \sqrt{\frac{\sum_{t=1}^{T}(R_t - \bar{R}_t)^2}{T-1}}, \text{ where } \bar{R}_t = \frac{\sum_{t=1}^{T} R_t}{T} \tag{3.5}$$

3.4.1.2 Semi-deviation (SEMD)

Semi-deviation is a downside risk measurement. Different from standard deviation, semi-deviation measures only the volatility below the mean return. Semi-deviation is a plausible risk measurement when the return distribution is left-skewed. The semi-deviation is estimated as follows:

$$SEMD_t = \sqrt{\frac{\sum_{i=1}^{n} Min\{(R_i - \bar{R}_t), 0\}^2}{n-1}} \text{, where } \bar{R}_t = \frac{\sum_{i=1}^{n} R_i}{n} \quad (3.6)$$

3.4.1.3 Value at risk (VaR)

Value at risk was developed to indicate the level of possible loss to a portfolio given a confidence level of $(1 - \alpha)$, over a certain period. VaR can be understood as a threshold loss that one may expect not to be exceeded in a period with a confidence level of $(1 - \alpha)$. The calculation of VaR relies on assumptions concerning the return distribution, the investment horizon, and the significance level $(1 - \alpha)$. In this thesis, VaR is used to evaluate the historical performance of hedge funds and FOFs. Therefore, I follow a non-parametric approach to estimate VaR. For each fund or portfolio, VaR with a 95 per cent confidence level is estimated as the fifth percentile of all observations in the estimation window.

3.4.1.4 Expected shortfall (ES)

VaR is widely employed by practitioners as a downside risk measurement; however, it has several limitations. For example, VaR only states the threshold loss at a given confidence level and does not indicate the size of the loss should the threshold loss be exceeded. Expected shortfall, also known as conditional VaR (CVaR), is introduced as a remedy to this problem. Expected shortfall measures the expected total loss conditional on VaR being exceeded. Compared with VaR, ES gives more attention to the lower tail of a distribution.

3.4.2 Orthogonalised return data

In Chapter 5, I will use cross-sectional hedge fund returns to produce a tail risk factor to measure the extreme shocks to the hedge fund industry and use it to explain hedge fund and FOF returns on the basis of Fung and Hsieh's (2004a) seven-factor model. A problem inherent in this process is the existing high correlation between hedge fund returns and the Fung–Hsieh (FH) seven factors. Without proper treatment, this correlation structure may be carried by the tail risk factor and lead to multicollinearity in the multifactor model. As a remedy, I orthogonalise individual hedge fund returns against the FH seven factors. In particular, I regress the returns of a hedge fund against the FH seven factors as follows:

$$R_t^i = \alpha^i + \sum_{k=1}^{7} \beta_k^i F_t^k + \varepsilon_t^i \tag{3.7}$$

where R_t^i is the return of fund i in month t, and β_k^i is the loading of fund i on factor F^k. The FH seven factors will be introduced in detail in Section 3.4.4. The residual ε_t^i is used as orthogonalised returns to generate the tail risk factor in Chapter 5.

3.4.2 Modelling the tail risk of hedge funds

The primary goal of this thesis is to investigate the influence of tail risk on the returns of FOFs. The first challenge in this task is to find a reliable tail risk measurement that captures the dynamics of the tail risk shocks to the hedge fund industry. Tail risk is usually defined in relation to distributional characteristics. In general, tail risk is the extreme loss caused by an event with a higher probability than one would expect under the assumption of normality. Tail risk events trigger more frequent occurrence of large losses, resulting in a "fat left tail" in a return distribution. A mounting volume of literature shows that hedge fund distributions greatly depart from normality and exhibit clear attributes of a fat left tail (Agarwal and Naik 2000a; Eling 2006; Brooks and Kat 2002). Intuitively, if a tail risk event constitutes a common shock to the hedge fund industry, we can distil this information from the cross-sectional return distribution of hedge funds and use it as a tail risk measurement. Extreme value theory (EVT) provides a framework for studying the behaviour in the tail of a distribution.

According to the Fisher–Tippett theorem, the sample maxima of independent and identically distributed random variables can be mapped to only three possible distribution families: the Gumbel, the Fréchet, or the Weibull family. As Gabaix (2009) pointed out, distributions in the Fréchet domain describe the decay of the density function in the tail by a power law and can be used to model the "fat tails". In this thesis, I follow the approach of Kelly and Jiang (2014) to estimate the tail risk index of the tail distribution function. The following description is a paraphrase of Kelly and Jiang's (2014) description of the methodology.

Kelly and Jiang (2014) assumed that lower tail risk events are described by a power law process, which takes the following form:

$$\mathrm{P}\left(\mathrm{R}_{\mathrm{i,t+1}} < r \,\middle|\mathrm{R}_{\mathrm{i,t+1}} < \mathrm{u_t} \text{ and } \mathcal{F}_{\mathrm{t}}\right) = \left(\frac{r}{u_t}\right)^{-a_i/\lambda_t} \tag{3.8}$$

where u_t represents a threshold return, and $R_{i,t+1}$ is the return of asset i at time $t+1$ with $r < u_t < 0$. Parameter a_i/λ_t determines the shape of the tail risk distribution and is named the tail exponent. A fat-tailed distribution has high value in the tail exponent. Because $\mathrm{r} < \mathrm{u_t} < 0$, $\frac{r}{u_t} > 1$. I follow Kelly and Jiang (2014) to require $a_i/\lambda_t > 0$ so that $\left(\frac{r}{u_t}\right)^{-a_i/\lambda_t}$ falls in the range between 0 and 1. In the tail component a_i/λ_t, a_i is an asset specific parameter, representing a constant tail risk level of asset i. In contrast, λ_t is a function conditional on the information set $\mathcal{F}_{\mathrm{t}}$. It measures the time-varying industry-wide extreme movements and is defined as the tail risk measurement. In Kelly and Jiang's (2014) specification, the dynamic tail risk exposure of a risky asset is mainly driven by λ_t. Thus, one needs to separately estimate λ_t to gauge the systematic tail risk shocks in the market.

Empirically, I need to capture the update in the tail risk measurement that reflects the change in the systematic tail risk. According to Kelly and Jiang (2014), the monthly update in the tail risk measurement λ_t can be estimated by applying Hill's (1975) power law estimator to the cross section of hedge fund monthly returns. The Hill estimator is defined as follows:

$$\widehat{\lambda_t}^{Hill} = \frac{1}{\mathrm{K_t}}\sum_{\mathrm{k=1}}^{\mathrm{K_t}} \ln \frac{\mathrm{R_{k,t}}}{\mathrm{u_t}} \tag{3.9}$$

where $\mathrm{R_{k,t}} = (\mathrm{P_{k,t}} - \mathrm{P_{k,t-1}})/\mathrm{P_{k,t-1}}$ is the $\mathrm{k^{th}}$ return that is lower than $\mathrm{u_t}$ during month t, and $\mathrm{K_t}$ counts the number of such exceedances within month t. Note that $\frac{\mathrm{R_{k,t}}}{\mathrm{u_t}}$ is assumed to follow a power law with exponent $^{-a_i}/_{\lambda_t}$; then $ln\left(\frac{R_{k,t}}{u_t}\right)$ should be exponentially distributed with scale parameter $^{a_i}/_{\lambda_t}$. According to the property of an exponential random variable, we have $E_{t-1}\left[ln(^{R_{i,t}}/_{u})\right] = {}^{\lambda_t}/_{a_i}$. As such, the cross-sectional harmonic average tail exponent represents the expected value of the tail index update as follows:

$$E_{t-1}[\frac{1}{K_t}\sum_{k=1}^{K_t} ln \frac{R_{k,t}}{u_t} |\mathcal{F}_{\mathrm{t}}] = \frac{\lambda_t}{\bar{a}}, \text{ where } \frac{1}{\bar{a}} \equiv \frac{1}{n}\sum_{i=1}^{n}\frac{1}{a_i} \tag{3.10}$$

In other words, the expected value of the Hill estimator is equal to the tail risk measurement λ_t scaled by the constant $\frac{1}{\bar{a}}$, which means that the Hill estimator is perfectly correlated with tail risk.

A key step in Hill estimator generation is to decide the threshold return u_t. There are sophisticated methods available to estimate u_t (Dupuis and Victoria-Feser 2006; Scarrott and MacDonald 2012, among others). However, these methods all require the estimation of extra parameters, which may lead to further bias in the estimator. Thus, I follow the suggestion of Gabaix (2009) to set u_t at the fifth percentile of the cross-sectional return distribution[18].

3.4.3 Multifactor model

Markowitz mean-variance analysis is widely used in portfolio analysis. Although the theoretical grounding of the mean-variance framework is solid, it suffers some limitations. Practically, mean-variance optimisation requires the estimation of a great number of parameters, including means, variances, and a variance-covariance matrix for all the assets in the investment universe. For a large panel of data with thousands of assets, parameter estimation work can be unduly heavy and lends mean-variance optimisation to sampling or modelling errors (Lai, Xing and Chen 2011). Factor models serve as a remedy to this problem. It is well known that asset returns are driven by changes in systematic risk. Factor modelling thus assumes a linear relationship between asset returns and the sources of systematic shocks, which are usually approximated by observable economic variables.

A multifactor model was introduced by Ross (1973) to explain the risk and return relationship in financial assets through the arbitrage pricing theory. Some other examples of multifactor models in asset pricing research include Chen, Roll, and Ross (1983) as well as Fama and French (1993). A general multifactor model reads:

$$R_t^i = \alpha^i + \sum_{m=1}^{M} \beta_m^i f_t^m + \varepsilon_t^i = \alpha^i + \beta_i' \mathrm{f}_t + \varepsilon_t^i \tag{3.11}$$

where R_t^i is the return of asset i $(i = 1,2, \ldots., N)$ during period t $(t = 1,2, \ldots, T)$, f_t^k is the kth $(m = 1,2, \ldots, M)$ common factor, and β_m^i is the factor loading of asset i on the mth factor. In the end, there are two asset-specific factors; α^i is the constant of

[18] Kelly and Jiang (2014) tried different threshold levels without experiencing major changes in their results.

the factor model and ε_t^i is the residual. The general factor model requires the following assumptions: $\varepsilon_t^i \sim (0, \sigma^2)$ is uncorrelated with any of the common factors, ε_t^i is serially uncorrelated and independent of the error terms of the other assets, and the factor realisations, $\mathbf{f}_t$, are stationary with unconditional moments. Thus, the expected return of any asset i is a combination of two components: an explained component as a weight average of $E[\mathbf{f}_t]$ and an unexplained component α^i, as described in the following way:

$$E(R_t^i) = \alpha^i + \boldsymbol{\beta}_i' \times E(\mathbf{f}_t) \tag{3.12}$$

In addition, assuming that the covariance matrix of the factors is Ω_f, the variance-covariance characteristics of any asset i can be described as follows:

$$\begin{aligned} \operatorname{var}\left(R_t^i\right) &= \beta_i' \Omega_f \beta_i + \sigma_i^2 \\ \operatorname{cov}\left(R_t^i, R_t^j\right) &= \beta_i' \Omega_f \beta_j \end{aligned} \tag{3.13}$$

Technically, three types of factor models can be constructed to describe an asset return generation process: characteristic-based, macroeconomic, and statistical factor (Connor 1995). In a statistical factor model, the value of factor is derived from asset return using either principal component analysis or factor analysis techniques. In a characteristic-based model, common factors are approximated by the observed asset characteristics such as capitalisation, industry classification, and so on. In a macroeconomic factor model, common factors are measured by observable market variables such as unemployment rate, inflation rate, market indices, or time series, derived from the observable market variables such as credit spreads and implied volatility. These factors are usually self-selected by researchers, but the relationship between asset return and the factors are unknown. Therefore, a macroeconomic factor model requires the estimation of betas based on the observed factor value. In the hedge fund literature, macroeconomic factor models have been intensively adopted to explain the risk and return relationship of hedge funds; see, for example, Liang (1999), Fung and Hsieh (2004a), and Agarwal and Naik (2004). Following this line of research, my thesis aims at enhancing the explanatory power of the existing hedge fund factor models by including the hedge fund tail risk factor. Thus, this thesis mainly uses the macroeconomic factor model to analyse the risk exposures of FOFs.

To estimate the coefficients in a macroeconomic factor model, by rewriting Equation (3.11 as a time series regression in vector form:

$$\boldsymbol{R_i} = \boldsymbol{1_T}\alpha_i + \boldsymbol{F\beta_i} + \boldsymbol{\varepsilon_i}, \boldsymbol{i} = \boldsymbol{1}, \dots, \boldsymbol{N} \tag{3.14}$$

where

$\boldsymbol{R}_i = (R_1^i \quad \cdots \quad R_T^i)\,'$, a (T×1) vector of asset return time series;

$\boldsymbol{1}_T = (1 \quad \cdots \quad 1)\,'$, a (T×1) vector;

α_i, a constant item;

$\boldsymbol{F} = \begin{pmatrix} f_{11} & \cdots & f_{M1} \\ \vdots & \ddots & \vdots \\ f_{1T} & \cdots & f_{MT} \end{pmatrix}$, a (T×M) matrix of the realised value of M common factors;

$\boldsymbol{\beta}_i = (\beta_1^i \quad \cdots \quad \beta_M^i)\,'$, a (M×1) vector of common factor exposures;

$\boldsymbol{\varepsilon}_i = (\varepsilon_1^i \quad \cdots \quad \varepsilon_T^i)'$, a (T×1) vector of a specific factor; and

$E(\boldsymbol{\varepsilon_i} \times \boldsymbol{\varepsilon_i}') = \sigma_i^2 \boldsymbol{I}_T$.

Because the realisations of $\boldsymbol{F}$ are observable, α_i, $\boldsymbol{\beta}_i$, and σ_i^2 may be estimated using time series regression:

$$\boldsymbol{R_i} = \hat{\alpha}_i \boldsymbol{1_T} + \boldsymbol{F}\boldsymbol{\widehat{\beta}_i} + \boldsymbol{\hat{\varepsilon}_i} = \boldsymbol{X}\boldsymbol{\widehat{\gamma}} + \boldsymbol{\hat{\varepsilon}_i}, \boldsymbol{i} = \boldsymbol{1}, \dots, \boldsymbol{N} \tag{3.15}$$

$$\boldsymbol{X} = [\boldsymbol{1_T} \vdots \boldsymbol{F}], \boldsymbol{\widehat{\gamma}} = \left(\boldsymbol{\widehat{\alpha}_i}, \boldsymbol{\widehat{\beta}_i}'\right)' = (\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}'\boldsymbol{R_i} \tag{3.16}$$

$$\boldsymbol{\widehat{\sigma}_i^2} = \frac{\boldsymbol{1}}{\boldsymbol{T-M-1}} \boldsymbol{\hat{\varepsilon}_i}'\boldsymbol{\hat{\varepsilon}_i} \tag{3.17}$$

3.4.4 Fung and Hsieh's (2004a) seven-factor model

Most of the hedge fund multifactor models take on a similar structure to that of a macroeconomic model, as described by Equation (3.14). In this thesis, I utilise the popular Fung and Hsieh (2004a) seven-factor model as the base model to explain the fund returns.

The construction of Fung and Hsieh's seven-factor model follows a top-down approach, and this project consists of a series of publications of Fung and Hsieh (1997b, 2001, 2002, 2004a, and 2004b). The modelling starts by identifying common components in the returns of hedge funds using principal component analysis (PCA) or factor analysis (Fung and Hsieh 1997). Five mutually orthogonal principal components were identified and approximated by five "style factors" that are highly correlated to the principal components. The next step of the modelling was to approximate the "style factors" using observable market risk factors.

In Fung and Hsieh (2001), the authors analysed the risk-return of trend-following funds and developed a portfolio of lookback straddles to model the returns of the trend-following funds. In Fung and Hsieh (2002), fixed-income hedge funds were studied. These funds were found to be significantly exposed to yield spread. The authors thus went on to prove that the difference between Moody's Investor Service Baa bonds and the yield on the 10-year Treasury bond can be used to approximate the yield spread. Equity long-short hedge funds were investigated by Fung and Hsieh (2004b), and these were found to exhibit significant exposure to the equity market and the spread between returns on large capitalisation stocks and returns on small capitalisation stocks. These equity risk factors are measured by the returns of the S&P500 and the return difference between the Wilshire Small Cap 1750 Index and the Wilshire Large Cap 750 Index, respectively. Fung and Hsieh (2004a) summarised these findings and formally introduced the seven-factor model. This model takes the following form:

$$R_t^k = \alpha_t^k + \sum_{i=1}^{7} \beta_i^k F_{i,t} + e_t^k \tag{3.18}$$

where R_t^k is the excess return of fund k at time t, and α_t^k is abnormal return caused by managers' skills. β_i^k is the k^{th} fund's risk exposure to the ith factor, and e_t^k is the residual. The factors to be used in the model include the excess monthly return of the S&P500, a small-minus-big factor represented by the difference between the Russell2000 and the S&P500 monthly return (SMB); the change in the monthly return of 10-year Treasury bonds (TYB); the credit spread represented by the difference between Moody's Baa yield and the 10-year Treasury bond yield (CRSP); and three option factors, the monthly returns of lookback straddles on treasury bonds, foreign exchange, and commodities (PTFSBD, PTFSFX, and PTFSCOM).

3.4.4 Cross-sectional regression on fund tail risk exposures

In Chapter 5, I use cross-sectional regression to investigate the relationship between fund characteristics and hedge fund tail risk exposures. The regressions take the following structure:

$$\beta_{\mathrm{k}}^{HFTR} = \alpha_{\mathrm{k}}^{HFTR} + \sum_{\mathrm{m}} \theta^{\mathrm{m}} \times C_{\mathrm{k}}^{\mathrm{m}} + \theta_{\mathrm{k}}^{mean} XMean_{\mathrm{k}} + \theta_{\mathrm{k}}^{vol} XVol_{\mathrm{k}} + e_{\mathrm{k}}^{HFTR} \tag{3.19}$$

In this equation, $\beta_{\mathrm{k}}^{HFTR}$ is the regression coefficient of HFTR for fund k, which is estimated in a multifactor model based on Equation 3.18 with HFTR being added as the eighth risk factor, shown by Equation 3.20.

$$R_t^k = \alpha_t^k + \sum_{i=1}^{7} \beta_k^i F_{i,t} + \beta_k^{HFTR} \times HFTR + e_t^k \tag{3.20}$$

α_i^{HFTR} is the intercept, C_i^k is the kth characteristics of fund i, and θ^k is the coefficient of the characteristics, which is to be estimated in the cross-sectional regression. $XMean_i$ and $XVol_i$ represent the previous 24 months' average return and variance for fund i, and e_i^{HFTR} is the error term of the regression model. C_i^k denotes the following fund characteristics: fund age, size (measured by AUM), survivorship (dummy variable, 1 for living and 0 for defunct), incentive fees, management fees, high water mark (dummy variable), closed to all investments[19] (dummy variable), leverage ratio, number of investments[20], lockup months, redemption frequency, and advance notice days.

3.4.5 Fama–MacBeth (1973) cross-sectional regression

The primary objective of Chapter 6 is to investigate the performance of tail risk exposure in predicting the cross-sectional variation in hedge fund returns. To achieve this goal, I follow Bali, Brown, and Caglayan (2011) to test this question using both parametric and non-parametric tests. The parametric tests in Bali, Brown, and Caglayan (2011) are performed in the Fama–MacBeth (1973) two-stage cross-

[19] This variable indicates whether a fund accepted external investments on inception.
[20] This variable shows the average number of investments of a fund on an annual basis.

sectional regression framework. The non-parametric tests are based on decile portfolio analysis. The two approaches are discussed in a general fashion below.

Asset pricing theories suggest that asset returns are driven by the changes in risk factors. Theoretically, the asset return generation process can be described by a factor model, which decomposes the total expected return of an asset into different portions as premium rewards to various factor risk exposures. The Fama–MacBeth (1973) two-stage regression (FM regression) was first developed to validate the CAPM but soon became a commonly adopted technique to estimate risk premiums and to validate the implications of a factor model. Assume that there are N assets with returns denoted as $R_t^i, (i = 1, \dots, N)$ and M factors with the value denoted as $F_{m,t}, (m = 1, \dots, M)$.

The first step in FM regression estimates the factor exposures for each asset, using N regression:

$$R_t^1 = \hat{\alpha}^1 + \sum_{m=1}^{M} \hat{\beta}_m^1 F_{m,t} + \hat{\varepsilon}_t^1$$

$$R_t^2 = \hat{\alpha}^2 + \sum_{m=1}^{M} \hat{\beta}_m^2 F_{m,t} + \hat{\varepsilon}_t^2$$

$$\vdots$$

$$R_t^N = \hat{\alpha}^N + \sum_{m=1}^{M} \hat{\beta}_m^N F_{m,t} + \hat{\varepsilon}_t^N \tag{3.20}$$

where $\hat{\alpha}^i$, $\hat{\beta}_m^i$, and $\hat{\varepsilon}_t^i$ are the estimated constant, factor loading and error term, respectively, of the ith regression.

The second step in FM regression is a cross-sectional regression between the returns of all the assets at time t as a dependent variable and their risk exposures as independent variables. The cross-sectional regression reads:

$$R_1^i = a_1 + \sum_{m=1}^{M} \gamma_{m,1} \hat{\beta}_m^i + \hat{\varepsilon}_t^1$$

$$R_2^i = a_2 + \sum_{m=1}^{M} \gamma_{m,2} \hat{\beta}_m^i + \hat{\varepsilon}_t^2$$

$$\vdots$$

$$R_T^i = a_T + \sum_{m=1}^{M} \gamma_{m,T} \hat{\beta}_m^i + \hat{\varepsilon}_t^N \tag{3.21}$$

The coefficient term $\gamma_{m,t}$ represents the market premium for the mth risk factor at time t. The average $\gamma_{m,t}$, such as $\bar{\gamma}_m = \frac{\sum_{t=1}^{T} \gamma_{m,t}}{T}$, is the risk premium throughout the sample period. To be validated as a risk premium, $\bar{\gamma}_m$ must be significantly greater than zero, as shown by the t-test.

Chapter 4: Overview of the fund of hedge funds industry

4.1 Introduction

Owing to the tremendous shock of the 2008 global financial crisis (GFC) to the entire hedge fund industry, tail risk in hedge funds has become a focal point of hedge fund research. In the pre-GFC era, the tail risk of hedge funds was generally believed to be caused by trading strategies, leverages, defective internal controls, fraud, or some other fund-specific factors and thus, in general, diversifiable. In light of this view, investors pursued funds of funds (FOFs) as a conservative alternative to hedge funds for risk diversification. However, the massive drawdown in the industry during the GFC seemed to be widespread, regardless of investment strategies, fund sizes, and locations, and across both FOFs and hedge funds. In recent years, several studies have shown that FOFs might not provide diversification of tail risk but rather aggregate the tail risk from the underlying hedge funds. Thus, FOFs may not be a conservative low-risk investment vehicle, as many have thought.

This chapter presents a study of the differences between individual hedge funds and FOFs with respect to management characteristics. It is essential to perform this comparative study for the following reasons. First, although it has been shown that FOFs tend to aggregate the tail risk in their holdings, the mechanism of the aggregation still remains unclear. This study will investigate such a mechanism from the perspective of fund-management characteristics. Second, from an investor's viewpoint, it is essential to understand how FOFs are managed and how risk in FOFs is controlled in comparison to individual hedge funds. Finally, the research findings will have important implications for policymakers under the current demand for stronger regulations of hedge funds and greater investor protection.

The rest of the chapter is organised as follows. In Section 4.2, the background information and the general operational characteristics of FOFs are summarised in comparison with hedge funds. Section 4.3 introduces the regulatory environment of FOFs with special focus on the hedge fund regulatory reforms in the United States (US) and the European Union (EU). The major legal structures adopted by FOFs and hedge funds are discussed in Section 4.4. Section 4.5 summarises the performance of FOFs and FOF strategies between 1995 and 2012. Finally, conclusions are drawn in Section 4.6.

4.2 General characteristics of funds of hedge funds

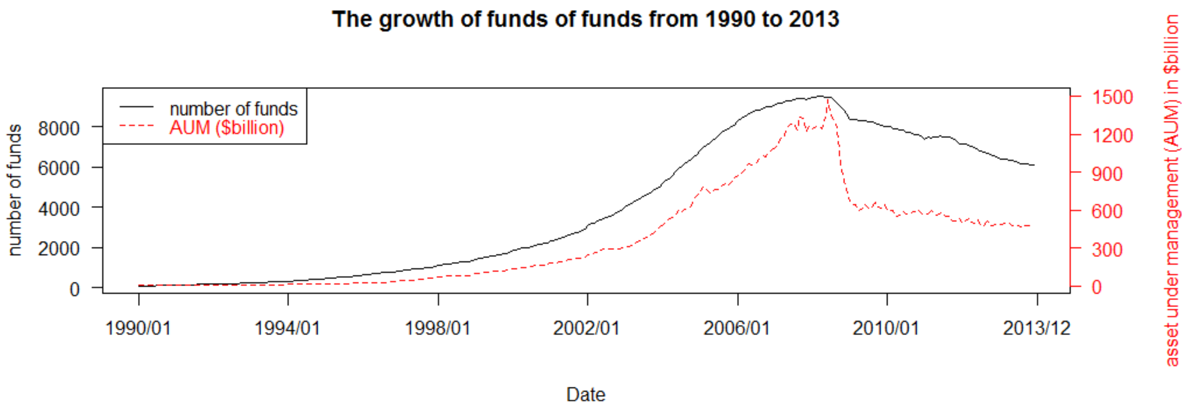
According to Glattfelder et al. (2009), Alfred Winslow Jones, the owner of the first typical hedge fund in history, should also be credited with initiating the idea of FOFs by his allocations to the in-house multiple fund managers in 1954. The first formal FOF, however, is believed to be Leveraged Capital Holdings, which was established in Switzerland in 1969. Since then, especially after hedge funds regained popularity in the 1980s, FOFs have gradually grown into a significant force in the hedge fund industry.

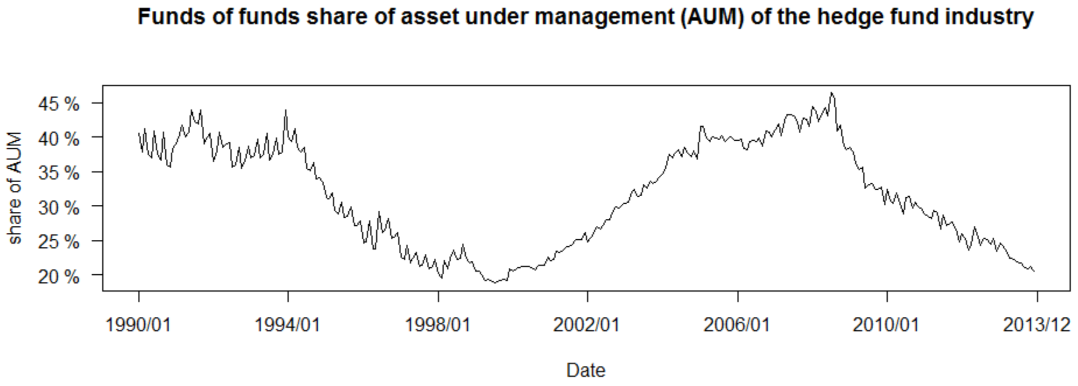
4.2.1 Industry size

In the last two decades, the number of FOFs[21] has increased sharply from less than 200 in the early 1990s to more than 9,000 just before the 2008 GFC (see Figure 4.1). Measured by total assets under management (AUM), FOFs controlled around two billion USD assets in January 1990, and this figure increased to more than 1,400 billion USD by early 2008, as indicated in Figure 4.1. However, the entire FOF industry was heavily struck by the GFC, which by the end of 2009 had caused around 1,500 FOFs to shut down.[22] Meanwhile, capital retreated fast from FOFs so that, in just a year, the AUM of FOFs more than halved its peak value in early 2008 and remained around 500 billion USD until 2013. The total market share of FOFs, measured by the share of total AUM of the hedge fund industry, has also dropped dramatically from above 40% prior to the GFC to around 20% by the end of 2013[23] (see the lower panel of Figure 4.1).

[21] As indicated by the number of reporting FOFs to the Morningstar hedge fund database.
[22] The shutdown fund number was derived from the Morningstar hedge fund database; 1552 FOFs reported fund liquidation between 1 July 2008 and 31 December 2009.
[23] A similar drop occurred during the 1994 to early 2000s period. However, the decrease in FOF market share in the 1990s is because the growth of individual hedge funds outpaced that of FOFs.

Figure 4.1 The growth and the market share of funds of hedge funds (FOFs) from January 1990 to December 2013





4.2.2 Operational characteristics of FOFs

In Table 4.1, I present the operational attributes of FOFs in comparison to hedge funds. FOFs are distinct from other hedge funds in many respects. For example, the survival rate of the sample FOFs is lower than that of the sample hedge funds, with only 30.76% of the FOFs having survived by the end of 2012. A higher proportion of FOFs do not accept further investments post inception. With regard to fund location, only 12.21% FOFs reside in the US, but about 27.9% hedge funds were domiciled in the US. Compared with hedge funds, a higher proportion of hedge funds (66.02%) use USD as the base currency, which means that hedge funds are more USA-centric.

The average hedge fund size is larger than that of an FOF, measured by either total assets or net asset value. The average life of the sample FOFs is about half a year longer than that of hedge funds. Moreover, FOF managers, on average, have about 1.25 years more tenure than hedge fund managers. All the differences in Table 1 are significant at the 1% significance level except for fund size.

Table 4.1 General management characteristics of hedge funds and fund of hedge funds[a]

This table reports the operational characteristics of funds of hedge funds in comparison with hedge funds. Survivorship, closed to all investment, closed to new investment, domicile (US), and base currency (USD) are constructed as binary data where 1 indicates "yes" and 0 indicates "no". The value of the five data points shows the percentage of the funds with value 1.

	Hedge funds (1)	Fund of hedge funds (2)	Difference (2-1)
Survivorship	37.38%	30.76%	-6.62%***[b]
Closed to all investment	6.31%	8.69%	2.37%***
Closed to new investment	7.01%	9.81%	2.79%***
Domicile (US)	27.90%	12.21%	-15.69%***
Base currency (USD)	66.02%	50.97%	-15.05%***
Average fund size (USD)	304,881,929	269,768,648	-35,113,281
Average net assets (USD)	173,221,470	103,114,720	-70,106,750***
Average manager tenure (years)	8.48	9.73	1.25***
Average fund age (years)	7.26	7.73	0.46

a. The test results of the differences for survivorship, closed to all investment, closed to new investment, domicile, and base currency are based on the chi-square test. The test results of average fund size, average net assets, average manager tenure, and average fund age are based on the t-test. "***" indicates that the difference is significant at the 1% significance level.

4.2.3 Fee structure of FOFs

FOFs are distinct from hedge funds in fee structure. Different from mutual-fund managers, who mainly earn management fees, hedge fund managers earn most of their fees based on performance. As such, a "two and twenty" fee structure is generally adopted by hedge funds. In contrast, FOFs charge another layer of fees in addition to the fees charged by the underlying funds. This double-layer fee structure is generally agreed to be a disadvantage of FOF investment to investors. The distribution of the FOF fee structure, in comparison with hedge funds, is reported in Table 4.2 in comparison with hedge funds.

Table 4.2 Fund of hedge fund (FOF) and hedge fund management fees and performance fees[a]

This table reports the distribution of FOF and hedge fund management fees and performance fees. The distribution is calculated by excluding the funds reporting "NA". Around 20% FOFs and 10% hedge funds report "NA" in the whole sample.

	FOFs	Hedge funds
Management fees (%)		
0	1.4%	2.1%
0-1.5	73.7%	58.5%
1.5-2	20.8%	35.5%
2-4	4.0%	3.8%
>4	0.0%	0.1%
Performance fees (%)		
0	18.4%	4.0%
0-10	61.9%	5.6%
10-15	8.1%	4.8%
15-20	10.0%	80.4%
>20	1.5%	5.2%
Average management fees (%)	1.37	1.53
Average performance fees (%)	9.09	18.7
Average hurdle rate (%)	2.19	1.4

The majority of FOFs (73.7%) charge management fees between 0 and 1.5%. Around 61.9% of FOFs charge performance fees between 0 and 10%. Compared with FOFs, a higher proportion (35.5%) of hedge funds charge management fees between 1.5% and 2%. Moreover, most hedge funds (80.4%) charge performance fees between 15% and 20%. On average, the fee structure of hedge funds is consistent with the "two and twenty" industry convention, with management fees being charged at 1.53% and performance fees at 18.7%, on average. By contrast, FOFs on average charge lower management fees (1.37%) and performance fees (9.09%). The hurdle rate used by the hedge funds is slightly lower than that of the FOFs. In other words, FOF managers have to deliver higher returns than hedge fund managers to earn performance fees.

4.2.4 Liquidity restrictions of FOFs

From the viewpoint of fund investors, liquidity is the length of time it takes to redeem their investments from a fund. Hedge funds impose restrictions on withdrawals, such as a lockup period, a notice period, and the frequency of redemption. All these requirements handicap withdrawals from the funds. Sometimes, a holdover provision is added in the investment agreement by which the fund manager can repay the full capital in steps, keeping the last payment until a predetermined date in the future (usually at the end of the financial year). Given the fact that hedge funds are able to return capital in different forms (cash or securities), FOFs may provide the redemption "in kind", which means that FOF investors will receive securities that might be paid from the underlying funds. Many hedge funds require a redemption notice to be given in advance, and the investor can only require a redemption a limited number of times in a year. Thus, an FOF investor may face dual liquidity issues where the repayment of cash is decided not only by the arrangement of the FOF but also by the liquidity of the constituent hedge funds. The liquidity restrictions of FOFs are reported in Table 4.3 in comparison with hedge funds.

The distributions of redemption frequency of FOFs and hedge funds are generally consistent. Monthly or quarterly redemption is the most popular in both FOFs and hedge funds. However, the majority (68.6%) of FOFs do not require investors to lock up their investment, and this ratio is only 52.7% in hedge funds. In contrast, most FOFs require investors to give a redemption notice. Around 73% of FOFs require notice to be given 30 to 120 days in advance, whereas only 37.7% of hedge funds require the same. Most hedge funds (58.3%) require a notice to be given less than 30 days in advance. The longer notice days required by the FOFs can be largely justified by the double-layer liquidity problem discussed earlier.

Table 4.3 Liquidity restrictions of funds of hedge funds (FOFs) and hedge funds

	FOFs	Hedge funds
Redemption frequency[a]		
Daily	2.9%	5.3%
Weekly	2.4%	3.5%
Monthly	51.2%	54.1%
Quarterly	34.8%	32.1%
Annually	8.7%	5.0%
Lockup months[b]		
0	68.6%	52.7%
1-6	4.6%	13.4%
7-12	24.0%	29.6%
13-24	1.5%	2.9%
above 24	1.2%	1.5%
Advance notice days[c]		
0	2.0%	3.0%
1-30	24.1%	58.3%
31-60	36.7%	26.0%
61-120	36.8%	11.7%
above 120	0.5%	1.0%

a. The distribution of redemption frequency is calculated by excluding the funds reporting “NA”. Around 40% FOFs and 35% hedge funds report “NA” in the whole sample.

b. The distribution of lockup months is calculated by excluding the funds reporting “NA”. Around 60% FOFs and 45% hedge funds report “NA” in the whole sample.

c. The distribution of advance notice days is calculated by excluding the funds reporting “NA”. Around 45% FOFs and 40% hedge funds report “NA” in the whole sample.

4.2.5 Leverage of FOFs

The information regarding fund leverage is reported in Table 4.4.

Table 4.4 Leverage of funds of hedge funds (FOFs) and hedge funds[a]

This table reports the information regarding fund leverage. All data points are structured as a binary value where 1 represents "yes" and 0 represents "no" except average leverage.

	Hedge funds	FOFs	Differences
Use leverage	79.96%	41.19%	-38.77%***b
Leverage with margin borrowing	63.06%	14.16%	-48.90%***
Leverage with bank credit	12.55%	28.22%	15.67%***
Leverage with futures	23.64%	6.67%	-16.97%***
Leverage with other derivatives	0.93%	0.07%	-0.86%***
Average leverage	**2.89**	**0.72**	**-2.17*****

a. The test results of the differences of use leverage, leverage with margin borrowing, leverage with bank credit, leverage with futures, and leverage with other derivatives are based on the chi-square test. The test result of average leverage is based on the t-test. "***" indicates significance at the 1% level.

Around 80% of the hedge funds have reported using leverage, whereas only 41.19% of the FOFs use leverage for their portfolios. Many funds have disclosed their channels of leverage, which include margin account borrowing, bank credit, and leverage via futures or other derivatives. From my data sample, I found that the vast majority (63.06%) of the hedge funds obtained leverage through margin borrowing, usually provided by prime brokers. FOFs, in contrast, prefer traditional bank credit, as only 14.16% of FOFs obtain leverage through margin borrowing. Because of the lack of derivatives on hedge funds, there is less demand from FOFs on derivatives for leveraging purpose. Thus, we have observed less than 7% of FOFs obtaining leverage in this way. Finally, the asset turnover of general hedge funds is much quicker than the FOFs. The average annual turnover of the hedge funds is about 20 times that of the FOFs. All the differences in the table are significant at the 1% significance level.

4.3 Funds of funds regulation

In the wake of the GFC, the hedge fund industry regained focus from regulators because of the growing concern for better investor protection, greater information transparency, and systemic risk monitoring in hedge funds. While rules vary by jurisdiction, hedge fund managers have seen regulatory reforms launched to accommodate rigorous restrictions on hedge fund registration, share offering, information disclosure, and other aspects of fund operation. This section provides an overview of the major regulatory reforms relating to the hedge fund industry around the world and explains the influences of the reforms on FOFs.

4.3.1 Global cooperation and IOSCO's (funds of funds) hedge fund regulatory framework

The global regulatory response to the 2008 GFC was initiated in a G20 meeting in November 2008, which called on a variety of international bodies such as the Financial Stability Board (FSB), the Basel Committee on Banking Supervision (BCBS), and the International Monetary Fund (IMF) to oversee global policy development and implementation (Schwartz, 2013). In this process, the International Organization of Securities Commissions (IOSCO) contributed substantially to the development of a regulation framework for hedge funds.

The IOSCO (2009) noted that hedge funds had enhanced the liquidity and efficiency of financial markets but also acknowledged that hedge funds had played an important role in transmitting and amplifying systemic risk. Holding this view, in the final report issued in 2009, the IOSCO raised six high-level principles on the regulation of hedge funds, such as the mandatory registration of hedge funds and hedge fund managers, ongoing regulation on the registered funds, registration and risk control of primary brokers, mandatory disclosure of information relevant to systemic risk, and so on.[24]

The 2009 IOSCO report did not pay special attention to FOFs, but it did mention that hedge funds had become more accessible to retail investors by means of FOFs. In fact, FOFs have been under the microscope of the IOSCO since 2002, when its Technical Committee launched a study on the regulatory issues arising from retail investors participating in hedge funds through FOFs. Further enquiries were carried out in 2007, and the final report of this study was issued in June 2008, almost at the same time as the housing-bubble burst in the US, which led to the GFC. The IOSCO (2008) reviewed the regulations on FOFs in a variety of jurisdictions and found that many countries did regulate or authorise FOFs under their existing regulatory framework for common collective investment schemes. However, some areas in these existing frameworks were found to be lightly or too generally regulated, such as the mandate of due diligence to be performed by FOF managers before and during investments. These identified problems were addressed in IOSCO's 2009 report titled *Elements of International Regulatory Standards on Funds of Hedge Funds*. The standards written in this report, together with the six high-level principles on the regulation of hedge funds, constitute the foundation for the regulatory reforms in different jurisdictions in the aftermath of the 2008 GFC.

4.3.2 US regulation

Hedge funds and hedge fund managers in the US were largely unregulated in the pre-GFC era, thanks to a variety of exemptions set in fund- or securities-related legislation (Kaal and Oesterle, 2016). A typical hedge fund in the US could avoid a number of

[24] The final IOSCO hedge fund oversight report can be found at the following link: http://www.iosco.org/library/pubdocs/pdf/IOSCOPD293.pdf

regulations by offering itself to "accredited investors" only and limiting investor numbers below the threshold. For this reason, many early-established hedge funds were structured under limited partnership structures and mainly offered shares to high net worth individuals or "sophisticated" investors. Although regulators have taken action to broaden their regulatory scope to cover hedge funds, such efforts turned out to be in vain because of strong opposition from the industry.[25]

A major change in the US hedge fund regulation took place with the enactment of the Dodd–Frank Wall Street Reform and Consumer Protection Act 2010 (Dodd–Frank). Under this legislation, the SEC, as well as other regulatory agencies, was authorised to bring hedge funds under supervision. In particular, all hedge fund advisers with $150 million or more in assets were required to register with the SEC. This is to say, hedge fund advisers in the US could no longer seek SEC registration exemptions under the safe harbour clause of the Investment Advisers Act 1940. In addition, as explained by PricewaterhouseCoopers (2010), the registered hedge fund advisers were required to disclose information on assets under management, use of leverage, counterparty risk exposure, trading and investment positions, types of assets held, trading practices, valuations policies, and other information deemed by the SEC necessary and appropriate for the assessment of systemic risk .

4.3.3 European Union regulation

Prior to 2011, Undertakings for Collective Investment in Transferable Securities (UCITS) directives served as the major regulation at the EU level for UCITS-qualified hedge funds.[26] As a result, many unqualified hedge funds were not strictly regulated

[25] One example given in Kaal and Oesterle (2016) is *Goldstein v. SEC*, where the DC circuit vacated the hedge fund rule as an instance of arbitrary rulemaking by the SEC.
[26] Such as open-ended, liquid, well diversified, limited leverage, etc.

until the implementation of the Alternative Investment Fund Managers (AIFM) directive. The AIFM directive was enacted in 2011 as part of a broader financial regulatory reform of the EU following the GFC. It was introduced to regulate alternative investment funds (AIFs) that did not fall under the UCITS classification. Similar to Dodd–Frank, the AIFM directive affects hedge funds through regulating fund managers directly. Technically, the AIFM directive also regulates overseas hedge funds marketing in European markets. According to the directive, fund managers have to comply with a vast range of requirements, including information disclosure, capital, conduct of business, leverage, and so on to be authorised under the AIFM directive to conduct business in EU countries. As such, most hedge funds operating in the EU will be overseen by either UCITS or the AIFM directive unless they qualify for an exemption.[27]

4.3.4 Australian regulation

Hedge funds in Australia are regulated under the same framework as open-ended retail funds. Like other types of managed funds, hedge funds are mainly governed by the Corporations Act 2001, which is enforced by the Australian Securities and Investments Commission (ASIC). Specifically, if a hedge fund offers to retail investors, it must register with ASIC and fulfil a variety of requirements on operation and information disclosure. The regulation on the hedge funds' offering to institutional investors is comparatively lax, as their investors are better placed than retail investors to monitor the performance of their investment.

In June 2013, ASIC issued its first direct ruling on hedge funds, known as Regulatory Guide 240 (RG240) – Hedge Funds: Improving Disclosure. RG240 introduced a broad

[27] The AIFM directive exempts the hedge funds controlling less than 100 million euros or less than 500 million euros when unleveraged.

definition of “hedge fund” that captures a vast range of funds, especially the funds that were traditionally not thought to be hedge funds. In particular, ASIC (2013) defined hedge funds in two ways – a fund promoted by its responsible entity as a “hedge fund” or a fund that exhibits at least two of five specified characteristics: complex investment strategy or structure; use of leverage; use of derivatives; use of short selling; and charging a performance fee. In addition, RG240 explicitly includes FOFs under its oversight. For retail investors to make informed decisions, hedge funds are required to follow two “benchmarks” and nine disclosure principles to disclose information in their product disclosure statements (PDSs). In the viewpoint of ASIC (2013), the independent valuation of assets and periodical reporting should be followed by all hedge funds as two benchmarks. Moreover, a PDS should disclose information regarding investment strategy, investment management of the fund, fund structure, custody of the assets, liquidity, use of leverage, derivatives, and short selling, as well as withdrawals.

The recent reform of hedge fund regulation around the world proceeded within the hedge fund and FOF regulatory framework of IOSCO to achieve better investor protection, information transparency, and systemic risk monitoring in the hedge fund industry. The influence of the reforms on FOFs, however, is sophisticated and needs further study.

Tighter regulation – for example, the demand for higher transparency – may benefit FOFs and other hedge fund investors with lower costs for preforming due diligence. Moreover, there is a requirement on hedge funds to maintain higher liquidity and relax redemption restrictions. As such, FOFs are able to implement active portfolio and risk-management techniques (Zanolin, 2013). Finally, by complying with the higher-level regulation, FOFs are able to raise capital in the market where they were not allowed to previously.

Despite the potential benefits, the change in hedge fund regulation will cause extra costs for FOFs. Higher compliance costs including registration, disclosure, and auditing fees will be the most explicit costs brought by the regulatory reforms. In addition, a general trend of global hedge fund regulation is to bring all funds under the oversight of regulators (such as in the EU) and require the funds to perform due diligence to a higher standard. As Brown, Gregoriou, and Pascalau (2012) reported, the due diligence cost can be at least $12,500 for an industry-circulated report or as high as $50,000 for a customised report. Consider a well-diversified, midsize FOF with $200m AUM (assets under management) allocated across 30 underlying funds. The due-diligence cost will be around 0.2-0.8% of its AUM, which consumes a large portion of the fund-management fee (1% of the AUM). Thus, the tightened regulation on due diligence will also add a heavy burden on small or midsize FOFs.

4.4 Funds of funds legal structure

Table 4.5 reports the summary statistics of the 10 commonly adopted hedge fund legal structures. The chi-square test suggests that the legal structure compositions of hedge funds and FOFs are significantly different at the 1% significance level. The open end investment company (OEIC) is adopted by around 20.5% of hedge funds, which leads limited liability company (LLC), partnership (3C1), and others narrowly. The latter three legal structures, of almost equal weight, account for almost 15% of the hedge fund structure. By contrast, about 37.6% of FOFs have been structured as OEIC, and the second-largest proportion (13.7%) of FOFs are registered as SICAV, an open-ended collective investment scheme named *Société d'investissement à capital variable* in French and commonly adopted in Western European countries.

Table 4.5 Legal structure of hedge funds and funds of funds (FOFs)

This table reports the legal structures adopted by global hedge funds and FOFs according to the Morningstar database.

	Hedge funds	FOFs	Difference***b
Corporation	6.4%	4.0%	-2.4%
Exempted limited partnership	4.8%	1.8%	-3.0%
FCP	1.6%	6.4%	4.8%
Limited liability company	15.1%	12.4%	-2.7%
Open ended investment company	20.5%	37.6%	17.1%
Partnership (3C1)	14.1%	5.5%	-8.6%
Partnership (3C7)	8.2%	6.2%	-2.0%
SICAV	4.4%	13.7%	9.3%
Unstructured hedge fund	11.1%	8.0%	-3.1%
Others	13.8%	4.4%	-9.4%

a. The chi-square test shows that the difference in the legal structure compositions of hedge funds and FOFs is significant at the 1% level.

The variation in legal structures can be partly explained by fund domicile. For example, most of the funds structured as partnerships (3C1) were established in the US, whereas the majority of the funds adopting OEIC were incorporated outside the US (usually in the UK). Traditional hedge funds are formed under a general or limited partnership structure, by which the activities of hedge funds are subject to less regulation than they would be if under a company structure. In addition to regulation, a variety of other factors may influence the decision on the suitable legal structure, such as tax, target clients, and so on. The influence of the legal structure on the operation, investment, and payout of a fund can be marked. For example, should a fund be organised as a limited partnership (LP), the limited liability designation will not provide liability protection to the general partner, who is usually the administrator and manager of the fund. By contrast, under the limited liability company (LLC) structure, all members including fund managers are responsible for only limited liability.

Figure 4.2 presents the change in FOF and hedge fund legal structure compositions by AUM from 1995 to 2012. As reflected in the top panel, OEIC dominated the other legal structures in the late 1990s but since the early 2000s has gradually lost its market share. By the end of 2012, OEIC FOFs controlled more than 25% of the total AUM of the FOF industry. The other legal structures, including corporation, partnership 3C7, and unstructured hedge fund were almost equal in weight by the end of 2012. The change in the legal structure of hedge funds, as exhibited in the bottom panel of Figure 4.2 is comparatively moderate. The most striking change is in the growth of hedge funds that are adopting an LLC or OEIC structure. In contrast, corporation and partnership 3C1 and 3C7 have gradually lost market share since the early 2000s.

Figure 4.2 Fund of hedge funds (FOF) and hedge fund legal structure composition by assets under management (AUM)

As shown in my sample, the most commonly adopted structure for FOFs are OEIC and SICAV. OEICs are collective investment vehicles established as companies to invest in other companies with adjustable investment strategy and fund size. SICAV, usually adopted by funds domiciled in Luxemburg and other Western European countries, can be viewed as the European version of OEIC, as the two structures are very similar with respect to regulation, corporate governance, and fund custodian (UK Trade and Investment, 2015). The Financial Conduct Authority (FCA) in the UK regulates OEICs under the Open-Ended Investment Companies (Companies with Variable Capital) Regulations, 2001. As open-ended investment vehicles, OEICs provide shareholders great flexibility to enter or quit the companies. Moreover, the minimum investment charged by an OEIC is only £25 per month or £500 in a lump sum, which makes it easier to attract retail investors. OEIC funds are subject to strict regulations. For example, OEIC funds have to file their prospectuses, instruments of incorporation, key investor information documents, and annual and periodic reports with the FCA. An Authorised Corporate Director (ACD), who is also registered with and regulated by the FCA, is responsible for managing the daily operation of the OEIC. Furthermore, there are restrictions on the diversification of an OEIC's portfolio, which are imposed by the FCA in relation to UCITS schemes. An appealing feature of the OEIC structure to fund management groups is its capacity to act as umbrella funds, where the OEIC is structured as a combination of many sub-funds. Each of the sub-funds pursues a specific investment objective so that the investors of the OEIC can switch between the sub-funds at almost no cost.

4.5 Funds of hedge funds investment strategies

4.5.1 FOF investment strategy composition

FOFs are reported as a category of hedge fund investment strategies[28] in the Morningstar database, which classifies hedge fund strategies into 22 categories. For ease of reporting, I aggregated these strategies according to their focus asset classes. Thus, in my sample, hedge fund strategies are classified as equity, debt, event driven, multi-strategy, systematic futures, and macro. Furthermore, the FOFs sample is classified into six strategy groups (following the classification of the Morningstar database): equity, debt, event, multi-strategy, systematic, and relative value. It should be noted that the investment strategy classifications for hedge funds and FOFs are based on different definitions. As a result, the equity FOF strategy differs from the equity hedge funds in many respects, such as holdings, benchmarks, and liquidity. The description of FOF strategy can be found in Appendix A.

Table 4.6 Investment strategy composition of hedge funds and funds of hedge funds

This table reports the investment strategy distribution of hedge funds and FOFs by fund number. The left panel reports the strategy distribution of all sample funds including both FOFs and hedge funds. The right panel reports the strategy distribution of FOFs only.

	% of total funds	FOF strategy	% of total FOFs
Debt	8.52%	Debt	4.87%
Equity	37.42%	Equity	27.88%
Event driven	4.28%	Event	4.91%
Multi-strategy	5.60%	Multi-strategy	49.52%
Systematic futures	6.15%	Systematic	8.42%
Volatility	0.44%	Relative value	4.40%
Macro	6.00%		
Funds of funds	37.59%		

[28] A comprehensive explanation of the strategies can be found at www.morningstar.com.

Table 4.6 shows the investment strategy composition (by fund number) of hedge funds and FOFs. With regard to hedge fund investment strategy, I found that FOFs constituted the largest strategy group in the total fund sample, while equity hedge funds ranked second. Almost 80% of the funds in the sample have adopted the above two strategies. It should be noted that FOFs differ from other hedge funds in the investment activities by diversification. An FOF may have intensive exposure to one asset class while diversifying across managers or dispersed risk exposures achieved by diversification across asset classes. The two types of diversification seem to share the strategy composition of FOFs evenly. Around 50% of the FOFs choose to diversify across asset classes by pursuing a multi-strategy. In the remaining 50% of the FOFs, the equity strategy dominates the others. The change in FOF strategy composition from 1995 to 2012 is plotted in the upper chart of Figure 4.3.

Figure 4.3 Fund of hedge funds (FOF) and hedge fund investment strategy composition by assets under management (AUM)

According to the area plot of FOF strategy composition, multi-strategy FOFs dominated the other strategies, while equity FOFs lost most market share from 1995. Another notable observation is that macro FOFs have grown rapidly in the share of AUM since the 2008 GFC. By the end of 2012, macro FOFs accounted for around 17% of total AUM, which was about the same as that of equity FOFs. In contrast, hedge fund strategy composition by AUM displays a distinct picture. Equity hedge funds' share in total hedge fund AUM has significantly shrunk. By contrast, macro, as well as systematic futures hedge funds, has won more market share in the post-GFC era.

4.5.2 The performance of FOF investment strategies

The performance of the sample FOFs is reported in Table 4.7. Although the average variance of the FOFs is lower, they have underperformed the hedge funds pertaining to the higher moments, especially with regard to skewness. I found that the average skewness of the FOFs was triple the skewness of the hedge fund, which means that an investor will receive extreme loss with higher probability in a FOF's portfolio. All the general difference in performance measurements are significant at the 1% level except kurtosis.

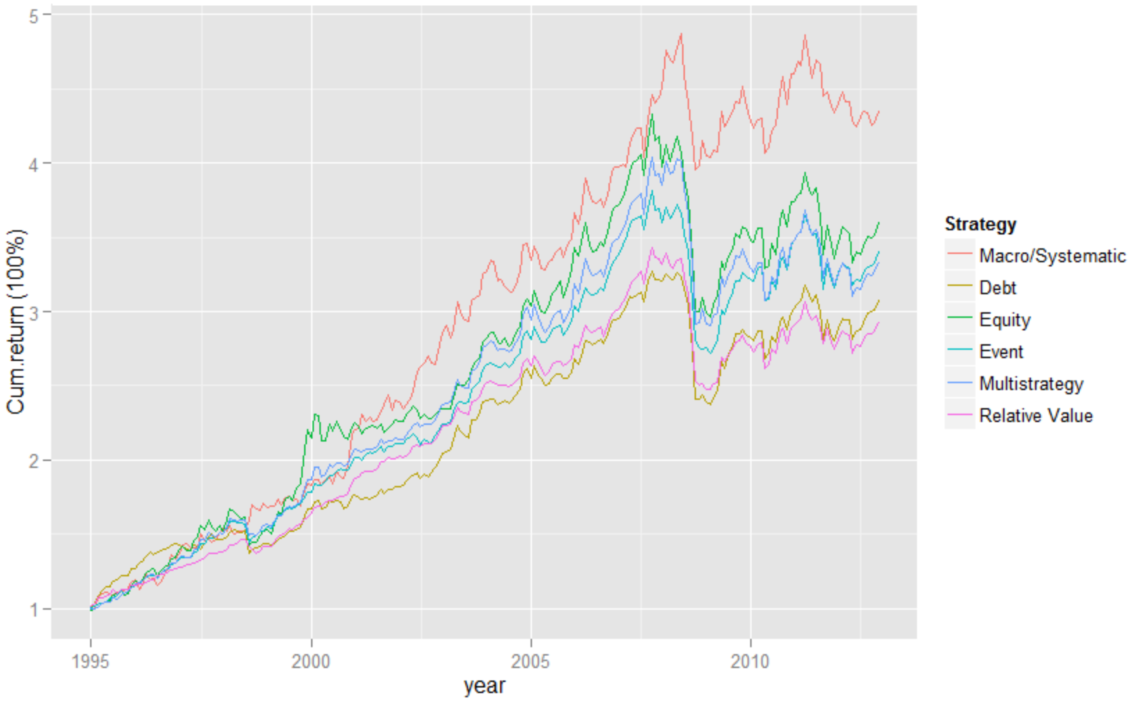
Table 4.7 The performance of funds of hedge funds (FOFs) and hedge funds

	FOFs (1)	Hedge funds (2)	Differences (1-2)
Average monthly return	0.18	0.49	-0.31***[a]
Average variance	28.20	52.88	-24.68***
Average kurtosis	5.51	5.33	0.18
Average skewness	-0.61	-0.20	-0.41***

a. The asterisk symbols indicate the significance level of the test results, being significant at the 1% level "***", 5% level "**", and 10% level "*".

To investigate the performance of FOF investment strategies, I formed six equally weighted FOF strategy portfolios and plotted the cumulative returns of the portfolios (see Figure 4.4).

Figure 4.4 Cumulative returns of equally weighted fund of hedge funds strategy portfolios between 1995 and 2012



We can roughly partition the whole period into three sub-periods: 1995 to the early 2000s, including the dot-com bubble burst; the early 2000s to mid-2007, before the GFC; and the post-GFC period of mid-2008 to 2012.

It is clearly shown in the chart that the Russian default and the collapse of LTCM (the Long-Term Capital Management hedge fund) in 1998 hit the FOF industry heavily. Debt FOFs, which had led the industry from 1995, experienced a sharp drawdown around 1998 and has lagged behind the other strategies since then. The only strategy that has benefited from this crisis is macro/systematic FOFs. During the first sub-period, equity FOFs led the other strategies most of the time, mainly because of the high-tech boom of the late 1990s. The rapid increase in equity FOF cumulative return halted around 2001, which coincided with the dot.com bubble burst. The other FOF strategies, however, were not heavily influenced by the downturn in the equity market and maintained the upward trend in their cumulative returns. Macro/systematic FOFs won large returns at the same time and hence led the industry until 2012.

The second sub-period can be viewed as a golden age of FOFs because all the strategy portfolios experienced rapid growth until the 2007–2008 GFC. Most of the strategies managed to double their value during this period. Another striking feature of this period is the co-movements of the strategies. The cumulative return charts of some strategies have even tackled and moved in parallel between 2005 and 2008, such as those of relative value and debt FOFs.

At the beginning of the last sub-period, we have observed the magnificent impact of the GFC on the entire FOF industry. In only a few months, the large drawdown brought most portfolios back to around their 2004 valuations. Since 2008, the FOF industry entered a period featured by high fluctuation. In addition, there is a clear trend that the returns of the portfolios become more correlated. With regard to the performance of specific portfolios, the macro/systematic portfolio has once again exhibited good resilience in a crisis period. It maintained its rise at the start of the GFC, while the growth in other portfolios turned weak. In addition, the drawdown in the macro/systematic portfolio lasted for the shortest period among the six portfolios, fully recovering in the aftermath of the GFC by the end of 2010.

4.6 Conclusions

This chapter presented a comprehensive overview of the FOF industry, with most of the characteristics of FOFs introduced in comparison with hedge funds.

I found that only 12.7% FOFs were established in the US, but a large number of FOFs are operating offshore. Because hedge funds in general have lower liquidity than the other asset classes, i.e., equity and debts, FOFs tend to set more handicaps in investor redemption, mainly by requiring more notice days in advance. Consistent with previous studies, we found that FOFs charge lower management fees and performance fees than hedge funds. Leverage is another area where FOFs exhibit clear distinctions. Only around 40% of the FOFs have reported to use leverage, and the average leverage ratio of the FOFs is much lower than that of the hedge funds.

Different from hedge funds, a higher proportion of FOFs AUM was controlled by OEIC FOFs in Europe and partnership 3C7 in the US as of the end of 2012. There is no such dominating legal structure in hedge funds.

Multi-strategy and macro/systematic FOFs have taken the market share of the other strategies in the last decade, while the entire FOF industry size has shrunk rapidly since the 2007–2008 GFC. Equity FOFs have attracted most of the investment compared with the other FOFs following a single investment strategy. By investigating the cumulative returns of six equally weighted FOF strategy portfolios, I found that the co-movements of the portfolios have become more prominent in the post-GFC era. Most of the portfolios were deeply influenced by the worst hedge fund crisis in history. The macro/systematic FOF portfolio is the only one that has exhibited good crisis resilience. Finally, I found the return distribution of the equally weighted FOF portfolio is more left skewed than the equally weighted hedge fund portfolio.

The recent global hedge fund regulation reforms are also reviewed in this chapter. The current regulation framework aims at better investor protection, information transparency, and systemic risk monitoring in the hedge fund industry. Although the influences of the reforms on FOFs can be sophisticated, the tightened regulation will nevertheless impose higher compliance and due-diligence costs on FOFs. Except for the stricter regulation, FOF managers also face other challenges, such as deteriorated investor confidence and tail risk management. Higher transparency in the hedge fund industry makes hedge fund cloning or indexing easier. It is quite clear that the other investment vehicles specialising in hedge fund investment will compete with FOFs in the foreseeable future.

Chapter 5: Tail risk of funds of hedge funds

5.1 Introduction

A fund of hedge funds (FOFs) is a pool of money that is directly invested in individual managed funds. In the last few decades, an increasing amount of capital has flowed into the hedge fund industry via FOFs. In a recent industry report issued by eVestment (2016), the total value of assets under management (AUM) of FOFs reached USD 840 billion during the first quarter of 2016, which represented approximately 28.25% of the total market value of the entire hedge fund industry.

FOFs have several characteristics that are appealing to the investment community. For example, FOFs require lower minimum investments, which allows retail or small institutional investors to gain broad exposure to hedge fund investments. Moreover, the dynamic investment strategies of a hedge fund, as well as the secretive nature of the same, lead to a higher search cost for retail investors. FOFs provide an effective channel for investors to access the scarce skills of successful hedge funds through their due-diligence selection process. Although FOF investors are charged at both the underlying fund level and the FOF manager level, the extra cost is believed to be justified by the fund selection skills of a FOF manager[29]. Finally, FOFs are usually considered well-diversified investment vehicles with average returns and lower levels of volatility.

Despite the popularity of FOFs within the investment community, the risk of investing in hedge fund portfolios is not that clear. Though there is extensive literature on the

[29] While most hedge funds have a "two and twenty" fee structure or, in other words, a 2% charge on asset management and a 20% charge on any profits earned, funds of funds usually have lower performance-based fees and about the same level of management fees.

performance and risks of hedge fund investments, the majority of risk-return analysis in the hedge fund literature removes FOFs from their sample because FOFs do not invest directly in traditional asset classes. The poor performance of FOFs during the recent financial crisis has cast doubt on the capability of FOF risk management practices. According to a recent study by Dai and Shawky (2013), the 2008 global financial crisis (GFC) has caused a severe amount of deterioration in the returns of FOFs despite the fact that they hold a large number of hedge funds.

The severe loss of FOFs during the crisis period is surprising. Conventional mean-variance analysis suggests that FOFs should have at least average returns with lower volatility. But why do FOFs seem to suffer more in a severe industry-wide downturn? I wish to investigate this question by employing the rich literature that is available on extreme value theory (EVT) and tail risk studies.

In this chapter, I will place particular interest on the tail risk exposure of FOFs in an attempt to understand the role of tail risk in explaining FOF performance. I examine to what extent the tail risk exposure of FOFs differs from that of hedge funds. Furthermore, I aim to identify the characteristics of FOFs that determine their tail risk exposure. I found that the average return of FOFs was substantially lower than that of hedge funds and the return distribution of FOFs is more skewed to the left. I also found that the risk of FOFs has experienced a structural change since mid-2006. As indicated by various risk measures, FOFs display an inability to diversify risk. The risk of FOFs during the 2007-2008 GFC was even higher than that of other hedge fund strategies. Furthermore, I developed a tail risk estimator by using cross-sectional hedge fund returns (HFTR). I found that 44.64% (3474 out of 7782) hedge funds have significant negative exposure to HFTR, and this ratio increases to 83.79% (3582 out of 4275) in the sample of FOFs. At the strategy level, all hedge fund and FOF portfolios exhibit significant negative exposures to HFTR except for the hedge funds that adopt a volatility strategy[30]. The explanatory power of HFTR remains significant over the pre-GFC period, even after controlling for further risk factors. By introducing HFTR into Fung and Hsieh's (2004a) seven-factor model, the explanatory power of the model is substantially increased. The enhancements are prominent at both the individual fund level and the portfolio level. I have also documented a relationship between fund characteristics and the tail risk exposures of FOFs and hedge funds. In particular, I found that FOFs with a short history, higher management fees, and requiring a shorter lockup period are more sensitive to tail risk in particular. My simulation analysis confirms that, while FOFs are more diversified, the systematic component of risk becomes more dominant in a risk-return determination. This result explains why tail risk is more concentrated at FOFs level.

To further examine the source of FOFs' tail risk exposure, I replicated Kelly and Jiang's (2014) tail risk factor, also known as an equity market tail risk factor (EMTR), using global equity market data. I found that the EMTR acted quite distinctively in explaining the returns of FOFs and hedge funds. I suggest that the tail risk in the hedge fund industry is not purely caused by equity market extreme events. My results provide strong evidence that, given the higher exposure to tail events, it could be a danger to depict FOFs investment as a low-risk category to retail investors.

The chapter is organised as follows. I will introduce the approaches of the study in Section 5.2. The empirical results are presented and analysed in Section 5.3. I then present further discussion on the implications of the results in Section 5.4. Conclusions are provided in the last section.

[30] Volatility hedge funds trade volatility as assets, such as VIX index assets.

5.2 Description of approaches

As explained in Section 5.1, the primary objective of this chapter is to investigate the influence of hedge fund tail risk on the returns of FOFs. I will perform the following steps to achieve this objective. First, I will develop a tail risk measurement that captures the dynamic tail risk shocks in the hedge fund industry. Based on the tail risk factor, I will examine whether tail risk exposures explain the variation of FOFs returns in both a time series and the cross-section. Finally, I will study the relationship between FOF characteristics and the tail risk exposure.

5.2.1 Hedge fund tail risk factor

I selected 7,782 sample hedge funds and unsmoothed the returns of the funds following the description in Section 3.3.1. Furthermore, I orthogonalised the return time series of each hedge fund using Fung and Hsieh's (2004a) seven-factor model, following the steps described in Section 3.4.2. Next, in month t, I plotted the distribution of the cross-sectional orthogonalised returns of the sample hedge funds and used the return at the fifth percentile on the left tail as the threshold return u of the Hill estimator. Thus, all the returns falling below the threshold return will be used to derive the Hill estimator $\widehat{\lambda_t}^{Hill}$ following Equation 3.9. By performing this process for each month from January 1995 to December 2012, I eventually obtained a time series of the monthly Hill estimator. After this, I standardised the monthly estimators as follows[31]:

$$\rho_t = \frac{\widehat{\lambda_t}^{Hill} - \mu_{\lambda^{Hill}}}{\sigma_{\lambda^{Hill}}} \tag{5.1}$$

[31] By standardising the estimator, we can interpret alpha in the multi-factor model as the expected return when the risk factor premia are set to their means. However, I hope to note that the standardised tail risk estimator is not directly observable in reality. Thus, care should be taken when interpreting the coefficient (beta) of the tail risk factor.

where ρ_t is the standardised Hill estimator of month t while $\mu_{\lambda^{Hill}}$ and $\sigma_{\lambda^{Hill}}$ are the mean and standard deviation of the $\widehat{\lambda_t}^{Hill}$ time series, respectively. I named ρ_t as the hedge fund tail risk measurement (HFTRM). Finally, I fitted the AR(q) processes to the tail risk measurements. The innovations of the AR(q) process are used to proxy the tail event shocks, which I refer to as the hedge fund industry tail risk factor (HFTR) hereafter. The parameter q is decided by the Akaike Information Criterion (AIC).

5.2.2 Equity market tail risk factor

In the spirit of Kelly and Jiang (2014), I used the daily prices of the constituents of the Thomson Reuters Global Equity Index from 1 January 1995 to 31 December 2013 to derive the EMTR. There are approximately 6,000 to 10,000 stocks with valid data in each year. I applied the Fama–French three-factor-model and kept the residuals for each stock to remove the influences of the other common factors. Then, for each month, I used the orthogonalised return at the fifth percentile on the left tail as the threshold return u of the Hill estimator. Following the same procedure described in Section 5.2.1, I developed a time series of equity market tail risk measurement (EMTRM) and fit the AR(q) process to the time series. The innovations of the AR(q) process are defined as the equity market tail risk factor (EMTR). One of the main arguments of this chapter is that, besides the extreme drawdowns in the equity market, the tail risk in the hedge fund industry can be caused by a variety of other reasons. It follows that the HFTR can better explain the tail risk exposure of FOFs than a pure equity market tail risk factor. Thus, in most of the empirical tests of this chapter, the EMTR will be used as a comparison tail risk estimator of the HFTR.

5.2.3 Can tail risk explain the return variation in a time series?

I utilised the popular Fung and Hsieh (2004a) seven-factor model as the base model to explain the fund returns; however, my interest was to see whether the tail risk factor can add explanatory power to the existing hedge fund return factor models. My multi-factor model takes the following general form:

$$\mathrm{R}_{\mathrm{t}}^{\mathrm{k}} = \alpha_{\mathrm{t}}^{\mathrm{k}} + \sum_{\mathrm{i}=1}^{8} \beta_{\mathrm{i}}^{\mathrm{k}} \mathrm{F}_{\mathrm{i,t}} + \mathrm{e}_{\mathrm{t}}^{\mathrm{k}} \tag{5.2}$$

where R_t^k is the excess return of fund k at time t, and α_t^k is abnormal return caused by managers' skills. β_i^k is the k^{th} fund's risk exposure to the ith factor, and e_t^k is the residual. The first seven factors are Fung and Hsieh's (2004a) seven factors, as explained in Section 3.4.5. The eighth factor is the tail risk factor HFTR/EMTR (as described in Section 5.2.1/5.2.2). The coefficient of HFTR/EMTR was estimated using multivariate regression as described by Equation 3.14. I have also added the Fama–French momentum factor (MMT), the innovation in aggregate liquidity factor (LQD), and the monthly return of VIX to form an eleven-factor model for a robustness check. I used Treasury-bill yield to represent the risk-free interest rate.

5.2.4 Can fund characteristics explain the variation in the cross-section of hedge fund tail risk exposures?

I performed cross-sectional regression to investigate the relationship between fund characteristics and the fund's tail risk exposure. The regressions take the following structure:

$$\beta_i^{HFTR} = \alpha_i^{HFTR} + \sum_k \theta^k \times C_i^k + \theta_i^{mean} XMean_i + \theta_i^{vol} XVol_i + e_i^{HFTR} \tag{5.3}$$

In this equation,

β_i^{HFTR} is the regression coefficient of HFTR for fund i, which is estimated over the whole period, α_i^{HFTR} is the intercept, C_i^k represents the kth characteristics of fund i, and θ^k is the coefficient of the characteristics to be estimated in the cross-sectional regression. $XMean_i$ and $XVol_i$ represent the past 24 months' average return and standard deviation for fund i, and e_i^{HFTR} is the error term of the regression model. I include the following fund characteristics in the regression: fund age, size (measured by AUM), fund attrition (dummy variable, 1 for living and 0 for defunct), incentive fees, management fees, high-water mark (dummy variable), closed to all investment[32] (dummy variable), leverage ratio, lockup months, redemption frequency, and advance notice days.

[32] This variable indicates whether a fund accepted external investments on inception.

5.3 Empirical results

5.3.1 Preliminary performance analysis

First, I constructed equally weighted portfolios for both hedge funds and FOFs according to their investment strategies. The performance of the portfolios is reported in Table 5.1. Compared to an average monthly return of 1% by hedge funds, FOFs, on average, have a lower monthly return of 0.67%. The variance of the monthly return of the FOFs is 5.88%, which is marginally less than the hedge funds' variance of 6.15%. Hedge funds using the volatility strategy record the highest monthly mean return and variance. This is not surprising because the sample size is only 50 and there are some extreme outliers, such as the VIX Portfolio Hedging (VXH) Program, which reports a 22% monthly return and a 3251% monthly variance. In addition, volatility hedge funds usually bet on the magnitude of asset volatility and implement strategy using derivatives such as straddles and strangles. Such option strategies may lead to significant losses when market volatility moves against expectations. Both hedge fund and FOF portfolios display negative skewness, but the distribution of FOF returns is more left skewed at -0.83 compared to -0.28 for hedge funds. The historical VaR of FOFs is 2.6, which is 0.6 higher than that of hedge funds. Shapiro-Wilk test results reveal non-normality in the returns of both portfolios, which is consistent with the findings in other hedge fund studies, such as Olmo and Sanso-Navarro (2012). In general, FOFs tend to underperform their counterpart HF portfolios. For example, debt FOFs gain a 0.51% monthly return with a 5.58% variance, whereas debt hedge funds receive a 0.9% monthly return and a 5.27% variance. In summary, both hedge fund and FOF returns, on average, tend to be non-normally distributed. Some hedge fund or FOF strategies are more prominent in extreme losses, such as the volatility strategy for hedge funds and debt strategy for FOFs.

Table 5.1 The performance of hedge funds and funds of hedge funds (January 1991 to December 2012)

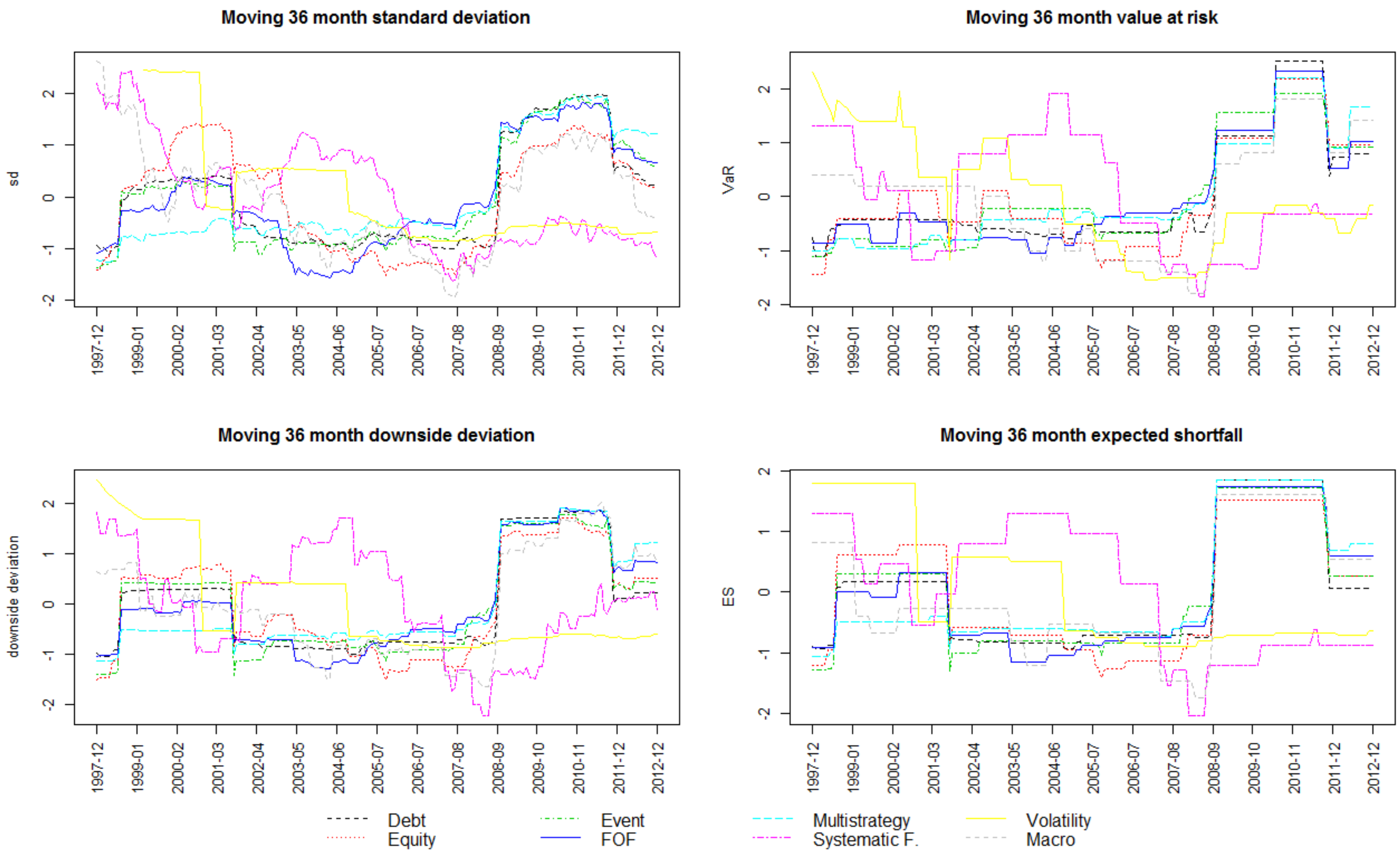
This table reports the performance statistics of hedge fund and fund of hedge funds (FOF) strategies. Each strategy group is represented by an equally weighted portfolio of the funds in that strategy group.

		Counts	% of subtotal	Mean	Variance	Skewness	Kurtosis	Historical VaR	Normality test[a]
Hedge fund strategies	**Hedge funds**	**7782**	**100.0%**	**1.01**	**6.15**	**-0.28**	**2.03**	**2**	**0.98*** [b]**
	Debt	969	12.5%	0.90	5.27	-1.30	10.35	1.7	0.87***
	Equity	4256	54.7%	1.05	10.07	-0.61	2.05	2.9	0.97***
	Event.driven	487	6.3%	0.95	4.72	-1.47	5.88	1.6	0.90***
	Multi-strategy	637	8.2%	0.92	4.23	-1.16	4.85	1.4	0.93***
	Systematic futures	700	9.0%	1.15	20.42	1.21	5.71	4.9	0.94***
	Volatility	50	0.6%	1.25	50.07	-2.54	52.23	2.1	0.48***
	Macro	683	8.8%	0.85	4.60	0.72	2.34	2.1	0.97***
Funds of hedge funds strategies	**FOFs**	**4275**	**100.0%**	**0.67**	**5.88**	**-0.83**	**3.09**	**2.6**	**0.95*****
	Macro/systematic	360	8.4%	0.81	7.86	0.24	0.12	3.4	0.99
	Debt	208	4.9%	0.51	5.58	-1.31	5.93	2.1	0.91***
	Equity	1192	27.9%	0.71	8.73	-0.59	2.35	2.8	0.96***
	Event	210	4.9%	0.58	4.62	-1.28	4.40	1.9	0.91***
	Multi-strategy	2117	49.5%	0.62	5.75	-1.01	3.96	2.5	0.94***
	Relative value	188	4.4%	0.50	3.81	-1.28	5.78	2.2	0.91***

a. Shapiro-Wilk normality test was used in this research to test normality.
b. The asterisk symbols indicate the significance level of the test results, being significant at the 1% level "***", 5% level "**" and 10% level "*".

Figure 5.1 The series of the risk measures of hedge fund strategies vs funds of hedge funds (December 1997 to December 2012)

The time series of each risk measure is calculated using the monthly returns of equally weighted strategy portfolios on a 36-month rolling window. All the risk measures are standardised before plotting, so the diagrams show the changes in the risk of hedge funds relative to their historical average.



Next, I calculated the standard deviation, downside deviation (semi-deviation), historical value at risk (VaR), and expected shortfall (ES) for each hedge fund and FOF strategy portfolio on a 36-month rolling window. As such, I received 15 time series for each risk measure and plotted these time series in Figure 5.1 and Figure 5.2. To enhance the comparability of the graphs, I standardised the time series using

$$C_t = \frac{c_t - \bar{c}}{\sigma_c} \tag{5.4}$$

where c_t is the risk measure at time t, $\bar{c}$ is the average of $\{c_t\}$ over the entire period, and σ_c is the standard deviation of the risk measure over the entire period.

Figure 5.1 shows the time series of all hedge fund strategies compared with the equally weighted FOF portfolio in relation to standard deviation, downside deviation, VaR, and ES. In each of the graphs in Figure 5.1, the FOFs time series is represented by a blue solid line, and the other hedge fund strategies are depicted by various dot lines. The graph on the top left indicates the standard deviation time series, which can be roughly separated into three sub-periods: December 1997 to May 2003, June 2003 to August 2007, and September 2007 to December 2012. During the first sub-period, the standard deviations of hedge fund strategies do not exhibit any sign of clustering or co-movement. There is a sharp increase in the volatility of equity hedge funds (the red dot line) in the early 2000s, which could be caused by the burst of the high-tech bubbles. Moving into the second sub-period, I observe some trend of convergence and co-movements. For example, most of the strategies show below-average standard deviation and indicate a stable change in the time series during this period. Systematic futures and volatility hedge funds are the exemptions. Both strategies exhibit high volatility during this period; however, by the end of the second sub-period, the volatility of these two strategies experience consistent decreases. By the end of August

2007, all the strategies exhibit below-average volatility. Focusing on FOFs, the volatility of FOFs starts to increase in mid-2005 and exceeds all the other strategies around June 2006. This structural change results in a high-level volatility that persists until the end of the sample period. The last sub-period starts in September 2007, or roughly the period in which the GFC took place. The volatility of all strategies tended to increase during this period. In mid-2008, there was a dramatic surge in the volatility of all funds except systematic futures and volatility hedge funds. FOFs do not provide any diversification benefit, as its relative level of standard deviation still leads the other strategies until the end of 2008. The other three graphs reveal similar patterns in the change of the downside risk of these hedge fund strategies. All of them show a structural change in the risk of FOFs relative to the other hedge funds around mid-2006. In addition, the downside risk of FOF is among the highest during the GFC period and shows no sign of dropping until late 2011. Figure 5.1 shows some visual evidence that FOFs is as risky as the other hedge fund strategies. In extreme market conditions, such as the GFC, FOFs do not display a diversification benefit, which is consistent with the conclusions of Amin and Kat (2002) as well as Brown, Gregoriou, and Pascalau (2012).

Figure 5.2 shows the risk measurement time series of FOF strategies compared with the equally weighted hedge fund portfolio (in this section, hedge funds). In all four graphs, the hedge fund time series is represented by a solid red line, and the FOF time series is indicated by a solid blue line. In the standard deviation graph on the top left, I find a clear pattern of co-movement in the volatility of FOF strategies. During the period from 2003 to mid-2007, all the strategies deliver lower-than-average volatilities, but they all experience a sharp increase in volatility around September 2008. In the aftermath of the GFC, the volatility of all FOFs remains high and has never returned to that low level. The volatility of hedge funds is below that of most of the FOF strategies since 2006, even during the period of the GFC.

Figure 5.2 Time series of the risk measures of fund of hedge fund strategies vs hedge funds (December 1997 to December 2012)

The time series of each risk measure is calculated using the monthly returns of equally weighted strategy portfolios on a 36-month rolling window. All the risk measures are standardised before plotting, so the diagrams show the changes in the risk of hedge funds relative to their historical average.

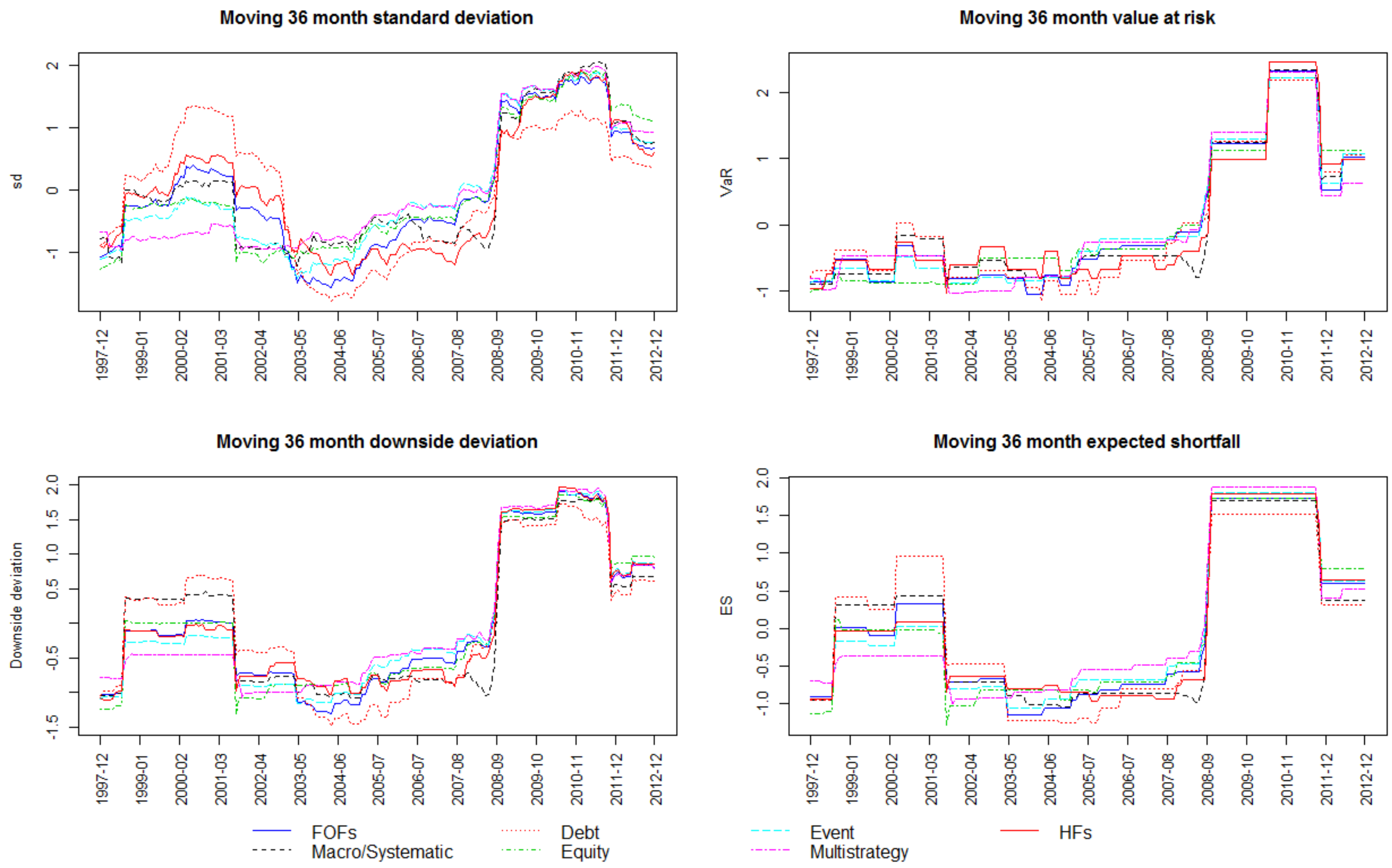
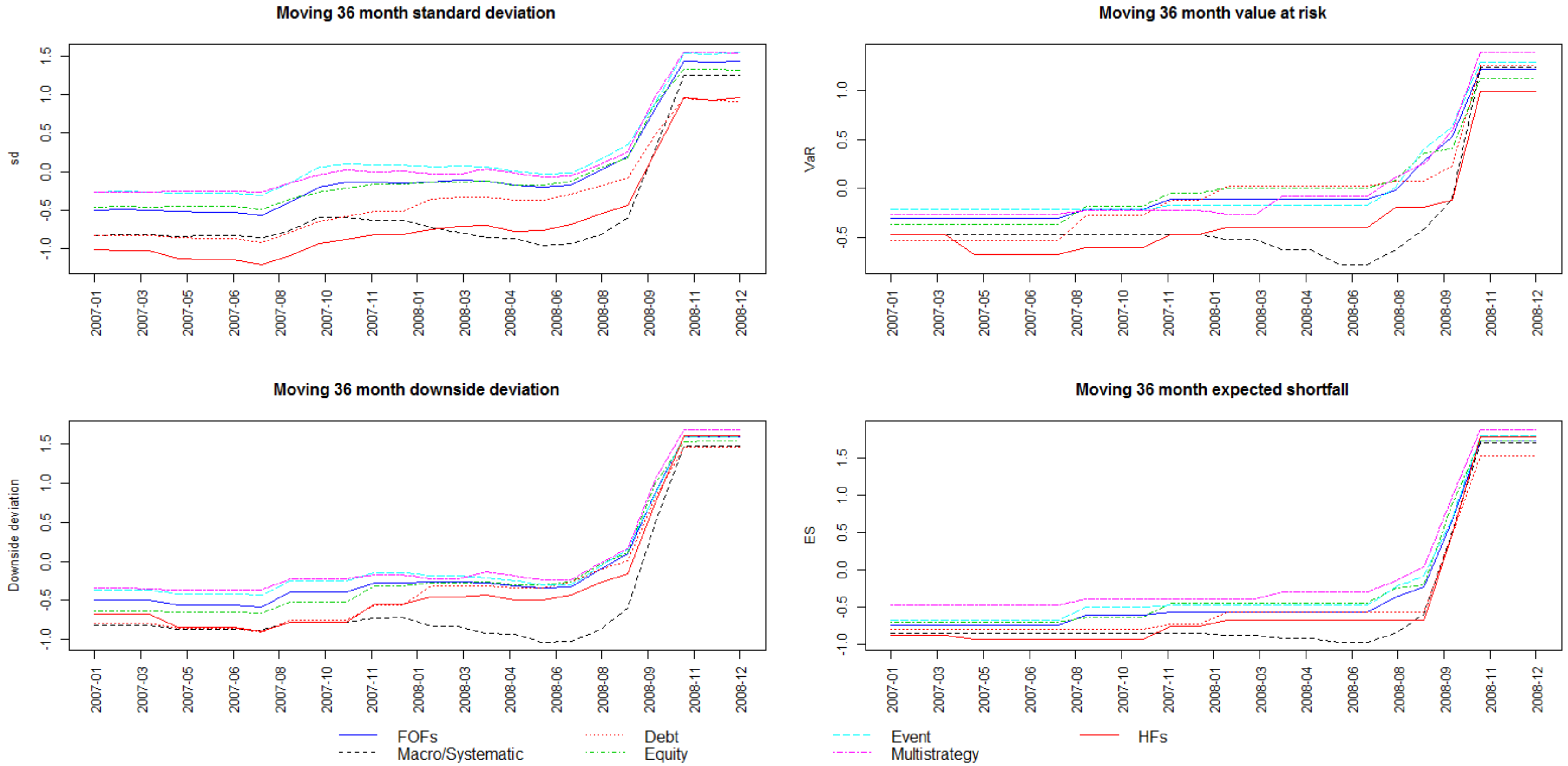


Figure 5.3 Time series of the risk measures of fund of hedge fund strategies vs hedge funds (January 2007 to December 2008)

The time series of each risk measure is calculated using the monthly returns of equally weighted strategy portfolios on a 36-month rolling window. All the risk measures are standardised before plotting, so the diagrams show the changes in the risk of hedge funds relative to their historical average.



As the lines in Figure 5.2 become entangled during the GFC period, I plotted the same time series on a shorter horizon and show these graphs in Figure 5.3. The sample period of the plots in Figure 5.3 is from January 2007 to December 2008, which covers the majority of the GFC. These graphs show clear evidence that most of the FOF strategies experienced higher volatility or downside risk during the GFC relative to their historical average. In contrast, the increase in the relative risk of hedge funds is not as high as that of the FOFs. Specific to FOF strategies, macro/systematic FOFs tend to outperform their peer groups with regard to all the risk measures prior to the GFC but eventually aligned with the others when the GFC took place. Multi-strategy FOFs, however, lead the other strategies during the two-year period with respect to all the downside risk measures.

5.3.2 The tail risk factors HFTR and EMTR

The standardised time series of HFTRM and EMTRM are depicted in Figure 5.4. I plotted the two measurements respectively with the cumulative return of the S&P500 index over the same period in the top and middle panel. In addition, in the bottom panel, I presented the two tail risk measurements on the same plot to highlight the differences.

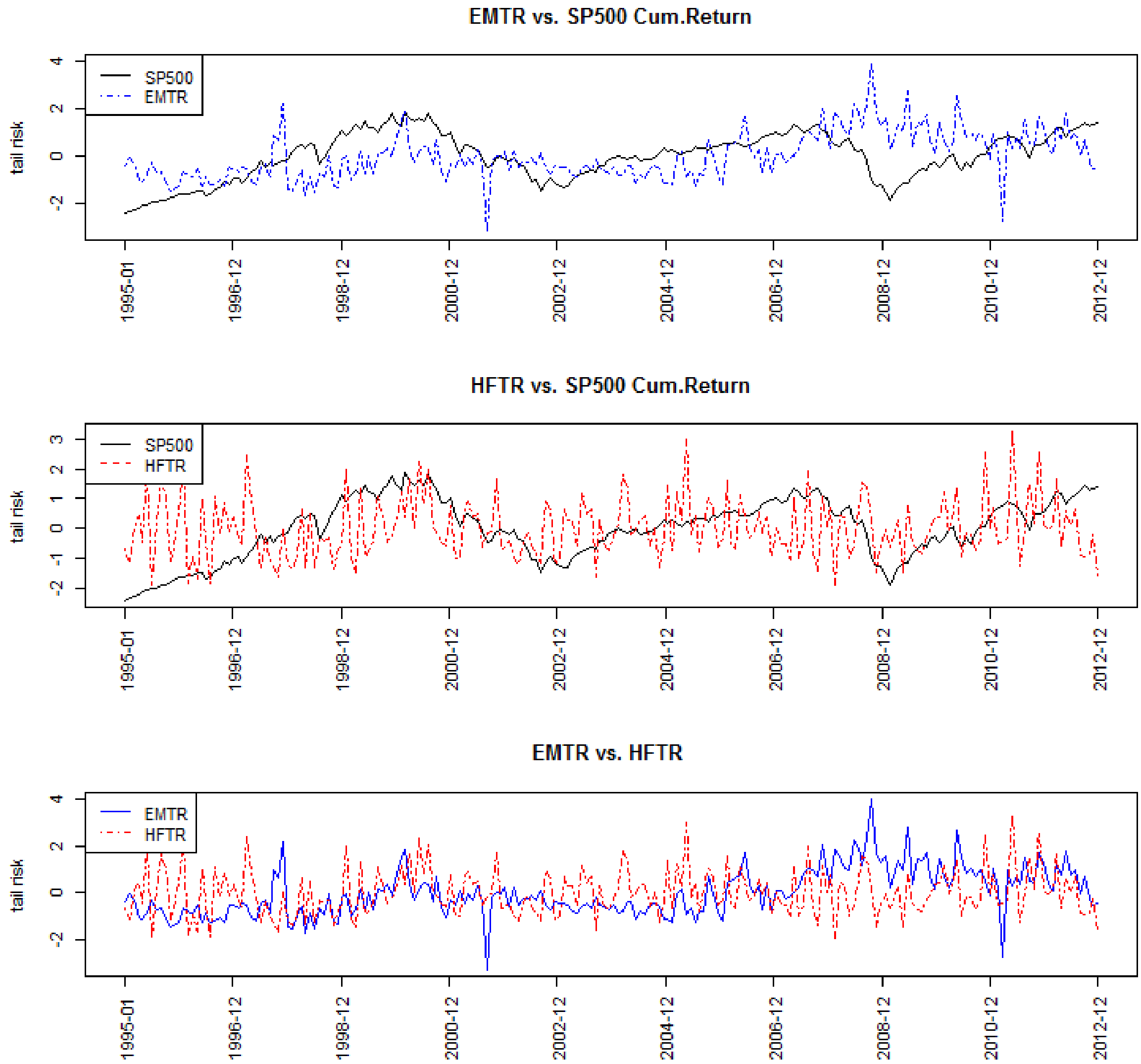
I found that EMTRM captures the major equity market drawdowns. Some remarkable peaks in the EMTRM chart correspond to the troughs in the S&P500 cumulative return chart. For example, EMTRM reaches its historical peak around late 2007 and stays at a high level until early 2010. During the same time, the S&P500 cumulative return experiences the largest drawdown. However, there are several mismatches, such as the one around 1997. A possible explanation is that EMTRM is generated using global market data, whereas the S&P500 return depicts the fluctuations in the US market.

The tail risk in 1997 was sourced mainly from Asian markets, so its impact on the US market is comparatively limited.

In general, I find that HFTRM does not capture the major equity market drawdowns, although on limited occasions, some peaks in HFTRM correspond to the troughs in the S&P500 cumulative return chart. This is not surprising given that hedge funds have broad exposure to different asset classes. As a result, systemic shocks to the hedge fund industry do not always originate from the equity market. For example, the collapse of Long-Term Capital Management (LTCM) in 1998 was triggered by the Russian default in the debt market. For the same reason, the plot of HFTR is not always consistent with the EMTR shown in the bottom panel of Figure 1. For example, the EMTRM series hit its local peak around 1997, but it corresponds to a trough in the HFTRM series. It would not be an unexpected observation, as many hedge funds profited during the Asian market turmoil in 1997.

Figure 5.4 Tail risk measurements and SP500 cumulative returns

This diagram shows the time series of the tail risk measurements compared with the cumulative return of SP500 index from 1995 to 2012. The blue line in the top and bottom panel represent equity market tail risk measurement (EMTR), and the red line in the middle and bottom panel shows the hedge fund market tail risk measurement (HFTR).



It has been well documented in the finance and econometrics literature that using non-stationary time series in a regression model may lead to the spurious regression problem (Granger and Newbold, 1974; Entorf, 1997; Ferson, Sarkissian and Simin, 2003). Thus, I perform KPSS and Dickey-Fuller test on the stationarity of the two tail risk measurements. The KPSS test (Kwiatkowski et al. 1992) is designed to test the null hypothesis that a time series is non-stationary around a deterministic trend. In contrast, the null hypothesis of the Dickey-Fuller test assumes that there is a unit root in the time series so that the time series is difference non-stationary. For both tests, a p-value lower than 10% indicates significant evidence against the null hypothesis. Table 5.2 reports the KPSS test and Dickey-Fuller test results of EMTRM and HFTRM. According to Panel A, the KPSS test indicates no evidence that the EMTRM follows a deterministic trend, and the augmented Dickey-Fuller test can reject the null hypothesis of a unit root at the 10 percent significance level. We can observe similar test results of HFTRM in Panel B. In summary, we find no significant evidence that EMTRM and HFTRM series are trend-non-stationary or difference-non-stationary.

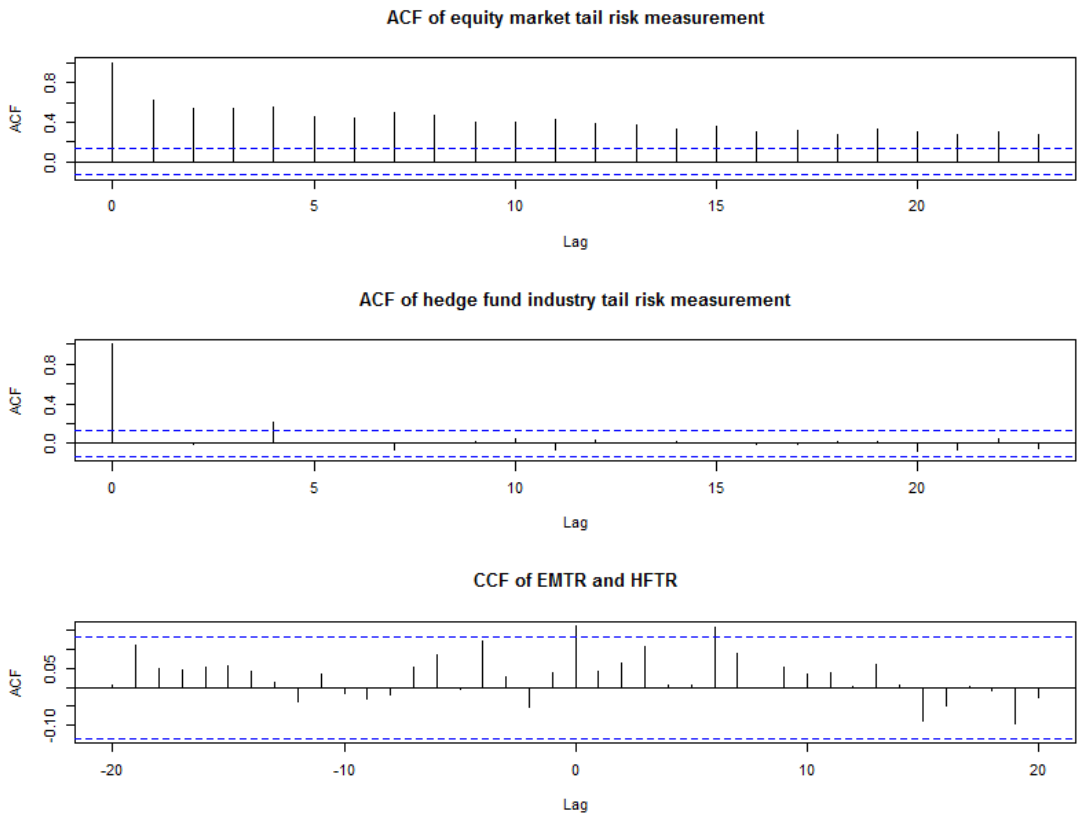
Table 5.2 Stationary test results of the tail risk measurements

Panel A: equity market tail risk measurement		
	KPSS Test for Trend Stationarity	
KPSS Trend = 0.2256	Truncation lag parameter = 3	p-value = 0.01
Alternative hypothesis: non-trend-stationary		
	Augmented Dickey-Fuller Test	
Dickey-Fuller = -3.4172	Lag order = 5	p-value = 0.05291
Alternative hypothesis: stationary		
Panel B: Hedge fund industry tail risk factor		
	KPSS Test for Trend Stationarity	
KPSS Trend = 0.0499	Truncation lag parameter = 3	p-value = 0.1
Alternative hypothesis: non-trend-stationary		
	Augmented Dickey-Fuller Test	
Dickey-Fuller = -4.7192	Lag order = 5	p-value = 0.01
Alternative hypothesis: stationary		

a. The two tests are performed on the tail risk measurement time series from May 1996 to Feb 2010.

I also performed the autocorrelation function (ACF) test to capture the autocorrelation in the tail risk measurements, and the results are provided in Figure 5.5. I can find some signs of autocorrelation in EMTRM. The partial ACF chart of EMTRM reveals the persistence of equity market tail event shocks. In contrast, HFTRM follows a white noise process, while the influence of the previous tail risk shock disappears in the following month. Moreover, the bottom panel of Figure 5.5 shows the result of the ACF test for the two factors. If a change in either of the measurements leads to changes in another, I should observe significant autocorrelation exceeding the significance line; however, the chart reveals that there is no strong lead-lag effect between the two tail risk measurements.

Figure 5.5 ACF of tail risk measurements



As mentioned in Section 5.2.1 and Section 5.2.2, I fitted the AR (q) process to both HFTRM and EMTRM to derive the tail risk factors HFTR and EMTR. I report the correlation between the risk factors that will be used in the remaining studies in Table 5.3. Because the HFTR is derived from the cross-sectional residuals of Fung and Hsieh's seven-factor model (2004a), it naturally displays weak correlations with other factors. Moreover, HFTR is the only factor that is insignificantly correlated to VIX, which reflects market expectations for future volatility. I found that EMTR is significantly correlated with S&P500 excess returns, Fung and Hsieh (2001) trending following factors, and VIX. The two tail risk factors are significantly correlated, but the correlation coefficient is only 0.2. On one hand, the significant correlation between the two tail risk factors indicates that HFTR does contain information regarding the tail risk shocks from the equity market. On the other hand, the low value of the correlation also suggests that HFTR covers some different information that is not reflected in EMTR. These findings lead to my view that the tail risk in the hedge fund industry can only be partially explained by the tail risk event in the equity market. Therefore, I expect HFTR to work better than EMTR in depicting the tail risk in the hedge fund industry to better explain the returns of FOFs.

Table 5.3 The correlation matrix of market risk factors

This table shows the pairwise Pearson correlation between the factors to be used in the regression analysis. The top diagonal shows the significance of the correlation, and the bottom diagonal shows the value of the correlations.

	SP500[b]	SMB	TBY	CRSP	PTFSBD	PTFSFX	PTFSCOM	MMTM	LQD	VIX	EMTR	HFTR
SP500	1.00		***	***	***	***	**	***	***	***	***	
SMB	0.07	1.00	***	***	*					***		
TBY	0.21	0.19	1.00	***	***	**	**	***		***		
CRSP	-0.31	-0.28	-0.69	1.00	***	***	**	***		***		
PTFSBD	-0.23	-0.13	-0.35	0.29	1.00	***	***			***	***	
PTFSFX	-0.21	-0.02	-0.17	0.22	0.27	1.00	***	*		***	***	
PTFSCOM	-0.17	-0.06	-0.14	0.17	0.23	0.38	1.00	***		*		
MMTM	-0.33	0.07	-0.18	0.22	0.02	0.12	0.22	1.00	*	**		
LQD	0.25	0.01	0.11	-0.04	-0.05	-0.09	-0.10	-0.12	1.00	***		*
VIX	-0.67	-0.19	-0.21	0.29	0.29	0.23	0.11	0.16	-0.20	1.00	***	
EMTR	-0.19	-0.03	0.00	0.09	0.18	0.23	0.07	0.01	0.00	0.24	1.00	***
HFTR	0.02	-0.01	0.07	-0.05	-0.01	0.00	0.01	-0.07	-0.12	-0.02	0.20	1.00

a. The asterisk symbols indicate the significance level of the test results, being significant at the 1% level "***", 5% level "**" and 10% level "*".

Table 5.4 Hedge funds and funds of hedge funds (FOFs) with significant negative hedge fund industry tail risk betas

This table shows the statistics of hedge funds and FOFs with negative exposures to the hedge fund industry tail risk factor (HFTR). I classify these funds using three criteria: living or defunct, investment strategies, and whether the funds generate excess returns after controlling for the tail risk exposure.

Number of hedge funds: 7782				Number of FOFs: 4275			
Panel A: hedge funds with significant negative tail risk beta				Panel B: funds of hedge funds with significant negative tail risk beta			
Number of hedge funds with sig. neg.		3474	44.64% of 7782	Number of FOFs with sig. neg. beta		3582	83.79% of 4275
		No. of funds	% of 3474			No. of funds	% of 3582
Living[b]		1381	39.75%	Living		1144	31.94%
Defunct		2093	60.25%	Defunct		2438	68.06%
Hedge funds strategies	Debt	415	11.95%	FOFs strategies	Macro/systematic	286	7.98%
	Equity	1904	54.81%		Debt	142	3.96%
	Event driven	204	5.87%		Equity	994	27.75%
	Multi-strategy	311	8.95%		Event	174	4.86%
	Systematic futures	333	9.59%		Multi-strategy	1848	51.59%
	Volatility	16	0.46%		Relative value	138	3.85%
	Macro	291	8.38%				
Sig +alpha[c]		409	11.77%	Sig +alpha		205	5.72%
Sig -alpha		42	1.21%	Sig -alpha		58	1.62%

a. Morningstar database defines living funds as the funds reporting return information until the census date. Defunct funds include the funds liquidated before the census date and the funds that stop reporting to Morningstar before the census date.

b. Alpha is the excess return calculated using the following model: $R_t^k = \alpha_t^k + \sum_{i=1}^{8} \beta_i^k F_{i,t} + e_t^k$ where R_t^k is the excess return of a fund in month t and $F_{i,t}$ represents the monthly returns of eight factors, including Fung and Hsieh's (2004a) seven factors, the Fama–French momentum factor, the Pastor and Stambaugh aggregate liquidity factor, and EMTR, an equity market tail risk factor.

5.3.3 The tail risk exposure of individual hedge funds and FOFs

I ran a linear regression for each fund in my sample to obtain their exposure to HFTR over the whole sample period. According to the significance of HFTR exposure, beta, I classified the hedge funds and the FOFs into three groups, respectively: funds with significant negative betas, funds with significant positive betas, and funds with insignificant betas. Table 5.4 reports the summary statistics of the funds with significant negative tail risk betas. To investigate the cross-sectional variation of the tail risk exposure of hedge funds and FOFs, I classified the funds in Table 5.4 using three criteria: the status of the funds (living or dead), the investment strategy of the funds, and the excess return of the funds after controlling for tail risk exposure.

Approximately 44.64% of 7,782 hedge funds have significant negative exposure to HFTR, but 60.25% of these funds became defunct before 2013, as shown in Panel A. The strategy composition of the tail-risk-sensitive hedge funds is consistent with the strategy composition of the entire hedge fund universe. Hence, there is no particular hedge fund strategy that is effectively immune to the industry-wide tail risk shocks. I found that approximately 11.77% of 3,474 HFTR-sensitive hedge funds were able to deliver significant positive alpha.

The HFTR regression results of individual FOFs are reported in Panel B of Table 5.4. The results are quite distinct from the results in Panel A. I found that around 83.79% of FOFs in the total sample had significant negative exposures to HFTR, and nearly 68% of these funds became defunct before 2013. The implication of this finding is twofold. First, there does not seem to be a risk reduction despite FOFs holding diversified hedge fund portfolios. Instead, the tail risk exposures of individual hedge funds tend to be aggregated in a FOF's portfolio. Second, tail risk exposure may help to explain the attrition ratio of FOFs. A smaller number of FOFs, approximately 5.7% of my FOFs sample, are able to deliver significant positive alpha after controlling for their exposure to HFTR. Similar to hedge funds results in Panel A, I found no particular FOFs strategy that is more sensitive or immune to the tail risk when comparing the strategy composition of the tail-risk-sensitive FOFs with that of the entire FOF sample. This observation is also consistent with the evidence documented in Figure 5.3, where the time series plot of all FOF strategies increased collectively during the GFC.

I have repeated the above process using EMTR and the tail risk factor, and the test results are reported in Table 5.5. In total, the majority of hedge funds (87.3%) and FOFs (77.8%) are not influenced by EMTR to a significant extent. 888 (11.41% of 7,782) hedge funds report significant negative tail risk beta, while a higher proportion of FOFs (21.87% of 4,275) are significantly exposed to EMTR. This result might challenge the traditional belief that FOFs are more diversified and less influenced by tail risk shocks than hedge funds. With regard to the investment strategy, I found that the funds pursuing equity strategies are prominent in EMTR exposure. Equity hedge funds account for approximately 63.63% of the EMTR-sensitive hedge funds, which is approximately 10% higher than the normal proportion of equity hedge funds in the total hedge fund sample (54.7% in Table 5.1 column 2). Similar to equity hedge funds, approximately 38.61% of EMTR-sensitive FOFs follow an equity strategy, while they account for only 27.9% in the whole FOF sample. In contrast, other HF and FOF strategies take lower shares in the EMTR-sensitive fund sample. Finally, I found that approximately 13.63% of EMTR-sensitive hedge funds gained significant excess return, and this ratio is lower in EMTR-sensitive FOFs (5.56%).

In summary, the results of individual fund time series regression support my claim that the tail risk in the hedge fund industry cannot be eliminated by FOF diversification. Instead, FOFs are more sensitive to the tail risk shock than hedge funds. In addition, HFTR can significantly explain the returns of the vast majority of FOFs and a large proportion of hedge funds.

Table 5.5 Hedge funds and funds of hedge funds with significant negative exposures to the equity market tail risk factor[a]

This table shows the statistics of hedge funds and funds of hedge funds with negative exposure to the equity market tail risk factor (EMTR). I classify these funds using three criteria: living or defunct, investment strategies and whether the funds receive excess return after controlling for tail risk exposure.

Number of hedge funds: 7782				Number of FOHFs: 4275			
Panel A: hedge funds with significant negative tail risk beta				Panel B: funds of hedge funds with significant negative tail risk beta			
Number of hedge funds with sig. neg.		888	11.41% of 7782	Number of FOHFs with sig. neg. beta		935	21.87% of 4257
		No. of funds	% of 888			No. of funds	% of 935
Living[b]		376	42.34%	Living		397	42.46%
Defunct		512	57.66%	Defunct		538	57.54%
Hedge funds strategies	Debt	108	12.16%	FOHFs strategies	Macro/systematic	49	5.24%
	Equity	565	63.63%		Debt	25	2.67%
	Event driven	55	6.19%		Equity	361	38.61%
	Multi-strategy	60	6.76%		Event	35	3.74%
	Systematic futures	51	5.74%		Multi-strategy	448	47.91%
	Volatility	3	0.34%		Relative value	17	1.82%
	Macro	46	5.18%				
Sig +alpha[c]		121	13.63%	Sig +alpha		52	5.56%
Sig +alpha		2	0.23%	Sig +alpha		3	0.32%

a. The Morningstar database defines living funds as the funds reporting return information until the census date. Defunct funds include funds liquidated before the census date and funds that stop reporting to Morningstar before the census date.

b. Alpha is the excess return calculated using the following model: $R_t^k = \alpha_t^k + \sum_{i=1}^{8} \beta_i^k F_{i,t} + e_t^k$ where R_t^k is the excess return of a fund in month t and $F_{i,t}$ represents the monthly returns of eight factors, including Fung and Hsieh's (2004a) seven factors, the Fama–French momentum factor, the Pastor and Stambaugh aggregate liquidity factor, and EMTR, an equity market tail risk factor.

5.3.4 Tail risk factor contribution to the explanatory power of factor models

I performed further regressions at an individual fund level to investigate whether the explanatory power of selected models can be enhanced by adding the tail risk factors. Traditional CAPM and the Fung and Hsieh (2004a) seven-factor model are adopted as the base models in this analysis. I require all the funds in the sample to report at least 36 monthly returns so that 5,301 hedge funds and 3,311 FOFs remain in the final sample. For each fund in the sample, I ran CAPM and the Fung and Hsieh seven-factor model, respectively, and kept a record of the adjusted R^2 of both models. In the next step, I added HFTR/EMTR to the base models. I reported the cross-sectional average adjusted R^2 in Table 5.6. In addition, I reported the percentage of the funds with significant betas to show the trade-off effect of the additional factors.

The explanatory power of CAPM is, on average, 0.202 for hedge funds and 0.256 for FOFs. Adding EMTR to CAPM, the average adjusted R^2 increases marginally by approximately 4%-6% for both hedge funds and FOFs; however, by replacing EMTR with HFTR, the average adjusted R^2 increases by 34.7% to 0.272 for the hedge fund sample. This enhancement is even higher for the FOFs sample. I received an approximate 71.5% enhancement in average adjusted R^2 and the explanatory power for the CAPM plus HFTR model reached 0.439. The addition of the two tail risk factors does not reduce the explanatory power of the equity market factor because the percentage of the funds with significant equity beta does not vary to a significant extent at each step of the test. Similar effects were obtained using the Fung and Hsieh (2004a) seven-factor model as the base model. HFTR enhances the explanatory power of the seven-factor model by 27.2% for the hedge fund sample and 59.2% for the FOF sample.

The explanatory power of the equity market factor remains stable after adding the tail risk factors.

Table 5.6 The contribution of tail risk factors to the selected factor models

This table reports the enhancements in adjusted R^2 of selected models because of the addition of the equity market tail risk factor (EMTR) or hedge fund industry tail risk factor (HFTR). I report the results on the hedge fund sample and fund of hedge funds (FOF) sample in Section A and Section B respectively. I require all the funds in my sample to report at least 36 monthly returns. I use 5% as the threshold of significance.

Pricing models:	CAPM[a]			Fung and Hsieh seven-factor model[b]		
	Original model	Extra factor EMTR[c]	Extra factor HFTR	Original model	Extra factor EMTR	Extra factor HFTR
Section A: hedge fund sample, total 5301 funds						
Average adjusted R^2	0.202	0.211	0.272	0.257	0.265	0.327
% increase of the original adj. R^2	-	4.5%	34.7%	-	3.1%	27.2%
Sig[d] equity beta (% of total)	71.4%	67.9%	71.2%	64.6%	62.8%	63.6%
Sig EMTR beta (% of total)	-	18.5%	-	-	16.6%	-
Sig HFTR beta (% of total)	-	-	54.9%	-	-	55.1%
Section B: FOF sample, total 3311 funds						
Average adjusted R^2	0.256	0.271	0.439	0.306	0.321	0.487
% increase of the original adj. R^2	-	5.9%	71.5%	-	4.9%	59.2%
Sig equity beta (% of total)	89.2%	84.9%	89.5%	84.7%	82.3%	85.0%
Sig EMTR beta (% of total)	-	28.0%	-	-	27.6%	-
Sig HFTR beta (% of total)	-	-	91.7%	-	-	92.0%

a. In CAPM, $R_t^k = \alpha_t^k + \beta_i\ (SP500_t - Rf_t) + e_t^k$ where R_t^k is the excess return of a fund in month t and $SP500_t - Rf_t$ represents the monthly excess return of the SP500 index over the risk free rate.

b. Fung and Hsieh seven-factor model: $R_t^k = \alpha_t^k + \sum_{i=1}^{8} \beta_i^k F_{i,t} + e_t^k$ where R_t^k is the excess return of a fund in month t and $F_{i,t}$ represents the monthly returns of eight factors, including Fung and Hsieh's (2004a) seven factors and HFTR, the hedge fund industry tail risk factor derived using the cross-sectional monthly return of the Morningstar hedge fund database.

5.3.5 The tail risk exposure of HF and FOF portfolios

In this section, I tested the significance of HFTR/EMTR betas at the portfolio level. Fung and Hsieh's (2004a) seven factors were used as control variables, and all the portfolios were equally weighted. The EMTR regression results are reported in Table 5.7. I found that all portfolios gained negative exposure to EMTR, which coincides with the indication that the higher the exposure to tail risk events is, the higher the losses to the funds will be. At the aggregated level, the influences of the tail risk on the equally weighted HF and FOF portfolios are significant and at similar magnitudes of -0.481 and -0.574, respectively. Controlling for the impacts of various risk exposures, the HF portfolio has earned a very significant excess return of 0.431% monthly, whereas the FOF portfolio failed to earn a significant excess return. The results in Table 5.7 demonstrate strong evidence that, despite the fact that FOFs are diversified investment vehicles, on average, FOFs do not provide excess returns but have higher exposure to EMTR.

Table 5.7 Hedge funds and fund of hedge funds exposure to EMTR from Jan 1995 to Dec 2012, controlling for FH seven factors

	(Intercept)	SP500	SMB	TBY	CRSP	PTFSBD	PTFSFX	PTFSCOM	EMTR	Adj. R
Hedge fund portfolio	**0.431*** **	**0.397*** **	**0.233*** **	**-1.171** **	**-0.769**	**0.001**	**0.012** *	**0.012**	**-0.481*** **	**0.658**
HF – Debt	0.288**	0.246***	0.102***	-2.879***	-2.708***	-0.014*	-0.004	-0.007	-0.376**	0.507
HF – Equity	0.404***	0.562***	0.349***	-0.343	-0.102	-0.002	0.009	0.002	-0.453**	0.737
HF – Event driven	0.413***	0.313***	0.192***	-0.724	-1.326***	-0.022***	0.005	-0.007	-0.370***	0.682
HF – Multi-strategy	0.399***	0.258***	0.124***	-0.945	-1.392**	-0.003	0.008	-0.001	-0.452**	0.466
HF – Systematic futures	0.796***	0.100*	0.076	-2.697**	-0.363	0.047***	0.053***	0.079***	-0.804**	0.305
HF – Volatility	0.923*	0.223*	0.077	-0.122	-0.332	0.008	0.015	-0.038	0.636	-0.009
HF – Macro	0.369***	0.199***	0.124***	-1.603***	-0.660	0.001	0.012**	0.027***	-0.271*	0.375
Fund of hedge funds portfolio	**0.129**	**0.325*** **	**0.186*** **	**-1.734*** **	**-1.290** *	**-0.010**	**0.012**	**0.019** *	**-0.574*** **	**0.479**
FOHF – Macro/systematic	0.349**	0.180***	0.116**	-2.968***	-1.359	0.020*	0.036***	0.037***	-0.770***	0.290
FOHF – Debt	0.090	0.250***	0.152***	-2.049***	-1.960***	-0.016*	0.013*	-0.009	-0.496***	0.412
FOHF – Equity	0.100	0.429***	0.278***	-1.122	-0.665	-0.014	0.009	0.023**	-0.569***	0.559
FOHF – Event	0.155	0.269***	0.128***	-0.697	-1.315**	-0.017**	0.008	0.004	-0.417***	0.506
FOHF – Multi-strategy	0.117	0.294***	0.150***	-2.000***	-1.619**	-0.011	0.010	0.015	-0.602***	0.420
FOHF – Relative value	0.133	0.152***	0.063*	-1.521**	-2.021***	-0.017*	0.011	0.007	-0.485***	0.276

a. The regression model: $R_t^k = \alpha_t^k + \sum_{i=1}^{8} \beta_i^k F_{i,t} + e_t^k$ where R_t^k is the excess return of a fund in month t and $F_{i,t}$ represents the monthly returns of eight factors, which are described above.

b. The asterisk symbols indicate the significance level of the test results, being significant at the 1% level "***", 5% level "**" and 10% level "*".

Table 5.8 Hedge funds and fund of hedge funds exposure to HFTR from Jan 1995 to Dec 2012, controlling for FH seven factors[a]

	(Intercept)	SP500	SMB	TBY	CRSP	PTFSBD	PTFSFX	PTFSCOM	HFTR	Adj. R
Hedge fund portfolio	**0.409 ***[b]**	**0.411 *** **	**0.230 *** **	**-1.010 ** **	**-0.674**	**-0.003**	**0.009 * **	**0.013 * **	**-0.948 *** **	**0.768**
HF – Debt	0.272 ***	0.256 ***	0.100 ***	-2.758 ***	-2.636 ***	-0.017 **	-0.006	-0.006	-0.728 ***	0.594
HF – Equity	0.384 ***	0.576 ***	0.346 ***	-0.146	0.015	-0.006	0.006	0.002	-1.022 ***	0.810
HF – Event driven	0.396 ***	0.324 ***	0.190 ***	-0.627	-1.268 ***	-0.025 ***	0.002	-0.006	-0.655 ***	0.742
HF – Multi-strategy	0.379 ***	0.271 ***	0.121 ***	-0.796	-1.303 **	-0.007	0.006	0.000	-0.887 ***	0.605
HF – Systematic futures	0.760 ***	0.121 **	0.073	-2.529 **	-0.264	0.040 **	0.047 ***	0.080 ***	-1.300 ***	0.392
HF – Volatility	0.953 *	0.213 *	0.073	0.241	-0.114	0.012	0.020	-0.040	-0.372	-0.010
HF – Macro	0.357 ***	0.208 ***	0.121 ***	-1.459 ***	-0.575	-0.002	0.011 **	0.027 ***	-0.685 ***	0.504
Fund of hedge funds portfolio	**0.115**	**0.340 *** **	**0.177 *** **	**-1.683 *** **	**-1.463 *** **	**-0.013 * **	**0.008**	**0.022 *** **	**-1.149 *** **	**0.652**
FOHF – Macro/systematic	0.329 **	0.200 ***	0.106 ***	-2.960 ***	-1.586 **	0.015	0.031 ***	0.041 ***	-1.319 ***	0.478
FOHF – Debt	0.077	0.263 ***	0.145 ***	-2.010 ***	-2.109 ***	-0.019 **	0.010	-0.007	-0.977 ***	0.554
FOHF – Equity	0.086	0.445 ***	0.269 ***	-1.070 *	-0.836	-0.017 *	0.005	0.026 ***	-1.143 ***	0.676
FOHF – Event	0.144	0.280 ***	0.121 ***	-0.655	-1.441 ***	-0.019 ***	0.006	0.007	-0.851 ***	0.639
FOHF – Multi-strategy	0.101	0.310 ***	0.141 ***	-1.951 ***	-1.800 ***	-0.015 *	0.007	0.018 **	-1.190 ***	0.609
FOHF – Relative value	0.121	0.165 ***	0.055 *	-1.481 **	-2.167 ***	-0.019 **	0.008	0.010	-0.959 ***	0.476

a. The regression mode: $R_t^k = \alpha_t^k + \sum_{i=1}^{8} \beta_i^k F_{i,t} + e_t^k$ where R_t^k is the excess return of a fund in month t and $F_{i,t}$ represents the monthly returns of eight factors, which are described above.

b. The asterisk symbols indicate the significance level of the test results, being significant at the 1% level "***", 5% level "**" and 10% level "*".

The HFTR regression results are reported in Table 5.8. Almost all the strategy portfolios tend to be influenced by HFTR significantly, except volatility hedge funds. In addition, I found that most FOF strategies are unable to deliver significant alpha, whereas almost all HF strategies can deliver significant alpha. Finally, the R^2 of each regression model in Table 5.8 is generally higher than the corresponding result in Table 5.7.

I performed robustness tests, including running regressions on a shorter time horizon from Jan 1995 to May 2007, to eliminate the influence of the 2008 GFC and added more controlling variables, such as MMT, LQD, and VIX. I found that the HFTR beta remains significant in all robustness tests. The test results are reported in Table 5.9 and Table 5.10. I received consistent robustness test results from EMTR regressions as well, but the results have not been disclosed in the interest of saving space. Moreover, I performed the same regressions using value weighted portfolios, and the results are consistent with the findings based on equally weighted portfolios.

My findings in this section strongly support the view that FOFs are significantly exposed to tail risk in the hedge fund industry. In addition to the HFTR, the credit spread factor (CRSP) and look-back straddle on treasury bonds (PTFSBD) have been found to explain returns of all FOF portfolios significantly.

Table 5.9 Hedge fund and fund of hedge funds exposure to HFTR from Jan 1995 to May 2007, controlling for FH seven factors[a]

	(Intercept)	SP500	SMB	TBY	CRSP	PTFSBD	PTFSFX	PTFSCOM	HFTR	Adj. R
Hedge fund portfolio	**0.577 ***[b]**	**0.385 *****	**0.273 *** **	**-1.240 ****	**-0.452**	**0.002**	**0.014 ****	**0.017 ****	**-0.530 *****	**0.780**
HF – Debt	0.371 ***	0.199 ***	0.137 ***	-1.512 **	-1.356 *	-0.020 ***	0.005	0.002	-0.335 ***	0.455
HF – Equity	0.552 ***	0.587 ***	0.415 ***	-0.285	0.297	-0.005	0.005	0.004	-0.556 ***	0.831
HF – Event driven	0.542 ***	0.266 ***	0.208 ***	-0.597	-0.808	-0.025 ***	0.009 *	0.000	-0.318 ***	0.707
HF – Multi-strategy	0.659 ***	0.192 ***	0.143 ***	-0.691	-1.068 *	0.000	0.014 ***	0.000	-0.443 ***	0.587
HF – Systematic futures	0.914 ***	0.061	0.070	-4.945 ***	-1.256	0.063 ***	0.068 ***	0.084 ***	-0.977 ***	0.445
HF – Volatility	1.089	0.312 *	0.101	-0.305	-2.784	-0.016	0.006	-0.067	-0.264	-0.006
HF – Macro	0.414 ***	0.202 ***	0.154 ***	-1.836 ***	-0.724	0.003	0.016 **	0.026 ***	-0.422 ***	0.456
Fund of hedge funds portfolio	**0.324 *****	**0.295 *****	**0.230 *****	**-1.484 ****	**-0.797**	**-0.011**	**0.015 *****	**0.026 *****	**-0.696 *****	**0.637**
FOHF – Macro/systematic	0.546 ***	0.135 ***	0.139 ***	-3.217 ***	-0.709	0.030 ***	0.047 ***	0.045 ***	-0.966 ***	0.527
FOHF – Debt	0.233 *	0.192 ***	0.184 ***	-1.564 **	-1.381	-0.017 **	0.018 ***	-0.003	-0.583 ***	0.428
FOHF – Equity	0.269 **	0.428 ***	0.337 ***	-1.051	-0.361	-0.017 *	0.008	0.034 ***	-0.686 ***	0.646
FOHF – Event	0.345 ***	0.222 ***	0.166 ***	-0.758 *	-0.796	-0.013 **	0.010 **	0.010	-0.420 ***	0.612
FOHF – Multi-strategy	0.335 ***	0.242 ***	0.184 ***	-1.629 ***	-1.119	-0.013 *	0.014 **	0.019 **	-0.700 ***	0.556
FOHF – Relative value	0.369 ***	0.064 ***	0.082 ***	-1.025 **	-1.468 **	-0.013 **	0.016 ***	0.012 *	-0.524 ***	0.352

a. The regression mode: $R_t^k = \alpha_t^k + \sum_{i=1}^{8} \beta_i^k F_{i,t} + e_t^k$ where R_t^k is the excess return of a fund in month t and $F_{i,t}$ represents the monthly returns of eight factors, which are described above.
b. The asterisk symbols indicate the significance level of the test results, being significant at the 1% level "***", 5% level "**" and 10% level "*".

Table 5.10 Hedge fund and fund of hedge fund exposure to HFTR controlling for ten risk factors, with equally weighted portfolios[a]

	(Intercept)	SP500	SMB	TBY	CRSP	PTFSBD	PTFSFX	PTFSCOM	MMT	LQD	VIX	HFTR	Adj. R
Hedge fund portfolio	**0.453 ***[b]**	**0.366 *** **	**0.215 *** **	**-1.125 ** **	**-0.793 * **	**-0.001**	**0.011 ** **	**0.011**	**0.016**	**2.418 * **	**-0.016 ** **	**-0.915 *** **	**0.777**
HF – Debt	0.326 ***	0.198 ***	0.094 ***	-3.010 ***	-2.752 ***	-0.017 **	-0.004	-0.005	-0.018	4.149 ***	-0.014 *	-0.692 ***	0.613
HF – Equity	0.410 ***	0.546 ***	0.328 ***	-0.223	-0.163	-0.003	0.008	-0.001	0.037 *	2.411	-0.013	-0.980 ***	0.816
HF – Event driven	0.472 ***	0.247 ***	0.181 ***	-0.883 **	-1.344 ***	-0.025 ***	0.005	-0.006	-0.023	3.855 ***	-0.020 ***	-0.624 ***	0.768
HF – Multi-strategy	0.455 ***	0.197 ***	0.112 ***	-1.013 **	-1.332 ***	-0.007	0.009	0.001	-0.026	2.977 **	-0.021 ***	-0.867 ***	0.629
HF – Systematic futures	0.813 ***	0.072	0.052	-2.573 **	-0.349	0.044 ***	0.050 ***	0.077 ***	0.029	1.213	-0.021	-1.275 ***	0.390
HF – Volatility	1.386 ***	-0.186	-0.044	-0.325	-0.387	0.030	0.038	-0.055	0.061	9.159	-0.148 ***	-0.253	0.072
HF – Macro	0.385 ***	0.181 ***	0.110 ***	-1.503 ***	-0.647	0.000	0.012 **	0.025 ***	0.017	1.133	-0.011 *	-0.666 ***	0.508
Fund of hedge funds portfolio	**0.129**	**0.321 *** **	**0.154 *** **	**-1.644 *** **	**-1.665 *** **	**-0.008**	**0.010 * **	**0.017 ** **	**0.066 *** **	**2.139**	**-0.013 * **	**-1.108 *** **	**0.675**
FOHF – Macro/systematic	0.383 ***	0.160 ***	0.087 **	-2.876 ***	-1.586 **	0.019 *	0.033 ***	0.038 ***	0.026	-0.475	-0.019 *	-1.316 ***	0.483
FOHF – Debt	0.089	0.251 ***	0.139 ***	-2.033 ***	-2.161 ***	-0.018 **	0.010 *	-0.007	0.009	0.963	-0.005	-0.965 ***	0.549
FOHF – Equity	0.086	0.432 ***	0.238 ***	-1.005 *	-1.154 *	-0.011	0.007	0.018 *	0.103 ***	3.144 *	-0.014 *	-1.080 ***	0.711
FOHF – Event	0.186 **	0.241 ***	0.109 ***	-0.719	-1.545 ***	-0.017 **	0.007	0.005	0.016	2.245 *	-0.014 **	-0.826 ***	0.648
FOHF – Multi-strategy	0.116	0.292 ***	0.120 ***	-1.913 ***	-1.979 ***	-0.011	0.008	0.013	0.060 ***	1.868	-0.012	-1.153 ***	0.626
FOHF – Relative value	0.142	0.139 ***	0.048	-1.586 ***	-2.306 ***	-0.018 **	0.009	0.009	0.013	2.963 **	-0.007	-0.927 ***	0.483

a. The regression mode: $R_t^k = \alpha_t^k + \sum_{i=1}^{8} \beta_i^k F_{i,t} + e_t^k$ where R_t^k is the excess return of a fund in month t and $F_{i,t}$ represents the monthly returns of eight factors, which are described above.

b. The asterisk symbols indicate the significance level of the test results, being significant at the 1% level "***", 5% level "**" and 10% level "*".

5.3.6 Tail risk exposure and fund characteristics

I further investigated the relationship between fund characteristics and the magnitude of their tail risk exposures. I applied additional filters to require all funds to report the variables used in equation 4. It should be noted that, in all the regression analysis performed, I use cross-sectional tail risk beta as a dependent variable. According to my specifications, the lower the value of tail risk beta, the higher the loss of a fund under a standard unit tail risk shock will be[33]. The regression results are reported in Table 5.11. When explaining the regression results, I have introduced only the characteristics that have significant coefficients.

Table 5.11 Cross-sectional regression of fund characteristics and fund tail risk exposures

	HF	FOF
Dependent variable[a]	Beta to HFTR	Beta to HFTR
Intercept	-0.551***[b]	-0.366*
Age	0.084***	0.198***
Size	-0.022	-0.001
Survivorship	-0.191***	-0.018
Incentive fees	-0.006	-0.054
Management fees	-0.044**	-0.097***
High-water mark	0.088	-0.144*
Closed to all	-0.074	-0.095
Leverage ratio	0.005	-0.032
Lockup months	0.013*	0.048***
Redemption frequency	0.107***	0.090**
Advance notice days	0.025	0.010
x24 month mean	0.054***	0.129***
x24 month volatility	-0.436***	-0.350***
Adj R^2	0.179	0.325

a. I run avregression 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).
b. The asterisk symbols indicate the significance level of the test results, being significant at the 1% level "***", 5% level "**" and 10% level "*".

[33] By construction, a negative HFTR beta indicates a loss caused by tail risk. Therefore, the lower the value of the HFTR beta, the higher the loss that will be caused by a unit increase of the tail risk in the hedge fund industry.

In general, tail-risk-sensitive hedge funds and FOFs share several characteristics, such as younger ages, higher management fees, and closure to new capital. In addition, tail risk exposure is positively related to restrictions on redemption. For both FOFs and hedge funds allowing more frequent redemptions and shorter lockup periods, the losses caused by HFTR exposure are higher. Living hedge funds have been found to be more tail sensitive; however, most of the defunct funds stopped reporting prior to the 2008 GFC. Finally, I found that FOFs that use a high-water mark (HWM) tend to suffer from increases in HFTR. A high-water mark works to reward fund managers for net profits (after the previous losses are recovered) so that a fund manager with a HWM has to balance the return and risk. To avoid extreme losses, an HF with an HWM in performance appraisal will tend to reduce their exposure to tail risk. This can be realised by either holding a more diversified portfolio or hedging for the tail risk exposure to a specific asset class; however, a FOF manager who wishes to avoid extreme losses might have difficulty managing exposure to HFTR. This is partially due to the lack of a hedging instrument for tail risk in the hedge fund industry. More importantly, as my previous findings suggest, the tail risk of individual hedge funds tends to be aggregated in the portfolio of a FOF. As a result, a FOF manager relying on diversification to control risk tends to load on higher exposure to tail risk in the hedge fund industry.

The findings in Table 5.11 are consistent with my intuition regarding fund tail risk exposure. For example, younger funds tend to gamble on tail risk events to improve track records for attracting more investments. The funds charging higher management fees have incentives to improve performance by taking higher tail risk exposure to compete with the other funds charging lower fees. If a fund is closed to new investors, the manager will lack an incentive to maintain a stable track record and would rather take on a higher risk for better returns. Additionally, funds requiring shorter lockup periods, a lower redemption frequency, or fewer lockup months are more likely to liquidate their positions at a loss to meet urgent redemption requirements.

5.4 Discussion

"...diversification implosion, although style exposures are still diverse, market exposures can converge" (Fung and Hsieh, 1997a, p. 300).

Intuitively, the skills of hedge fund managers show an enormous amount of variation and can be diversified in a FOF portfolio. As a result, FOFs gain returns mainly from their systematic risk exposure. We assume that a hedge fund return can be explained by the following factor model:

$$r_{i,t} = \sum_{k=1}^{K} \beta_{i,k} f_{k,t} + e_{i,t} \tag{5.5}$$

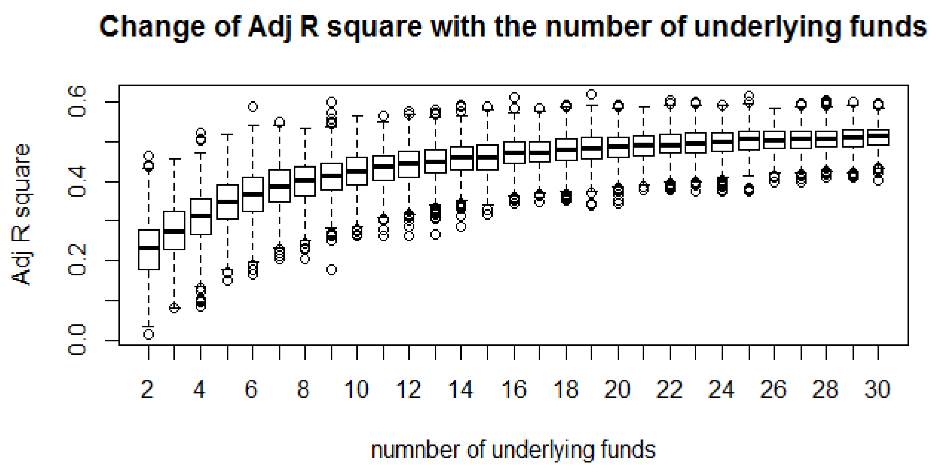
where $r_{i,t}$ is the return of fund i at time t, f_k is the kth factor that explains the fund return, and e_i is the residual of the model. According to my specifications, $\sum_{k=1}^{K} \beta_{i,k} f_{k,t}$ captures the return from the exposure to systematic risk. Furthermore, $e_{i,t}$ contains the return gained by fund managers' skills and other fund-specific risks that can be diversified. Now, assume a FOF manager who allocates a proportion w_i of his/her capital to the i^{th} fund in a pool of N hedge funds. Thus, the return of the FOF is given by

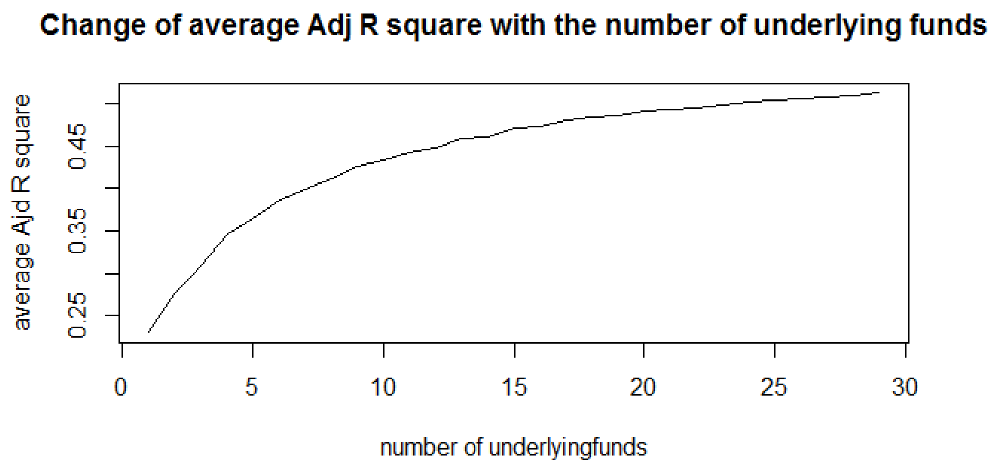
$$\sum_{i=1}^{N} w_i r_{i,t} = \sum_{i=1}^{N} \sum_{k=1}^{K} w_i \beta_{i,k} f_{k,t} + \sum_{i=1}^{N} w_i e_{i,t} \tag{5.6}$$

Given the diversification effect, $\sum_{i=1}^{N} w_i e_{i,t}$ moves close to zero, so the return of a hedge fund portfolio is further explained by its systematic risk exposures. Technically, I expect the R^2 of the multi-factor regression to increase with the number of underlying funds in the FOF.

I performed the following test to verify my proposition. First, I ranked all the funds according to their performance in the last two years and randomly selected two hedge funds in the top 10% to construct an equally weighted portfolio. The portfolio is liquidated and reconstructed at the end of every year following the same strategy. Eventually, I had a portfolio containing two hedge funds from the top 10% of the performing funds and named it the “base portfolio”. With replacement, I increased the number of the constituents of the base portfolio by one each time until there were 30 hedge funds in the portfolio. As such, I constructed 29 equally weighted FOFs with an increasing number of constituents. Second, I regressed the excess returns of the simulated FOFs on HFTR, controlling for the FH seven factors, and kept a record of the adjusted R^2s for each regression. Repeating the above process 1000 times so that I received 1000 observations, I adjusted R^2s for each group of the FOFs with the same number of constituents. The box plots of adjusted R^2 are depicted in Figure 5.6. This figure provides evidence on my proposition wherein the explanatory power of the multifactor model improves with the number of underlying funds.

Figure 5.6 Adjusted R^2 changes with the number of underlying funds

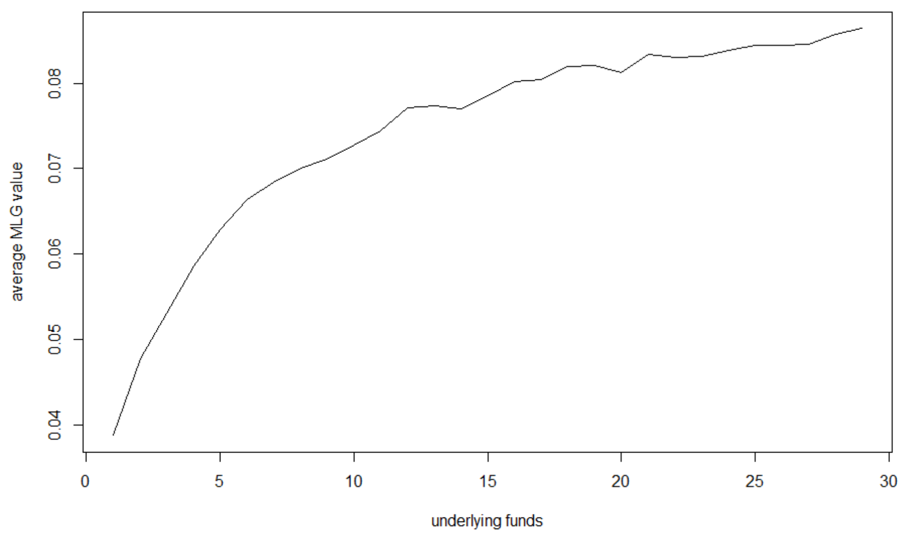




Next, I need to show that the change in adjusted R^2 is mainly or partially caused by the aggregation of tail risk. I refer to the rich literature on total variance decomposition to evaluate the contribution of HFTR to the total variance of the simulated FOFs. As the regressors in my model are correlated, I adopted the approach of Lindeman et al. (1980). A more well known name for this approach is “Shapley value regression”. Technically, each order of regressors yields a different decomposition of the model sum of squares. Thus, Lindeman et al. (1980) suggested measuring the relative importance of a specific regressor using the average of sequential sums of squares over orderings of regressors, which I call the LMG value in the remaining discussion. An explanation of the LMG value can be found in Appendix B.

I use the R package "*relaimpo*" developed by Grömping (2006) to calculate the LMG value for each simulated FOF and plotted the results in Figure 5.7. This figure shows the average LMG of the FOFs with the same number of underlying funds in the simulated tests. As shown in the chart, the mean LMG increases with the number of underlying funds. This observation provides evidence for my proposition that hedge fund tail risk aggregates in a well-diversified FOF portfolio. The results remain robust after adjusting various parameters, i.e., the number of constituents, the number of control factors, the repeating test times, sampling with or without replacement, and portfolio construction strategies.

Figure 5.7 Relative contribution of HFTR to total R^2



5.5 Conclusion

The objective of this chapter is to investigate the tail risk of FOFs relative to hedge funds. I constructed the hedge fund tail risk factor (HFTR) using monthly returns of 7,782 hedge funds. I examined the tail risk exposures at the individual fund level as well as the strategy level by comparing FOFs and hedge funds. The major research findings are summarised below.

My regression results using HFTR provide significant evidence against the tail risk management ability of FOF managers. At the individual FOF level, I found that the majority of my sample FOFs (83.79% of 4,275 FOFs) have significant negative exposure to HFTR during the sample period. At the portfolio level, all FOF portfolios exhibit significant negative exposure to this factor. This leads to the view that FOFs actually aggregate the tail risk from their constituent hedge funds. This result indicates that there is a limitation/negligence in tail risk management during the fund selection process of FOFs. In the regressions at both the individual fund level and the portfolio level, I documented significant enhancements in adjusted R-squares after HFTR was added. Thus, I suggest that HFTR is a systematic risk factor that influences the returns of both hedge funds and FOFs.

In addition, I documented a number of relationships between fund characteristics and tail risk exposure. I found that tail-risk-sensitive hedge funds and FOFs share some characteristics, such as younger ages, higher management fees, and closure to new capital. There are also unique characteristics that explain the cross-sectional HFTR beta variations in FOFs. For example, HFTR-sensitive FOFs use a high-water mark in performance evaluation.

My study highlights a few interesting issues subject to further investigation. For example, previous studies such as Jiang and Kelly (2012) and Agarwal, Ruenzi, and Weigert (2016) attempted to link the tail risk in hedge funds to the extreme events in the equity market. My results suggest that there are other sources of tail risk in the industry itself that are more critical for FOFs. In addition, my results show that the tail risk seems to be amplified at the FOF level despite the claim that the selection of funds by FOF managers is a result of due diligence and operation monitoring. How to effectively incorporate the tail risk in FOF managers' risk management practices obviously is a more challenging but important issue to the investment community.

Chapter 6: Can tail risk exposure predict the return of a fund of hedge funds in different market states?

6.1 Introduction

In this chapter, I investigate the extent to which the tail risk exposure of a fund of funds (FOF) is capable of predicting its return in the next period. The predictability of a hedge fund return is of great importance given the massive drawdowns of FOFs during the 2007–2008 GFC. FOFs were marketed as a conservative investment vehicle for retail investors to gain exposure to the hedge fund industry (Dai and Shawky, 2012). In particular, an investor with limited capital and lacking fund-selection skills can invest in multi-hedge funds via a single investment in a FOF. The growth in FOFs before the GFC was mainly driven by the trust that a FOF could help to secure the absolute returns of individual hedge funds and, in the meantime, reduce the excessive risks through diversification. Although doubts were raised in the early 2000s – see, for example, Lhabitant and Learned (2002), among others – it is the substantial losses of FOFs in the GFC that rang alarm bells that such believers might be too naïve. In recent decades, the hedge fund industry has experienced several systematic turbulences, and we have observed very strong industry contagions on each of these occasions. For example, the collapse of the Long-Term Capital Management (LTCM) hedge fund in 1998 finally led to large-scale capital withdrawals from the entire hedge fund industry. Another well-known example of massive capital withdrawals from the hedge fund industry occurred in 2008 with the revelation of the Ponzi scheme run by Madoff. According to Wilson (2015), the Madoff affair took a heavy toll on FOFs, even though most FOFs did not have direct exposure to Madoff. As shown in Chapter 5, FOFs tend to aggregate the tail risk in the underlying hedge funds, which means that a turmoil in the hedge fund market may eventually turn out to be a disaster for FOFs. Thus, understanding the tail risk in an FOF portfolio becomes a matter of urgency for both practitioners and researchers.

In practice, a FOF manager can hardly adjust the holdings when the market turns sharply weaker because of the many restrictions set by hedge funds on redemptions. Chapter 4 noted that most hedge funds allowed only monthly or quarterly redemptions. Moreover, they also required investors to give a redemption notice well before the redemption, i.e., 30 days, and there were quite a few hedge funds requiring a redemption notice to be given 60 to 120 days in advance. With such restrictions, a FOF manager normally has to wait at least one to two months to actually liquidate a position in an underlying fund. In a worst-case scenario, hedge funds may implement a gate[34] and/or suspension provision to handle the massive redemption caused by a market disruption, such as in the 2007–2008 GFC. As a result, the tail-risk-sensitive hedge funds may remain in a FOF's portfolio well after the shock of the tail risk event. Thus, it is reasonable to expect that the tail risk exposure of FOFs may possess certain predictive power on returns, at least during a bearish period.

In contrast, there is mounting literature on investors earning tail risk premiums in a variety of asset classes, such as equity (Chollete and Lu 2012; Kelly and Jiang 2014; Rauch and Alexander 2016) and fixed-income securities (Li and Song 2016). We have also documented in Chapter 5 that FOFs have significant exposure to the tail risk (measured by HFTR) in the hedge fund industry and charge a tail risk premium when

[34] A gate provision sets the maximum percentage of total assets that can be withdrawn on a scheduled redemption date (Stowell 2010), while a suspension provision bans all redemption requests for a certain period.

investing in hedge funds. If FOFs tend to lose during a bearish market period, we should expect them to be rewarded by writing tail risk insurance for the hedge funds in normal time, which means that the predictive power of tail risk exposure may exist in a normal or bullish period. Taken together, FOFs may benefit from tail risk exposure in a bullish market but suffer in a bearish market. Such a state-dependent relationship between FOF returns and tail risk exposure forms a challenge to performing predictability research on tail risk exposure under the traditional framework. Therefore, in this research, I will investigate the return predictive power of FOF tail risk exposure under different market states.

I followed two approaches that are generally adopted in research into hedge fund return predictability. First, I performed Fama and MacBeth's (1973) regression to investigate the relation between the tail risk exposure of a FOF and its return one, two, and three months ahead. Using ordinary least square (OLS) regression, I documented state-dependent predicting power in HFTR beta. I further performed quantile regression to examine whether the predictive power of tail risk exposure varies along the distribution of hedge fund returns. My results indicate that, controlling for Fung and Hsieh's seven factors, the tail risk beta significantly explains the FOFs' return in both low and high percentile in the next one to three months regardless of market states. I have also documented similar explanatory powers for the tail risk betas calculated on various rolling windows. Second, I sorted FOFs according to their tail risk exposures and constructed tail-risk-sensitive and insensitive portfolios. I found very significant differences between the portfolio returns assuming monthly, quarterly, semi-annual, and annual rebalancing frequency. My tests were performed over the whole sample period, bullish months and bearish months. In general, I found that the predictive power of tail risk exposure was marked under different market states but neutralised over the whole sample period.

This research contributes to the hedge fund return predictability literature in the following respects. First, I constructed a new tail risk factor, which directly measures the extreme movements in the hedge fund industry rather than the tail risk shocks in the equity market only. My measurement reflects a broader range of sources for the extreme losses in the hedge fund industry. Second, I presented evidence of the predictive power of FOF tail risk exposure. The results remain robust after controlling for Fung and Hsieh's seven factors. Third, I found that the possible losses to a unit HFTR exposure in a bearish market were double the gain of the same exposure in a bullish market. My results indicate a lack of hedging strategy for hedge fund tail risk. From a practical point of view, FOF investors and managers should be aware of the non-linear payoff from HFTR exposures.

The remainder of this paper is structured as follows. Section 2 describes the data and introduces my procedures to reduce hedge fund data bias. Section 3 presents the methodology and models. The results are discussed in Section 4, and I conclude the study in Section 5.

6.2 Description of approach

6.2.1 Identifying bullish and bearish months in the hedge fund market

In this paper, I apply the hidden Markov model (HMM) to identify bull and bear markets in the hedge fund industry. In the economics literature, HMM was introduced by Hamilton (1989) to model the business cycle in the US economy, and it was quickly adopted in financial studies for regime-dependent time-series modelling – see, for example, Thomas, Allen, and Morkel-Kingsbury (2002) and Rossi and Gallo (2006). In this study, I fit the two-state HMM to the HFRI Fund Weighted Composite Index from January 1995 to December 2012.

A standard HMM consists of a state space S, value space V, and a set of arrays $\lambda = (A, B, \pi)$. Let us define the following:

$S = (s_1 \dots s_k)$ to represent the k possible states;

$V = (v_1, v_2, \dots, v_n)$ to represent possible observation value;

$Q = (q_1, q_2, \dots, q_T)$ to be the hidden states sequence from time 1 to time T, taking value in the state space S; and

$O = (o_1, o_2, \dots, o_T)$ to be the space of the observed value from time 1 to time T, taking value in the value space V.

Furthermore, I define A as a transition array, sorting the probability of transition among the k states from time $t-1$ to time t:

$A = [a_{ij}],\ a_{ij} = P(q_t = s_i | q_{t-1} = s_j), i \in \{1, \dots, k\}, j \in \{1, \dots, k\}$

I set B as an emission array, sorting the probability of observing a return under state i at time t:

$$B = [b_i(k)],\ b_i(k) = P(o_t = v_k | q_t = s_i), i \in \{1, \dots, k\}, k \in \{1, \dots, n\}$$

Last, π is set as an initial probability array setting the probability of the initial market state:

$$\pi = [\pi_i], \pi_i = P(q_1 = s_i), i \in \{1, \dots, k\}$$

There are three types of questions where an HMM can be applied:

1. For the evaluation question where HMM λ and observation O are given, calculate the probability of the observation $P(O|\lambda)$;
2. For the decoding question where HMM λ and observation O are given, calculate the most likely state sequence $P(Q|O, \lambda)$;
3. For the learning or optimisation problem, where HMM λ and observation O are given, find another HMM λ_1 such that $P(O|\lambda_1) > P(O|\lambda)$.

My interest in Chapter 6 is to estimate the hidden state sequence Q given the observed value series O, which is a typical decoding problem as described above. The decoding question is usually solved using the Viberbi algorithm (Viterbi, 1967). In principle, Viberbi algorithm aims to find the maximum probability state path $Q = (q_1, q_2, \dots, q_T)$ that ends in state i at time T. This can be done by solving the best score function:

$$\boldsymbol{\delta_T(i) = \max_{q_1, q_2, \dots, q_{T-1}} P(q_1, q_2, \dots, q_T = i, o_1, o_2, \dots, o_T \mid \lambda)} \tag{6.1}$$

A recursive calculation is required to solve $\delta_T(i)$:

$$\boldsymbol{\delta_{T+1}(j) = \max_{i}[\delta_T(i)a_{ij}]b_i(o_{T+1})} \tag{6.2}$$

with initialization

$$\boldsymbol{\delta_1(i) = \pi_i b_i(o_1)} \tag{6.3}$$

and termination

$$\boldsymbol{P^* = \max_{1 \le i \le k}[\delta_T(i)]} \tag{6.4}$$

which means we start from the endpoint with the highest probability, and then backtrace from there to find the best path to the beginning. I used the R package *depmixS4* to implement the Viberbi algorithm and set $S = (s_1, s_2)$ to represent a state space with two states: bull market and bear market. For a detailed explanation of HMM and decoding a hidden state, please refer to Rabiner (1989).

6.2.2 Predictability tests: Fama and MacBeth cross-sectional test

I applied Fama and MacBeth's (1973) two-step regression to test the predictive power of HFTR; a recent similar application of the method can be found in Bali, Brown, and Caglayan (2011). At step one, for each FOF in the sample, I regressed its excess return against HFTR and various risk factors. An HFTR time series was generated following the description in Chapter 3. The mathematics representation of step one is as follows:

$$\boldsymbol{R_t^i = \alpha^i + \beta_t^{i,HFTR} HFTR_t + \sum_{k=1}^{n} \beta_t^{i,k} Control_t^k + \varepsilon_t^i} \tag{6.5}$$

R_t^i is the excess return of FOF i in month t, α^i is the intercept of the regression model, $HFTR_t$ is the hedge fund tail risk factor, $\beta_t^{i,HFTR}$ is the HFTR exposure of FOF i in month t, and $\beta_t^{i,k}$ represents the risk exposure to the kth controlling risk factor $Control_t^k$ for FOF i in month t. The test was performed on a fixed 24-month window moving one month ahead starting from January 1995. This process generated a time series of monthly HFTR beta for each FOF. At step two, I regressed the cross-sectional beta exposures in one month against the cross-sectional excess returns in the next month:

$$\boldsymbol{R_{t+1}^{i} - r_{t+1}^{f} = \omega_t + \theta_t^{HFTR}\beta_t^{i,HFTR} + \epsilon_{t+1}} \tag{6.6}$$

where ω_t and ϵ_{t+1} are the intercept and error term, respectively, $R_{t+1}^{i} - r_{t+1}^{f}$ is the excess return of FOF i in month $t + 1$, $\beta_t^{i,HFTR}$ is the tail risk exposure of FOF i in month t as estimated in equation 3, and θ_t^{HFTR} is the slope of the Fama–MacBeth regression. Finally, I calculated the average of θ_t^{HFTR} and tested its significance using the Newey–West t-test. I concluded the predictive power of tail risk exposure if the average θ_t^{HFTR} was significantly different from 0. To test the robustness, I performed the above procedures for $\beta_t^{i,HFTR}$ estimated over different lengths of moving windows, controlling for two sets of risk factors.

Hedge fund tail risk exposure takes effect on the occurrence of extreme events, which are described by the left tail of a return distribution. However, during a normal period, FOFs will earn a stable tail risk premium. Thus, my next question is whether the predictive power of HFTR exposure varies along different portions of a distribution. Technically, OLS regression is unable to answer this problem. Thus, I employed quantile regression, as described in Section 3.4.2. In particular, the quantile regression run in this chapter follows the representation below:

$$\boldsymbol{R_{t+1}^{i} - r_{t+1}^{f} = \omega_{q,t} + \theta_{q,t}^{HFTR}\beta_t^{i,HFTR} + \epsilon_{q,t+1}} \tag{6.7}$$

where $\omega_{q,t}$, $\epsilon_{q,t+1}$ and $\theta_{q,t}^{HFTR}$ are the intercept, the error term, and the slope of a quantile regression around the qth percentile of the cross-sectional FOF returns at time $t + 1$.

6.2.3 β^{HFTR} decile portfolio analysis

Following the approach of Jegadeesh and Titman (1993), I constructed decile portfolios based on tail risk exposure and tested the significance of the return difference between high and low tail risk portfolios. In particular, each month, decile portfolios of FOFs were formed according to the ascending order of tail risk beta calculated by equation 6.5. The portfolios were held during a period of t and then liquidated. The monthly returns of the portfolios were aggregated to form 10 monthly return-time series. To test whether previous tail risk exposure predicts the next period's return, I applied a t-test on the mean return of a long/short portfolio, which sells the high tail risk beta portfolio and purchases the tail risk beta portfolio since we are interested in negative betas. In my specifications, the lower the value of β^{HFTR} is, the higher the sensitivity to the hedge fund tail risk factor will be. Therefore, if the β^{HFTR} in the prior month predicts the next period's return, we should expect the next month's excess return of the long/short portfolio to be significantly lower than zero. It should be noted that the above-mentioned approach does not have practical implications, as there is no readily available facility through which one may short a FOF. Besides, it is very costly to form a portfolio of FOFs because of triple-layer fees. However, our interest here is whether different tail risk exposures may cause cross-sectional variation in the future return, and decile portfolio sorting can effectively serve this purpose.

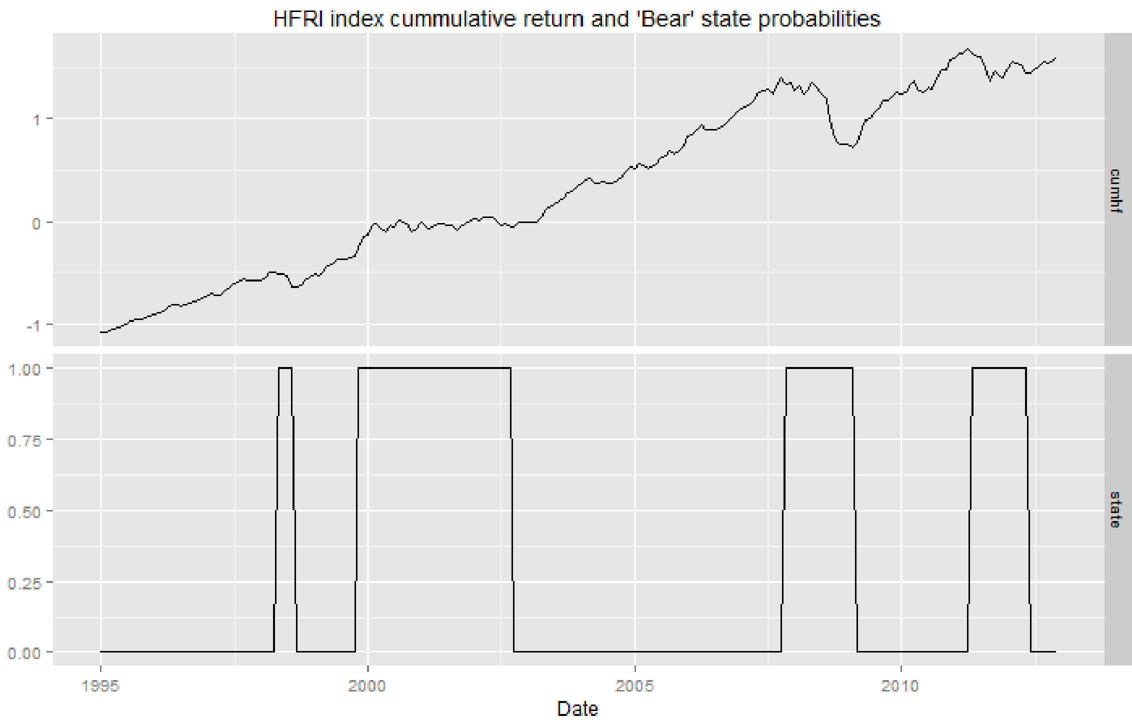
6.3 Empirical results

6.3.1 Bullish and bearish months in the hedge fund market

I classified the whole period from January 1995 to December 2012 into bullish and bearish periods by fitting a two-state HMM to an HFRI hedge fund composite index. The bearish period in the hedge fund industry contains the following 68 months: May to August 1998, November 1999 to September 2002, November 2007 to February 2009, and May 2011 to May 2012. Thus, the remaining months constitute the bullish period for the hedge fund market. In Figure 6.1, I plot the cumulative return of the HFTR hedge fund composite index from January 1995 to December 2012 in the top panel and the probability of the hedge fund market being bearish in the bottom panel.

Figure 6.1 HFRI hedge fund composite index cumulative return

The top panel of the diagram depicts the cumulative return of the HFTR hedge fund composite index from January 1995 to December 2012. Fitting the hidden Markov model (HMM) to the monthly return of the index, I classify the whole period into bullish and bearish periods. The probability of the hedge fund market being bearish is plotted in the bottom panel of the diagram.



As reflected in Figure 6.1, the bearish periods identified by the HMM are consistent with the major drops in the cumulative return of HFRI index, which also correspond to most of the tail-event shocks to the hedge fund industry, i.e., the Russian financial crisis in 1998, the dot.com bubble burst in the early 2000s, and the 2007–2008 GFC.

In reality, hedge fund managers are able to adjust portfolios when market conditions become unfavourable, but FOF managers have to lock in their positions for a longer period because of the various redemption restrictions being charged by hedge funds. Thus, it is expected that, in general, FOFs tend to underperform hedge funds when the overall hedge fund market falls in the bearish periods. In Table 6.1, I report the performance of hedge funds and FOFs under different market states.

The figures in Table 6.1 can be viewed as the performance of the equally weighted hedge fund and FOF strategy portfolios. In the following discussion, I refer to these portfolios using the names of fund strategies.[35] Over the sample period, the average monthly return of HFs is 0.927%, which is about 51% higher than the mean return of FOFs (0.613%). The difference in mean return drops in the bullish periods, where HFs yield a 1.433% average monthly return and FOFs yield a 1.079% average monthly return. However, during the bearish periods, FOFs incur a 0.402% monthly loss, which is about 2.3 times the average monthly loss of hedge funds (0.175%). Furthermore, FOFs do not show outstanding risk-diversification effects, as the variance of FOFs is consistently higher than that of hedge funds, notwithstanding the market states. Fung and Hsieh (2000) provided two possible justifications for the underperformance of FOFs. First, FOF investors have to pay management fees to both FOF managers and the managers of the hedge funds included in the FOF portfolio. The second-layer fee

[35] For example, HF represents an equally weighted hedge fund portfolio.

is suggested to be a reward for fund-selection skills and the due diligence applied by FOF managers (Ang et al., 2008), but, on average, it reduces the returns of FOFs. Second, FOF data are less subject to survivorship bias and back-selection bias than are hedge funds. That is, the return of a FOF usually contains unsatisfactory returns that are hidden from a data vendor by the hedge funds. This is especially the case when the market is in a bearish state, and it might lead to an abrupt decrease in the average return of FOFs in bearish periods, as reflected in Table 1. The observations in Table 1 indicate that most of the hedge fund and FOF strategy portfolios are not able to deliver positive returns in the bearish periods. The only exceptions are systematic futures, volatility and macro HFs, and macro/systematic FOFs.

Table 6.1 The performance of hedge funds (HFs) and funds of funds (FOFs) under different market states

This table reports the performance of equally weighted HF and FOF portfolios in different periods. The whole period is between January 1995 and December 2012. The whole period is partitioned into bullish and bearish periods according to the hedge fund market states identified by a hidden Markov model. The bearish periods include May to August in 1998, November 1999 to September 2002, November 2007 to February 2009, and May 2011 to May 2012. The remaining periods are classified as bullish periods.

		Number of funds	Whole Period Performance			Bullish Periods Performance			Bearish Periods Performance		
			Mean	Variance	Normality test[a]	Mean	Variance	Normality test	Mean	Variance	Normality test
HF strategy portfolios	**HFs**	**7782**	**0.927**	**6.483**	**0.978*****	**1.433**	**4.273**	**0.993**	**-0.175**	**9.628**	**0.978**
	Debt	969	0.741	4.726	0.829***	1.161	2.561	0.973***	-0.172	8.309	0.758***
	Equity	4256	0.990	11.561	0.976***	1.680	6.470	0.995	-0.511	19.567	0.979
	Event driven	487	0.909	5.266	0.896***	1.459	2.730	0.978**	-0.289	8.786	0.898***
	Multi-strategy	637	0.810	4.474	0.917***	1.229	2.578	0.965***	-0.103	7.468	0.928***
	Systematic futures	700	1.044	15.587	0.983**	0.991	15.917	0.990	1.158	15.076	0.944***
	Volatility	50	1.248	50.075	0.479***	1.316	61.563	0.416***	1.115	28.160	0.689***
	Macro	683	0.793	3.538	0.993	1.055	3.380	0.990	0.224	3.456	0.988
FOF strategy portoflios	**FOFs**	**4275**	**0.613**	**6.576**	**0.957*****	**1.079**	**4.435**	**0.987**	**-0.402**	**9.846**	**0.953****
	Macro/systematic	360	0.720	7.576	0.990	0.823	7.075	0.985*	0.496	8.712	0.981
	Debt	208	0.551	5.711	0.901***	1.027	3.542	0.974***	-0.485	8.968	0.862***
	Equity	1192	0.642	9.569	0.964***	1.225	5.721	0.990	-0.625	15.775	0.965*
	Event	210	0.592	4.737	0.912***	1.083	2.903	0.957***	-0.478	7.137	0.912***
	Multi-strategy	2117	0.590	6.430	0.942***	1.040	4.511	0.982**	-0.387	9.322	0.915***
	Relative value	188	0.518	3.961	0.901***	0.844	2.750	0.966***	-0.192	5.929	0.842***

a. Shapiro-Wilk normality test was applied to test the normality of return distributions. The asterisk symbols indicate the significance level of the test results, being significant at the 1% level “***”, 5% level “**” and 10% level “*”.

6.3.2 Fama–Macbeth cross-sectional OLS regression results

I tested the predictive power of HFTR in cross sections using Fama and MacBeth's two-step tests. Based on equation 3, I generated $\beta_t^{i,HFTR}$ for each FOF, controlling for Fung and Hsieh's (2004a) seven factors. To test the robustness, I changed the estimation window for $\beta_t^{i,HFTR}$ from 12 months to 18, 24, 30, 36, and 48 months. Next, I operated cross-sectional regressions, according to equation 4, for one month ahead of excess returns R_{t+1}^{i} on the cross section of β_t^{HFTR}. This helped to generate a time series of θ_t^{HFTR}. In this step, I estimated θ_t^{HFTR} during the whole sample period, both bullish periods and bearish periods. I used Newey–West (1987) t-statistics to examine the significance of mean θ_t^{HFTR}, and the results are reported in Panel A of Table 6.2. Furthermore, I performed the same procedure using 10 factors as controlling variables when estimating $\beta_t^{i,HFTR}$. The results of 10-factor β^{HFTR} are reported in Panel B of Table 6.2.

It is worth clarifying the implication of the average θ_t^{HFTR}. Recall that the value of HFTR is positively related to the level of tail risk in the hedge fund industry. In other words, the higher the HFTR is, the higher the chance is that the industry will experience a tail risk shock. It follows that $\beta_t^{i,HFTR}$ takes a negative value if fund i incurs a loss when tail risk increases. Thus, the lower the value of $\beta_t^{i,HFTR}$ is, the higher the exposure of a FOF to tail risk movements in the hedge fund market will be. Finally, θ_t^{HFTR} measured how $\beta_t^{i,HFTR}$ was related to the next month's return, R_{t+1}^{i}. A positive θ_t^{HFTR} indicated a positive relation between the two values; e.g., a large exposure to HFTR in the prior month led to a loss in the next month. Conversely, a negative θ_t^{HFTR} suggested that a large exposure to HFTR in the prior month led to a gain in the next month.

Table 6.2 Fama–Macbeth cross-sectional regressions of one-month-ahead fund of fund (FOF) returns on hedge fund tail risk factor (HFTR) beta under different market states

This table reports the average slope coefficients of Fama–Macbeth (1973) cross-sectional regressions of one-month-ahead FOF returns on the HFTR beta. Monthly HFTR betas (β^{HFTR}) are estimated for each FOF following $R_t^i = \alpha^i + \beta_t^{i,HFTR} HFTR_t + \sum_{k=1}^{n} \beta_t^{i,k} Control_t^k + \varepsilon_t^i$ where R_t^i is the excess return of FOF i in month t, α^i is the intercept of the regression model, $HFTR_t$ is the hedge fund tail risk factor, $\beta_t^{i,HFTR}$ is the HFTR exposure of FOF i in month t, and $\beta_t^{i,k}$ represents the risk exposure to the kth controlling risk factor $Control_t^k$ for FOF i in month t. The time series of β^{HFTR} are estimated over fixed 12-month, 18-month, 24-month, 30-month, 36-month, and 48-month rolling windows, respectively. Next, the cross-section of one-month-ahead funds' excess returns are regressed on the funds' β^{HFTR} in each month. The average slope coefficients of the cross-sectional regressions are tested by Newey–West (1987) t-statistics for significance. The whole period is partitioned into bullish and bearish periods according to the hedge fund market states identified by the hidden Markov model. The bearish periods include May to August in 1998, November 1999 to September 2002, November 2007 to February 2009, and May 2011 to May 2012. The remaining periods are classified as bullish periods.

Rolling window width	12 months	18 months	24 months	30 months	36 months	48 months
Panel A: average slope coefficients of the β^{HFTR} estimated controlling for Fung and Hsieh (2004a) seven factors						
Bearish period	0.164**[a]	0.331**	0.342**	0.233	0.218	0.177
Bullish period	-0.102**	-0.170**	-0.175**	-0.133	-0.128	-0.143
Whole period	-0.013	0.002	0.008	0.001	0.003	-0.021
Panel B: average slope coefficients of the β^{HFTR} estimated controlling for ten factors[b]						
Bearish period	0.017	0.265**	0.305**	0.293**	0.287*	0.173
Bullish period	-0.021	-0.121**	-0.167**	-0.123	-0.106	-0.130
Whole period	-0.008	0.011	0.000	0.029	0.042	-0.014

a. The asterisk symbols indicate the significance level of the test results, being significant at the 1% level "***", 5% level "**" and 10% level "*".

b. The ten factors include the seven factors in Panel A, Fama–French momentum factor, the innovation in Pastor and Stambaugh (2003) aggregate liquidity factor, and the monthly returns of VIX.

I documented interesting findings in Table 6.2. Controlling for seven factors and 10 factors, I found that short-term $\beta^{HFTR}s$ have very significant predictive power in either bullish or bearish periods but nil over the whole sample period. As reported in Panel B, the value of θ_t^{HFTR} for 12-, 18-, and 24-month β^{HFTR} is significantly positive during the bearish periods but significantly negative during the bullish periods. In other words, if a FOF takes large exposure to HFTR in the previous 12, 18, or 24 months, it tends to gain in the next month if the market is bullish but suffers losses if the market state turns bearish in the next month. Moreover, I found that the absolute value of average θ_t^{HFTR} during the bearish periods was more than double the average θ_t^{HFTR} in the bullish periods. This means, for a FOF taking a bet on the next month's market state, e.g., $\beta_t^{i,HFTR} = -1$, its next month's tail risk loss if the market turns bearish is more than double its possible gain if the market stays bullish. This finding is consistent with my claim in Section 4.2.3 that FOFs write crash insurance to hedge funds. Finally, because the length of bullish periods (150 months) is approximately double that of bearish periods (68 months), the bullish gains are large enough to offset the bearish losses. Thus, I could not find any significant evidence of the predictive power of HFTR exposure over the whole sample period.

Hedge funds are low-liquid assets thanks to the various restrictions on fund redemptions – such as long redemption frequency, lockups, and advance-notice requirements. Therefore, typical FOF managers can hardly rebalance their position promptly even if they have perceived high tail risk shocks in the industry. In light of this practical issue, I investigate the predictive power of HFTR beta over longer periods. In particular, I perform the same procedures as described for Table 6.2, but I use two-months-ahead and three-months-ahead cross-sectional returns as the dependent variables in Fama–MacBeth regressions. The regression results are reported in Table 6.3 and Table 6.4, respectively.

Table 6.3 Fama–Macbeth cross-sectional regressions of one-month-ahead fund of fund (FOF) returns on the hedge fund tail risk factor (HFTR) beta under different market states

This table reports the average slope coefficients of Fama–Macbeth (1973) cross-sectional regressions of one-month-ahead FOF returns on the HFTR beta. Monthly HFTR betas (β^{HFTR}) are estimated for each FOF following $R_t^i = \alpha^i + \beta_t^{i,HFTR} HFTR_t + \sum_{k=1}^{n} \beta_t^{i,k} Control_t^k + \varepsilon_t^i$ where R_t^i is the excess return of FOF i in month t, α^i is the intercept of the regression model, $HFTR_t$ is the hedge fund tail risk factor, $\beta_t^{i,HFTR}$ is the HFTR exposure of FOF i in month t, and $\beta_t^{i,k}$ represents the risk exposure to the kth controlling risk factor $Control_t^k$ for FOF i in month t. The time series of β^{HFTR} are estimated over fixed 12-month, 18-month, 24-month, 30-month, 36-month, and 48-month rolling windows, respectively. Next, the cross-section of one-month-ahead funds' excess returns are regressed on the funds' β^{HFTR} in each month. The average slope coefficients of the cross-sectional regressions are tested by Newey–West (1987) t-statistics for significance. The whole period is partitioned into bullish and bearish periods according to the hedge fund market states identified by the hidden Markov model. The bearish periods include May to August in 1998, November 1999 to September 2002, November 2007 to February 2009, and May 2011 to May 2012. The remaining periods are classified as bullish periods.

Rolling window width	12 months	18 months	24 months	30 months	36 months	48 months
Panel A: average slope coefficients of the β^{HFTR} estimated controlling for Fung and Hsieh's (2004a) seven factors						
Bearish period	0.164**[a]	0.331**	0.342**	0.233	0.218	0.177
Bullish period	-0.102**	-0.170**	-0.175**	-0.133	-0.128	-0.143
Whole period	-0.013	0.002	0.008	0.001	0.003	-0.021
Panel B: average slope coefficients of the β^{HFTR} estimated controlling for ten factors[b]						
Bearish period	0.017	0.265**	0.305**	0.293**	0.287*	0.173
Bullish period	-0.021	-0.121**	-0.167**	-0.123	-0.106	-0.130
Whole period	-0.008	0.011	0.000	0.029	0.042	-0.014

a. The asterisk symbols indicate the significance level of the test results, being significant at the 1% level "***", 5% level "**" and 10% level "*".
b. The ten factors include the seven factors in Panel A, Fama–French momentum factor, the innovation in Pastor and Stambaugh (2003) aggregate liquidity factor, and the monthly returns of VIX.

Table 6.4 Fama–Macbeth cross-sectional regressions of two-months-ahead fund of fund (FOF) returns on the hedge fund tail risk factor (HFTR) beta under different market states

This table reports the average slope coefficients of Fama–Macbeth (1973) cross-sectional regressions of one-month-ahead FOF returns on the HFTR beta. Monthly HFTR betas (β^{HFTR}) are estimated for each FOF following $R_t^i = \alpha^i + \beta_t^{i,HFTR} HFTR_t + \sum_{k=1}^{n} \beta_t^{i,k} Control_t^k + \varepsilon_t^i$ where R_t^i is the excess return of FOF i in month t, α^i is the intercept of the regression model, $HFTR_t$ is the hedge fund tail risk factor, $\beta_t^{i,HFTR}$ is the HFTR exposure of FOF i in month t, and $\beta_t^{i,k}$ represents the risk exposure to the kth controlling risk factor $Control_t^k$ for FOF i in month t. The time series of β^{HFTR} are estimated over fixed 12-month, 18-month, 24-month, 30-month, 36-month, and 48-month rolling windows, respectively. Next, the cross-section of one-month-ahead funds' excess returns are regressed on the funds' β^{HFTR} in each month. The average slope coefficients of the cross-sectional regressions are tested by Newey–West (1987) t-statistics for significance. The whole period is partitioned into bullish and bearish periods according to the hedge fund market states identified by the hidden Markov model. The bearish periods include May to August in 1998, November 1999 to September 2002, November 2007 to February 2009, and May 2011 to May 2012. The remaining periods are the bullish periods.

Rolling window width	12 months	18 months	24 months	30 months	36 months	48 months
Panel A: average slope coefficients of the β^{HFTR} estimated controlling for Fung and Hsieh's (2001) seven factors						
Bearish period	0.116	0.310**	0.315**	0.190	0.097	0.242
Bullish period	-0.097***	-0.199***	-0.146**	-0.108	-0.110	-0.146
Whole period	-0.025	-0.023	0.018	0.002	-0.031	0.002
Panel B: average slope coefficients of the β^{HFTR} estimated controlling for ten factors[b]						
Bearish period	0.030	0.330***	0.333**	0.276**	0.210	0.235
Bullish period	-0.025	-0.158***	-0.127	-0.094	-0.101	-0.135
Whole period	-0.006	0.010	0.037	0.042	0.017	0.006

a. The asterisk symbols indicate the significance level of the test results, being significant at the 1% level "***", 5% level "**" and 10% level "*".
b. The ten factors include the seven factors in Panel A, Fama–French momentum factor, the innovation in Pastor and Stambaugh (2003) aggregate liquidity factor, and the monthly returns of VIX.

As reflected in Table 6.3, short-term $\beta^{HFTR}s$, especially the betas after controlling for other risk factors, remain significant in predicting the two-months-ahead returns in bullish and bearish markets separately. I still cannot observe any predictability in the whole sample period. For three-months-ahead returns, as shown in Table 6.4, the predictive power of $\beta^{HFTR}s$ almost disappears, except for the β^{HFTR} estimated over an 18-month moving window.

6.3.3 Fama–Macbeth cross-sectional quantile regression results

Compared with OLS regression, quantile regression generates better estimation along the tails of a distribution. Thus, I repeat the second step test in Section 6.3.2, the cross-sectional regression, using quantile regression around the 10th, 20th, …., 90th percentile of the cross-sectional FOF excess returns. Eventually, I generated nine time series of $\theta_{q,t}^{HFTR}$. For each series of $\theta_{q,t}^{HFTR}$, I tested the significance of the mean using Newey–West (1987) *t* statistics. I operated cross-sectional quantile regression for the excess returns one, two, and three months ahead separately, and the results are reported in Table 6.5.

Panel A reports the significance of average $\theta_{q,\mathrm{t}}^{HFTR}$ using one-month-ahead return as a dependant variable. I found during the bearish period that the returns of the FOFs below the 50th percentile were significantly related to the tail risk exposure β^{HFTR} in the previous month, whereas the returns of FOFs above the 50th percentile did not show such a relationship. Moreover, all the significant average $\theta_{q,\mathrm{t}}^{HFTR}$s are positive, which indicates higher losses caused by an increase in tail risk exposure. In contrast, when the market state turns bullish, all the average $\theta_{q,\mathrm{t}}^{HFTR}$s of the FOFs in the above 40th percentiles become significantly negative, while the average $\theta_{q,\mathrm{t}}^{HFTR}$s of the lower percentiles become insignificant. As I have pointed out in the previous section, a positive $\theta_{q,\mathrm{t}}^{HFTR}$ indicates gains on higher tail risk exposure.

Table 6.5 Cross-sectional quantile regressions of fund of fund returns on hedge fund tail risk factor (HFTR) beta

This table reports the average slope coefficients of Fama–Macbeth (1973) cross-sectional regressions of one-month, two-months, and three-months-ahead FOF returns on the HFTR beta. Monthly HFTR betas (β^{HFTR}) are estimated for each FOF following $R_t^i = \alpha^i + \beta_t^{i,HFTR} HFTR_t + \sum_{k=1}^{n} \beta_t^{i,k} Control_t^k + \varepsilon_t^i$ where R_t^i is the excess return of FOF i in month t, α^i is the intercept of the regression model, $HFTR_t$ is the hedge fund tail risk factor, $\beta_t^{i,HFTR}$ is the HFTR exposure of FOF i in month t, and $\beta_t^{i,k}$ represents the risk exposure to the kth controlling risk factor $Control_t^k$ [a]for FOF i in month t. The time series of β^{HFTR} are estimated over a fixed 24-month rolling window. Next, the cross-section of one-month, two-months, and three-months-ahead funds' excess returns are regressed on the funds' β^{HFTR} in each month. The average slope coefficients of the cross-sectional regressions are tested by Newey–West (1987) t-statistics for significance. The whole period is partitioned into bullish and bearish periods according to the hedge fund market states identified by the hidden Markov model. The bearish periods include May to August in 1998, November 1999 to September 2002, November 2007 to February 2009, and May 2011 to May 2012. The remaining periods are classified as bullish periods.

Panel A: Predicting one-month-ahead return

	Quantile regression percentiles								
Sample period	10th	20th	30th	40th	50th	60th	70th	80th	90th
Bear	0.81***[a]	0.67***	0.49***	0.41***	0.30***	0.19	0.05	-0.08	-0.10
Bull	0.04	-0.03	-0.09	-0.17***	-0.22***	-0.28***	-0.36***	-0.46***	-0.48***
Whole	0.31***	0.22***	0.11	0.03	-0.03	-0.11	-0.22***	-0.33***	-0.34***

Panel B: Predicting two-months-ahead return

	Quantile regression percentiles								
Sample period	10th	20th	30th	40th	50th	60th	70th	80th	90th
Bear	0.83***	0.66***	0.50***	0.40***	0.30*	0.18	0.04	-0.09	-0.18
Bull	0.06	0.00	-0.06	-0.14*	-0.19***	-0.25***	-0.33***	-0.38***	-0.44***
Whole	0.33***	0.24***	0.14*	0.06	-0.02	-0.10	-0.20***	-0.28***	-0.35***

Panel C: Predicting three-months-ahead return

	Quantile regression percentiles								
Sample period	10th	20th	30th	40th	50th	60th	70th	80th	90th
Bear	0.81***	0.69***	0.55***	0.42***	0.33***	0.22	0.08	-0.05	-0.18
Bull	0.14*	0.03	-0.03	-0.09	-0.16*	-0.21***	-0.24***	-0.32***	-0.34***
Whole	0.38***	0.27***	0.17***	0.09	0.01	-0.06	-0.13	-0.22***	-0.29***

a. The asterisk symbols indicate the significance level of the test results, being significant at the 1% level "***", 5% level "**" and 10% level "*".

For the whole sample period, I documented significant positive $\theta_{q,\mathrm{t}}^{HFTR}$s along the left tail (the10th and 20th percentile) but significant negative $\theta_{q,\mathrm{t}}^{HFTR}$s along the right tail (the 70th, 80th, and 90th percentile). This result indicates a non-linear relationship between β^{HFTR} and FOF the next period's return. In general, if an investor invests in a FOF with significantly low β^{HFTR}, the next month's return from the fund tends to two extremes: either gaining from tail risk exposure and outperforming other FOFs or losing substantially because of tail risk so as to drop in the lower percentile of the industry. My quantile regression result remained robust for both two-months- and three-months-ahead returns, as reported in Panels B and C of Table 6.5.

I also performed other robustness tests, including estimating β^{HFTR} controlling for more risk factors (as reported in Table 6.6) and a rolling window size varying between 12 and 48 months, and received very stable results. In summary, I confirm that β^{HFTR} possesses return predictive power when the future market state is clear. However, if an investor randomly selects a FOF with significantly low β^{HFTR} without knowing the market state in the next period, the return should be largely unpredictable. In the next section, I will perform decile portfolio construction to further investigate the predictive power of β^{HFTR}.

Table 6.6 Cross-sectional quantile regressions of fund of fund returns on hedge fund tail risk factor (HFTR) beta controlling for ten risk factors[a]

This table reports the average slope coefficients of Fama–Macbeth (1973) cross-sectional regressions of one-month, two-months, and three-months-ahead FOF returns on the HFTR beta. Monthly HFTR betas (β^{HFTR}) are estimated for each FOF following $R_t^i = \alpha^i + \beta_t^{i,HFTR} HFTR_t + \sum_{k=1}^{n} \beta_t^{i,k} Control_t^k + \varepsilon_t^i$ where R_t^i is the excess return of FOF i in month t, α^i is the intercept of the regression model, $HFTR_t$ is the hedge fund tail risk factor, $\beta_t^{i,HFTR}$ is the HFTR exposure of FOF i in month t, and $\beta_t^{i,k}$ represents the risk exposure to the kth controlling risk factor $Control_t^k$ [a]for FOF i in month t. The time series of β^{HFTR} are estimated over a fixed 24-month rolling window. Next, the cross-section of one-month, two-months, and three-months-ahead funds' excess returns are regressed on the funds' β^{HFTR} in each month. The average slope coefficients of the cross-sectional regressions are tested by Newey–West (1987) t-statistics for significance. The whole period is partitioned into bullish and bearish periods according to the hedge fund market states identified by the hidden Markov model. The bearish periods include May to August in 1998, November 1999 to September 2002, November 2007 to February 2009, and May 2011 to May 2012. The remaining periods are classified as bullish periods.

Panel A: Predicting one-month-ahead return									
	Quantile regression percentiles								
Sample	10th	20th	30th	40th	50th	60th	70th	80th	90th
Bear	0.72***b	0.59***	0.45***	0.34***	0.24	0.15	0.03	-0.09	-0.03
Bull	0.00	-0.04	-0.12	-0.17***	-0.21***	-0.25***	-0.32***	-0.36***	-0.38***
Whole	0.26***	0.18***	0.08	0.01	-0.05	-0.11	-0.20***	-0.27***	-0.26***
Panel B: Predicting two-months-ahead return									
	Quantile regression percentiles								
Sample	10th	20th	30th	40th	50th	60th	70th	80th	90th
Bear	0.79***	0.66***	0.50***	0.38***	0.29*	0.19	0.07	-0.06	-0.15
Bull	0.04	-0.04	-0.09	-0.14*	-0.19***	-0.24***	-0.27***	-0.30***	-0.31***
Whole	0.31***	0.21***	0.12	0.05	-0.02	-0.08	-0.15*	-0.22***	-0.25***
Panel C: Predicting three-months-ahead return									
	Quantile regression percentiles								
Sample	10th	20th	30th	40th	50th	60th	70th	80th	90th
Bear	0.78***	0.65***	0.51***	0.41***	0.30*	0.19	0.09	-0.01	-0.10
Bull	0.05	0.01	-0.04	-0.10	-0.15*	-0.18***	-0.21***	-0.25***	-0.28***
Whole	0.31***	0.24***	0.16*	0.08	0.01	-0.05	-0.10	-0.16*	-0.21***

a. The ten factors include the Fung and Hsieh (2004a) seven factors, Fama–French momentum factor, the innovation in Pastor and Stambaugh (2003) aggregate liquidity factor, and the monthly returns of VIX.

b. The asterisk symbols indicate the significance level of the test results, being significant at the 1% level "***", 5% level "**" and 10% level "*".

6.3.4 Decile portfolio analysis of HFTR betas

Decile portfolio analysis has been widely adopted in return predictability analysis (Bali, Brown and Caglayan 2011) and performance persistence analysis (Capocci, Corhay and Hubner 2005; Capocci, 2009). The central idea is that, if a factor possesses return predictive power, portfolios with heavy exposures to this factor will perform distinctly from those with weak factor loadings. With respect to my research purpose, I expected the portfolios with heavy negative HFTR loadings to generate lower returns than those less sensitive to HFTR. Based on my findings in the previous section, short-term β^{HFTR} exhibits more significant state-dependent predictive powers. Thus, I started my tests using β^{HFTR} estimated on rolling 24-month windows. I performed the test over the whole sample period – both bearish periods and bullish periods – and the results are correspondingly summarised in Panels A, B, and C of Table 6.7.

In each panel, I report the post-sorting portfolio β^{HFTR}, alpha, and average excess return for each decile portfolio. The decile portfolios are numbered from 1 to 10, sorting in ascending order of their HFTR exposures in the prior month. Therefore, portfolio 1 contains all the FOFs with the largest loadings (lowest negative β^{HFTR}) on HFTR in the prior month, while portfolio 10 comprises the FOFs with the lowest HFTR loadings in the prior month. In the last column, I report the three performance measurements of the portfolio constructed by taking a long position in portfolio 1 and a short position in portfolio 10. I analysed the results by comparing the value of each performance measurement across different periods.

Table 6.7 Decile portfolios sorted by the risk exposure (β^{HFTR}) to the hedge fund tail risk factor (HFTR)

The decile portfolios are formed every month from Jan 1997 to Dec 2012 by sorting funds of hedge funds (FOF) based on their 24-month β^{HFTR}. Monthly HFTR betas (β^{HFTR}) are estimated for each FOF following $R_t^i = \alpha^i + \beta_t^{i,HFTR} HFTR_t + \sum_{k=1}^{n} \beta_t^{i,k} Control_t^k + \varepsilon_t^i$ where R_t^i is the excess return of FOF i in month t, α^i is the intercept of the regression model, $HFTR_t$ is the hedge fund tail risk factor, $\beta_t^{i,HFTR}$ is the HFTR exposure of FOF i in month t, and $\beta_t^{i,k}$ represents the risk exposure to the kth controlling risk factor $Control_t^k$ for FOF i in month t. All regressions in this table are based on eight factors including Fung and Hsieh's (2004a) seven factors and HFTR. Panel A reports β^{HFTR}, average excess return, and eight-factor alpha for each decile portfolio over the whole period. The low value of β^{HFTR} represent high sensitivity to HFTR and vice versa. In addition, the last column reports the performance of the portfolio formed by longing portfolio 1 and shorting portfolio 10. The whole period is partitioned into bullish and bearish periods according to the hedge fund market states identified by the hidden Markov model. Panel B and Panel C report the performance of the decile portfolios in the bearish periods and bullish periods, respectively. The significance of each value is tested using Newey–West (1987) t-statistics.

	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	**Low-High**
Panel A: Whole period (Jan 1997–Dec 2012)											
Post sorting β^{HFTR}	-2.266***[a]	-1.896***	-1.722***	-1.371***	-1.216***	-0.91***	-0.801***	-0.723***	-0.721***	-0.654***	**-1.612*** **
Next month's av. excess return	0.227	0.382	0.373	0.346	0.383*	0.308*	0.273*	0.24*	0.275*	0.284*	**-0.057**
Next month's eight-factor alpha	-0.099	0.063	0.09	0.091	0.167	0.147	0.134	0.115	0.156*	0.177	**-0.276**
Panel B: Bearish period (May to August 1998, November 1999 to September 2002, November 2007 to February 2009, and May 2011 to May 2012)											
Post sorting β^{HFTR}	-2.569***	-1.998***	-1.958***	-1.696***	-1.576***	-1.117***	-0.959***	-0.802***	-0.819***	-0.736***	**-1.833*** **
Next month's av. excess return	-1.361**	-0.853	-0.829	-0.738	-0.561	-0.418	-0.481	-0.443	-0.373	-0.234	**-1.127*** **
Next month's seven-factor alpha	-0.141	0.059	0.077	0.07	0.158	0.14	0.08	0.052	0.108	0.227	**-0.369**
Panel C: Bullish period (the whole period excluding the bearish periods stated in panel B)											
Post sorting β^{HFTR}	-2.128***	-1.869***	-1.6***	-1.172***	-0.973***	-0.762***	-0.657***	-0.629***	-0.619***	-0.581***	-1.574***
Next month's av. excess return	1.097***	1.059***	1.032***	0.941***	0.901***	0.706***	0.687***	0.615***	0.63***	0.568***	0.530**
Next month's seven-factor alpha	0.015	0.017	0.079	0.083	0.201*	0.114	0.201**	0.152	0.197**	0.131	-0.116
	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	**High-Low**

a. The asterisk symbols indicate the significance level of the test results, being significant at the 1% level "***", 5% level "**" and 10% level "*".

First, the results indicate very strong persistence in HFTR betas. In all three panels, the post-sorting HFTR betas monotonically increase from portfolio 1 to portfolio 10. This means that, if a FOF has high HFTR in the previous month, it tends to load on similar exposure in the following month. The persistence is well known under different market states.

Second, the excess returns of the decile portfolios are found to be state-dependent. According to Panel A, the next month's excess returns of the portfolios taking lower HFTR loadings (portfolio 6 to portfolio 10) are significantly higher than 0 at the 10% significance level. In contrast, the FOFs with higher tail risk exposure fail to generate significant excess returns. Separating bearish months and bullish months, the results in Panel B and Panel C deliver a more interesting message. During the bearish months, portfolio 1, which loads on the highest tail risk, suffers a significant loss of around 1.361% in the next month, while other portfolios deliver insignificant excess returns. In contrast, during the bullish months, all portfolios have generated significant positive excess returns, and the returns are monotonically descending from portfolio 1 to portfolio 10. Focusing on the performance of low/high portfolio, I find that the low portfolio significantly outperformed the high portfolio in bullish periods but underperformed the high portfolio in bearish periods. These results suggest that HFTR exposure performs well insofar as predicting the return of FOFs under different market states.

Last, the results of alpha across all portfolios in the three panels are mostly insignificant. The only exception is portfolio 9, which earns significant alpha over the whole sample period and also during the bullish months.

Table 6.8 Fama–Macbeth cross-sectional regressions of strategy-classified fund of fund (FOF) returns on hedge fund tail risk factor (HFTR) beta under different market states

This table reports the average slope coefficients of Fama–Macbeth (1973) cross-sectional regressions of strategy classified FOF returns on the HFTR beta. Monthly HFTR betas (β^{HFTR}) are estimated for each FOF following $R_t^i = \alpha^i + \beta_t^{i,HFTR} HFTR_t + \sum_{k=1}^{n} \beta_t^{i,k} Control_t^k + \varepsilon_t^i$ where R_t^i is the excess return of FOF i in month t, α^i is the intercept of the regression model, $HFTR_t$ is the hedge fund tail risk factor, $\beta_t^{i,HFTR}$ is the HFTR exposure of FOF i in month t, and $\beta_t^{i,k}$ represents the risk exposure to the kth controlling risk factor $Control_t^k$ for FOF i in month t. The time series of β^{HFTR} are estimated over fixed 12-month, 24-month, and 36-month rolling windows, respectively. Next, the cross-section of one-month-ahead and three-months-ahead excess returns are regressed on the funds' β^{HFTR} in each month respectively. The average slope coefficients of the cross-sectional regressions are tested by Newey–West (1987) t-statistics for significance. The whole period is partitioned into bullish and bearish periods according to the hedge fund market states identified by the hidden Markov model. The bearish periods include May to August in 1998, November 1999 to September 2002, November 2007 to February 2009, and May 2011 to May 2012. The remaining periods are classified as bullish periods.

		*Panel A: Fama–Macbeth regression of **1-month ahead return** on β_t^{HFTR}: $R_{i,t+1} = \alpha + \gamma_{t+1}\beta_t^{HFTR} + \varepsilon_{t+1}$. This panel reports the value of γ_{t+1} of β_t^{HFTR} estimated on 12-, 24-, and 36-month moving windows, respectively.*			*Panel B: Fama–Macbeth regression of **3-month ahead return** on β_t^{HFTR}: $R_{i,t+3} = \alpha + \gamma_{t+3}\beta_t^{HFTR} + \varepsilon_{t+3}$. This panel reports the value of γ_{t+3} of β_t^{HFTR} estimated on 12-, 24-, and 36-month moving windows, respectively.*		
FOF strategy	Market states	12 months	24 months	36 months	12 months	24 months	36 months
Debt	Bear	0.185	0.656*a	0.319	0.154	0.367	0.208
	Bull	-0.087	-0.387***	-0.419***	-0.137	-0.300**	-0.420***
	Whole	0.017	0.022	-0.140	-0.028	-0.035	-0.188
Equity	Bear	0.346**	0.413***	0.273**	0.144**	0.354***	0.273**
	Bull	-0.146***	-0.240***	-0.250**	-0.101**	-0.207**	-0.268**
	Whole	0.018	-0.009	-0.052	-0.019	-0.006	-0.061
Event	Bear	-0.215	-0.061	0.013	-0.057	0.098	0.288
	Bull	-0.116	-0.318**	-0.227	-0.098	-0.262**	-0.333**
	Whole	-0.149**	-0.227*	-0.136	-0.085	-0.133	0.095
Macro	Bear	0.104	0.361*	-0.028	0.183	0.468	0.107
	Bull	-0.153	0.084	-0.209	-0.183*	0.187	-0.188
	Whole	-0.067	0.182	-0.141	-0.059	0.288**	-0.075
Multi-strategy	Bear	0.168*	0.342**	0.325*	0.144*	0.426**	0.362*
	Bull	-0.075*	-0.284***	-0.197**	-0.106**	-0.138	-0.137
	Whole	0.006	-0.062	0.000	-0.022	0.064	0.053
Relative value	Bear	0.344	-0.049	-0.052	-0.082	-0.067	-0.011
	Bull	-0.047	-0.236**	-0.302**	-0.062	-0.249**	-0.316**
	Whole	0.092	-0.165	-0.207*	-0.069	-0.179*	-0.198*

a. The asterisk symbols indicate the significance level of the test results, being significant at the 1% level "***", 5% level "**" and 10% level "*".

6.3.5 Decile portfolio analysis of HFTR betas by FOF strategies

My previous results show that tail risk exposure may help to predict the performance of a FOF when the market state is certain. To gain more insights into whether the predictive power varies across FOF styles, I performed cross-sectional regression and portfolio sorting analysis using the FOFs in each investment style, and the results are shown in Table 6.8 and Table 6.9, respectively.

Panel A of Table 6.8 reports the cross-sectional regression of one-month-ahead return on HFTR betas. For most of the FOF styles, 24-month β^{HFTR} is found to predict the next month's excess return significantly if the market is bullish. When the market state turns bearish, β^{HFTR} can still help to predict the next month's return if the FOFs follow a debt, equity, macro, or multi-strategy style. I also found that 24-month β^{HFTR} predicts the return of the event FOFs regardless of market states. In general, if an event FOF manager increases exposure to HFTR by one unit, they will improve the fund return in the next month by 0.227%, regardless of the market state. This predictive power is more significant when I use 12-month β^{HFTR} as the regressor. In Panel B, I reveal the test results of β^{HFTR}, predicting three-months-ahead returns. Similar to the findings in Panel A, I find that 24-month β^{HFTR} possesses the highest predictive power. When the market is bullish, 24-month β^{HFTR} can significantly predict the three-months-ahead returns of debt, equity, event, and relative value FOFs. However, if the market is bearish, only the returns of equity and multi-strategy FOFs can be predicted. Moreover, I find that the 24-month and 36-month β^{HFTR} are able to predict the three-months-ahead returns of the relative value FOFs irrespective of market states.

Table 6.9 The returns of strategy classified FOFs holding long-short β^{HFTR} portfolios

This table reports the mean excess returns and HFTR betas of the portfolios adopting the following strategy. Each month (quarter), decile portfolios are formed from Jan 1997 to Dec 2012 by sorting funds of hedge funds (FOF) based on their previous β^{HFTR} estimated on a fixed size moving window (12-month, 24-month, or 36-month). Monthly HFTR betas (β^{HFTR}) are estimated for each FOF following $R_t^i = \alpha^i + \beta_t^{i,HFTR} HFTR_t + \sum_{k=1}^{n} \beta_t^{i,k} Control_t^k + \varepsilon_t^i$ where R_t^i is the excess return of FOF i in month t, $HFTR_t$ and is the hedge fund tail risk factor. This portfolio is held for a fixed period (one month or three months) and then reformed by repeating the above procedures. The next, a portfolio is constructed by taking a long position in the FOFs in the lowest decile (highest tail risk exposure) and a short position in the FOFs in the highest decile (lowest tail risk exposure). The long-short portfolios are constructed using FOFs following equity, multi-strategy, and other strategies respectively. All regressions in this table are based on eight factors, including Fung and Hsieh's (2001) seven factors and HFTR. The whole period is partitioned into bullish and bearish periods according to the hedge fund market states identified by the hidden Markov model. The significance of each value is tested using Newey–West (1987) t-statistics.

Panel A: One-month-ahead returns of the long-short portfolios

		Sorted on 12-month moving window β^{HFTR}			Sorted on 24-month moving window β^{HFTR}			Sorted on 36-month moving window β^{HFTR}		
FOF strategy		Whole period	Bear market	Bull market	Whole period	Bear market	Bull market	Whole period	Bear market	Bull market
Equity	Mean	-0.097	-1.379***a	0.544***	-0.103	-1.400***	0.609**	0.119	-0.849**	0.706***
	Beta	-1.186***	-1.414***	-1.169***	-1.380***	-1.530***	-1.281***	-1.696***	-1.848***	-1.591***
Multi-strategy	Mean	0.045	-0.731**	0.433**	0.059	-0.829*	0.546**	0.023	-0.701	0.463*
	Beta	-1.346***	-1.366***	-1.381***	-1.511***	-1.518***	-1.562***	-1.740***	-1.670***	-1.845***
Others	Mean	0.399	-0.079	0.638*	0.147	0.070	0.190	0.374	0.356	0.384
	Beta	-1.533***	-1.909***	-1.369***	-1.708***	-2.367***	-1.487***	-1.754***	-2.317***	-1.289***

Panel B: the one quarter ahead returns of the long-short portfolios

		Sorted on 12-month moving window β^{HFTR}			Sorted on 24-month moving window β^{HFTR}			Sorted on 36-month moving window β^{HFTR}		
FOF strategy		Whole period	Bear market	Bull market	Whole period	Bear market	Bull market	Whole period	Bear market	Bull market
Equity	Mean	-0.096	-1.172***	0.442***	-0.064	-1.334***	0.632***	0.156	-0.760*	0.712***
	Beta	-0.875***	-0.991***	-0.858***	-1.368***	-1.526***	-1.269***	-1.701***	-1.823***	-1.612***
Multi-strategy	Mean	0.066	-0.610*	0.404**	0.035	-0.844*	0.517**	0.002	-0.719	0.439*
	Beta	-1.146***	-1.150***	-1.170***	-1.548***	-1.687***	-1.495***	-1.792***	-1.779***	-1.818***
Others	Mean	0.405*	0.062	0.576**	0.037	-0.065	0.093	0.412	0.360	0.444
	Beta	-1.323***	-1.608***	-1.222***	-1.674***	-2.214***	-1.484***	-1.794***	-2.458***	-1.217**

a. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 6.9 reports the results of portfolio sorting for different FOF investment styles. I combine debt, event, macro, and relative value FOFs in a set called ‘others’ because, in some months, decile portfolio sorting is impractical because of the low number of funds in these strategy categories. Thus, this new category contains all the FOFs following non-equity strategies. Panel A reports the mean return of the long/short portfolio[36] in the month post-portfolio formation, and the portfolio sorting is on 12-month, 24-month, and 36-month moving windows. The results are very consistent, as equity and multi-strategy long/short portfolios in general generate significant state-dependant returns, while the ‘other’ long/short portfolio fails to do so. I document similar results in the one-quarter -ahead returns of the long/short portfolios, as reported in Panel B.

My style analysis suggests that the predictive power of β^{HFTR} is both state-dependent and style-dependent. For equity and multi-strategy FOFs, β^{HFTR} is able to predict their one-month-ahead or even, in some situations, three-months-ahead returns with good significance, whereas for debt FOFs, β^{HFTR} is strongly correlated to the next one-month and three-month returns if the market is bullish. Although the robustness is still under question, I do find that β^{HFTR} predicts the returns of event and relative value FOFs with good significance irrespective of the market state. This is to say, a FOF investor may benefit from tail risk exposure via investing in event and relative value FOFs.

[36] I assume that the portfolio takes a long position in the FOFs in the lowest β^{HFTR} decile and a short position in the FOFs with the highest β^{HFTR} decile.

6.4 Conclusion

This chapter has documented some evidence on the predictive power of FOF tail risk exposures. I applied a new tail risk factor, which directly measures the extreme movements in the hedge fund industry. This study is among the first to delink the tail risk in the hedge fund industry from the tail-event shocks in equity markets, which enables the measurement to reflect a broader range of sources for the extreme losses in the hedge fund industry. My findings suggest that FOFs write crash insurance for hedge funds so that they receive premiums in good market states while incurring serious losses in the bearish market. I find that the HFTR beta estimated over a short-time horizon, e.g., <= 24 months, possesses very strong predictive power for the FOF's return in the next month. This finding is based on the unsmoothed FOF data so that the influences of return smoothing have been largely removed. The results have important implications in the following aspects. First, they emphasise the importance of tail risk to FOF returns. The possible losses for a unit HFTR exposure in a bearish market are double the gain for the same exposure in a bullish market. Second, from a practical point of view, FOF investors and managers should be aware of the non-linear payoff from HFTR exposures. Finally, my results indicate a lack of hedging strategy for HFTR exposures. However, my style analysis results suggest that a small group of FOFs have managed to earn a positive return from tail risk exposure over the whole sample period, such as event and relative value FOFs. A closer look at these FOFs may help to develop an effective HFTR hedging strategy, and I leave this work to future studies.

Chapter 7: Conclusions

7.1 Summary of findings

FOFs are normally marketed as a safe alternative investment that provides retail investors access to the hedge fund industry. Keeping the modern portfolio theory in mind, investors expect FOFs to generate hedge-fund-like returns with lower risk than a stand-alone hedge fund because of diversification; however, an inherent problem of the modern portfolio theory is the assumption regarding the normality of the underlying asset distribution, which has been proven invalid for hedge funds (Fung and Hsieh, 1997a; Agrawal and Naik, 2004). In fact, FOFs may carry significant tail risk that was not recognised by the investors until the 2007–2008 GFC. This research was motivated by a desire to investigate the tail risk in the returns of FOFs. In addition, this thesis studied the differences between FOFs and other hedge fund strategies with respect to managerial characteristics as well as tail risk exposures.

FOFs are not merely portfolios of hedge funds. It is essential to know to what extent FOFs are different from other hedge funds for a better understanding of the tail risk in FOFs. In Chapter 4, I studied the differences between FOFs and hedge funds in terms of operational characteristics, fee structure, liquidity restrictions, leverage, and regulation and legal structure. The following differences stand out.

First, I documented several differences between FOFs and hedge funds with regard to operational characteristics. As shown in my sample, a lower proportion of FOFs are domiciled out of the US and use the US dollar as a base currency. The average size of FOFs, measured by AUM, is lower than that of hedge funds. A higher proportion of FOFs chose to close to additional investment from either existing or new investors.

Second, with regard to the fee structure, FOFs have been found to follow a “one-and-ten” structure with 73.7% of the FOFs charging management fees below 1 percent and more than 61.9% of FOFs charging performance fees below 10 percent. Hedge funds, in contrast, charge higher performance fees, but there is no clear evidence on hedge funds charging higher management fees.

Third, because hedge funds are highly illiquid assets, the liquid issue is usually a concern of hedge fund investors; however, my calculations indicate that FOFs do not set higher redemption restrictions in comparison to hedge funds. Furthermore, the majority of FOFs (68.6% in my sample) do not require investment lockup. The only disparity in liquidity restrictions is in the requirement of advance-notice days. Most of the FOFs (75%) in my sample require at least 30 days’ advance notice on a future redemption, but the majority of hedge funds require less.

Finally, there are striking differences between FOFs and hedge funds with respect to using leverage. Only 41.19% of FOFs report the use of leverage, but this ratio is 79.96% for hedge funds. FOFs also display a preference in using bank credit as the source of leverage. In contrast, most hedge funds add leverage using margin borrowing.

I reviewed the regulatory environment changes in the post-GFC era and found that FOFs may be disadvantaged in the following respects. On one hand, FOFs have to face higher compliance and due diligence costs. On the other hand, the higher transparency in the hedge fund industry erodes the informational advantage of FOFs. They will have to compete with hedge fund indexers and ETFs specialising in hedge fund investment in the foreseeable future.

Using the reported returns as indicators, I derived the change in the legal structure composition and investment strategy composition between 1995 and 2012 for both

FOFs and hedge funds. I found that OEIC FOFs still dominate the FOF market, but a large amount of the market share has been lost to FOFs structured as corporations, partnership 3C7, or unstructured hedge funds. In contrast, the legal structure composition of hedge funds has also experienced a structural change since 2000. Hedge funds organised as corporations or partnership 3C1/3C7 have lost a significant market share to funds under the structure of LLC or OEIC. The GFC in 2008 brought an important level of influence on the strategy composition of FOFs and HFs. In both samples, I found that the equity strategy has lost a large amount of market share to funds following a macro or systematic futures strategy; however, if we look at the entire hedge fund industry, FOF is the strategy that has suffered the highest losses from the GFC.

The main takeaway from Chapter 4 is that FOFs, as a subcategory of hedge funds, exhibit important differences from other hedge funds with respect to a variety of organisational and managerial characteristics. The focus market, leverage activities, fee structure, and liquidity restrictions of FOFs may all drive the return-risk profile of FOFs to be unique. Therefore, it is valid and necessary to study FOFs as a separate group from the other hedge fund strategies.

In Chapter 5, I investigated the tail risk in FOFs and compared the differences between FOFs and other hedge funds in relation to the tail risk exposure. My preliminary analysis shows that FOFs are more sensitive to the negative movements of markets compared with the other hedge fund strategies. As shown by the moving 36-month standard deviation, semi-variance, VaR, and ES charts[37], FOFs displayed higher comparative increases in the four risk measures than macro, debt, and equity hedge

[37] The risk measurements are standardised so the charts only show the risk of the strategies compared with their own historical risk.

funds during the 2007–2008 GFC. Another group of moving 36-month risk measure plots show further evidence that most FOF strategies have displayed a higher sensitivity to the changes in the market state in the GFC than hedge funds. These observations strongly support the claim raised in Brown, Gregoriou, and Pascalau (2012) that FOFs tend to aggregate the tail risk in their underlying hedge funds.

Following the spirit of Jiang and Kelly (2014), I generated a tail risk factor that measures the dynamic change in the tail risk of the hedge fund industry and named it HFTR. I found that the movements of HFTR do not correspond perfectly to tail risk events in the equity market. The correlation analysis further confirmed that HFTR may cover more information than the tail risk factor derived by using only equity market information (EMTR). The major findings of the tail risk factor regression analysis are summarised below.

First, using individual regressions based on HFTR or EMTR, I confirmed that FOFs are more sensitive to tail risk shocks. I found that approximately 44.64% of my sample hedge funds have significant negative exposures to HFTR, and 11.77% of these tail-risk-sensitive hedge funds are capable of generating excess returns. A higher proportion (83.79) of the sample FOFs were found to be sensitive to HFTR, and only 5.7% of these FOFs have generated significant excess returns. In addition, there is no particular FOF strategy that is immune to the changes in HFTR. The individual regressions based on EMTR yielded consistent results, where a higher proportion of FOFs are significantly exposed to the EMTR compared to hedge funds. The regressions at the portfolio level further confirmed the above-mentioned findings. All FOF strategies are significantly exposed to HFTR and EMTR except volatility hedge funds.

Second, I showed strong evidence that HFTR possesses additional explanatory power to the CAPM and Fung and Hsieh's (2004a) seven-factor model. At the individual fund-level regression, I found that CAPM plus HFTR explains 43.9% of the variance of FOF returns, while Fung and Hsieh's seven-factor model plus HFTR explains 48.7% of the variance of FOF returns. The explanatory power of CAPM and the seven-factor model have been improved by 71.5% and 59.2%, respectively. The enhancements to CAPM and the seven-factor model caused by EMTR are lower than HFTR but still significant. Thus, I suggest that HFTR should be included in hedge fund factor models when evaluating the performance of a hedge fund or FOF manager.

Third, I documented several hedge fund managerial characteristics that may explain the variation of the cross-sectional tail risk exposures. I found that high-water mark, management fees, and closed to new capital are negatively related to the HFTR exposures of both FOFs and hedge funds, but age is negatively related to the funds' tail risk exposures. Moreover, liquidity restrictions have been found to explain the HFTR exposures significantly. In particular, if a hedge fund or FOF allows more frequent redemption and a shorter lockup period, it tends to be more sensitive to tail risk shocks. This finding confirms the importance for both hedge funds and FOFs to use liquidity restrictions to protect their positions in bad market states.

Finally, I suggested that, by construction, factor models separate the total return of a FOF into model-explained returns (factor returns) and unexplained returns (abnormal and residual returns). Diversification reduces the effect of residual and abnormal returns, so the explanatory power of systematic risk factors increases correspondingly. I attempted to test this argument using a simple simulation analysis. By tracking the explanatory power of HFTR in the regressions of the simulated FOFs with an increasing number of constituents, I found that there is a positive relationship between the explanatory power of HFTR and the number of underlying hedge funds.

Chapter 5 conveys important information to both researchers and practitioners. For hedge fund research, my findings confirmed that FOFs tend to aggregate tail risk in the hedge fund industry. In addition, I provided some evidence that the tail risk in the hedge fund industry is not primarily caused by the extreme movements in the equity market. Thus, further studies are required to discover the sources of the tail risk in the hedge fund industry. For hedge fund managers and investors, the HFTR developed in Chapter 5 can be used as an appropriate measure in risk assessment and return attribution analysis.

According to the findings in Chapter 5, the HFTR significantly explains the returns of most of my sample FOFs. As described by the seven-factor plus HFTR regression results in Section 5.3.3, most of the FOFs are negatively exposed to the HFTR, which indicates potential losses caused by higher tail risk in the hedge fund industry. In reality, if a FOF invests heavily in tail-risk-sensitive hedge funds, the various redemption restrictions of the underlying hedge funds will impede the FOF from liquidating its position in the event of an extreme market downturn. Thus, the question that follows naturally is whether the HFTR can help to predict the performance of FOFs. I attempted to answer this question in Chapter 6.

Recognising the possible state-dependent relationship between FOF returns and tail risk exposure, I investigated the return predictive power of tail risk exposure under a bullish and bearish market separately. By applying the decoding algorithm of the HMM to the HFRI Fund Weighted Composite Index, I separated the whole sample period into a bearish period of 68 months and a bullish period of 148 months. I found that, during the bearish periods, FOFs incur a higher average monthly loss than hedge funds. Furthermore, when a hedge fund market turns bearish, only macro/systematic FOFs are capable of delivering positive returns, while the other FOF strategies suffer losses of approximately 0.4% monthly.

I investigated the return predictive power of the HFTR using Fama–Macbeth (1973) cross-sectional regressions based on OLS and quantile regression, respectively. In addition, I sorted HFTR decile portfolios and looked at the return differences between the high tail risk portfolio and the low tail risk portfolio during the post-portfolio formation period. This return predictability study documented the following findings.

First, both Fama–Macbeth (1973) cross-sectional regression and decile portfolio sorting analysis confirmed significant predictive power in FOF tail risk exposure under bullish and bearish markets separately; however, the predictability behaves differently under different market states. In particular, I found that the relationship between the return of a FOF i at time $t+1$, R_{t+1}^{i}, and its tail risk exposure, $\beta_t^{i,HFTR}$, at time t, is significantly positive during the bearish periods but significantly negative during the bullish periods. In other words, if a FOF experiences significant exposure to HFTR, it tends to gain in the next month if the market is bullish but suffers losses if the market state turns bearish in the next month. The decile portfolio sorting analysis documented consistent evidence. The strategy taking a long position in a low $\beta_t^{i,HFTR}$ (high tail risk exposure) portfolio and a short position in a high $\beta_t^{i,HFTR}$ (low tail risk exposure) portfolio yielded significant positive returns in the bullish period, but significant negative returns during the bearish period; however, there is no evidence that the mean return of the portfolio is significantly different from zero throughout the sample period.

Second, as indicated by my cross-sectional regression results, the sensitivity of R_{t+1}^{i} to $\beta_t^{i,HFTR}$ during the bearish periods is more than double the sensitivity in the bullish periods. This means that, for a FOF taking a bet on the next month's market state, e.g., $\beta_t^{i,HFTR} = -1$, its next month tail risk loss if the market turns bearish is more than double its possible gain if the market stays bullish. This observation confirms the claim that FOFs write tail risk insurance for hedge funds.

Finally, as shown by the results of the cross-sectional quantile regression, the predictive power of tail risk exposure behaves differently in predicting the extreme returns of FOFs. In particular, $\beta_t^{i,HFTR}$ and the lowest decile R_{t+1}^{i} are positively related, but $\beta_t^{i,HFTR}$ and the highest decile R_{t+1}^{i} are positively related. The observation implies that the investment in a FOF with significantly low β^{HFTR} tends to two extremes: either gaining from tail risk exposure and outperforming other FOFs or losing substantially because of tail risk and dropping to the lower percentile of the industry.

7.2 Contributions

The major contribution of this thesis is the generation of a tail risk factor (HFTR) that can significantly explain the returns of hedge funds and FOFs. HFTR directly reflects the tail risk dynamic in the hedge fund industry. Compared with the tail risk measurements based on equity market information, HFTR contains more information on the various causes of the extreme downside movements in the hedge fund industry. Indicated by the adjusted R^2 of the seven-factor plus HFTR model, HFTR significantly enhances the explanatory power of Fung and Hsieh's (2004a) seven-factor model.

Based on the HFTR, this thesis contributed evidence to the literature about tail risk aggregation in FOFs. Compared with other hedge fund strategies, the diversification of FOFs reduces the contribution of residual and abnormal returns to total returns. As a result, the returns caused by systematic risk account for a larger proportion of the returns of FOFs. As shown in the simulation study in Chapter 5, adding more hedge funds in the portfolio of a FOF will increase the relative importance ratio (LMG) of HFTR. Thus, the diversification provided by FOFs should be taken as a double-edged sword. On one hand, it works to reduce the idiosyncratic risk in the underlying hedge funds, as modern portfolio theory suggests. On the other hand, it tends to aggregate the tail risk in the hedge fund industry.

The findings of this thesis contain important implications for both regulatory bodies and FOF investors. FOFs are usually marketed as safe investment vehicles that help retail investors gain access to the hedge fund industry; however, as shown by the evidence in Chapter 5 and Chapter 6, FOF investors are heavily exposed to tail risk in the hedge fund industry. Although FOFs earn stable premium returns by writing tail risk insurance for other hedge fund strategies, they suffer great losses when tail risk events attack the industry. Both regulatory authorities and investors should be aware of the unique role of FOFs in relation to tail risk in the hedge fund industry. For FOF managers, it is essential to time the changes in the states of the hedge fund market and mitigate the influence of tail risk using a variety of both internal and external facilities.

7.3 Limitations and directions for future research

The findings of this thesis suggest that tail risk is a non-diversifiable risk for hedge fund investors; however, the sources of hedge fund tail risk and the mechanism of tail risk transfer remain unclear. Moreover, because of the limited availability of hedge fund data, the relationship between tail risk and hedge fund managerial characteristics could not be sufficiently investigated. In addition, as found in Chapter 6, there is a non-linear relationship between FOF returns and HFTR. This thesis, however, explains the return of hedge funds and FOFs mainly on the basis of multifactor models, which assume linearity in risk factor exposure.

Thus, future research can extend the study of this thesis in the following directions. One of the interesting questions involves investigating the tail risk of FOFs using the holding information of FOFs. A better understanding of the dynamic relationship between tail risk exposure and FOF returns can be developed by looking at the changes in the holdings of FOFs under different market states. Such information can be obtained by using 13F filing information provided by the SEC. Another challenge involves developing a tradable tail risk factor. The HFTR presented by this thesis contains an implied assumption that the threshold return u can be shorted, which is not practical in reality. The development of a tradable tail factor requires finding a trading strategy based on marketable securities that may yield returns highly correlated with the HFTR. This project would be of great interest to both FOF managers and hedge fund investors.

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Appendices

Appendix A. Definition of Morningstar hedge fund strategies

Morningstar (2012) defined 31 hedge fund investment strategies. To fit the needs of this research, I aggregated hedge fund strategies into the following seven groups: debt, equity, event-driven, multi-strategy, systematic futures, volatility, and macro. I list the sub-strategies of each group in Table A.1[38].

Table A.1 Aggregation of Morningstar hedge fund strategies

Hedge fund strategy groups of this thesis	Morningstar hedge fund strategies
Debt	Long/short debt Long-only debt Convertible arbitrage Debt arbitrage
Event-driven	Distressed securities Event-driven Merger arbitrage
Multi-strategy	Multi-strategy Long-only other Diversified arbitrage
Systematic futures	Systematic futures

[38]The definitions of the sub-strategies can be obtained at the following link: http://corporate.morningstar.com/us/documents/MethodologyDocuments/MethodologyPapers/MorningstarHedgeFundCategories_Methodology.pdf

Volatility	Volatility
Macro	Currency Global macro
Equity	Asia/Pacific long/short equity Bear-market equities Equity market neutral China long/short equity Emerging-market long/short equity Europe long/short equity Global long/short equity U.S. long/short equity U.S. long/short small-cap equity Emerging markets long-only equity Long-only equity

In addition, Morningstar (2012) defined six FOF investment strategies. I left the classification unchanged in this thesis. The definitions of the strategies are listed in Table A.2. The definitions are directly quoted from Morningstar (2012).

Table A.2 Morningstar (2012) FOF strategies

FoF investment strategies	Strategy description
Debt	"*Debt funds have statistically significant betas to at least one debt index or to a credit or duration spread. These funds primarily (50% or greater) derive their directionality from debt-related hedge fund strategies. Debt funds can diversify across geography or can concentrate in a particular region. These funds can invest in strategies other than directional debt strategies, but the systematic risk is dominated by correlations to fixed income investments.*" (Morningstar 2012, p. 12)

Equity	"*These funds have statistically significant betas to at least one equity index, and primarily (50% or greater) derive their directionality from equity-related hedge fund strategies. Equity funds can diversify across geography or concentrate in a particular region.*" (Morningstar 2012, p. 12)
Event	"*Event funds invest primarily in event-driven strategies, with 50% or more of the portfolio in one or more of the following event-driven strategies: merger arbitrage, distressed securities, and event-driven. Event funds tend to show high betas to the single-strategy Morningstar Index of the same name. If an event fund could also qualify for the equity, debt, or multistrategy categories, it shall be placed in the category with which its returns are most strongly related, considering cluster analysis and regression betas*." (Morningstar 2012, p. 13)
Macro/systematic	"*These funds invest primarily (50% or greater) in the Morningstar global derivatives categories, which include systematic futures, global macro, volatility, and currency. Global Derivatives funds predominantly invest in highly liquid instruments such as futures and options, and use various instruments to trade currencies. The underlying funds' strategies can be systematic or discretionary, technical or fundamental, or any combination of the four. These funds tend to be diversified across global derivative strategies*." (Morningstar 2012, p. 13)
Multi-strategy	"*Multistrategy funds generally have statistically significant betas to multiple asset classes (such as debt, equity, event–driven, and global derivatives), without enough asset-class concentration to belong to another hedge fund of fund category. That is, no one asset class drives a majority of the funds' directionality.*" (Morningstar 2012, p. 13)
Relative value	"*These funds produce returns that cannot be explained well by directional hedge fund factors. These funds generally show r-squared results of less than 30% in multifactor regressions using common factors of hedge fund returns. The underlying funds in which these funds invest generally include a majority allocation to relative value/arbitrage strategies. In some cases, if other information proves more valuable than the regression results, Morningstar's hedge fund analysts will have the discretion to make slight exceptions to the r- squared rule.*" (Morningstar 2012, p. 13)

Appendix B. Description of the LMG value

The following introduction to the LMG value is replicated from Grömping (2006, p. 9). In particular,

> "assume the order of the regressors in any model is a permutation of the available regressors $x_1, \dots x_p$ and is denoted by the tuple of indices $r = (r_1, \dots, r_p)$. Let $S_k(r)$ denote the set of regressors entered into the model before regressor x_k in the order r. Thus, the portion of R^2 allocated to regressor x_k in the order r can be represented as:
>
> $$seqR^2\left(\{x_k\}\middle|S_k(r)\right) = R^2\left(\{x_k\} \cup S_k(r)\right) - R^2(S_k(r))$$
>
> Thus, LMG value of regressor x_k can be given by:
>
> $$LMG(x_k) = \frac{1}{p!}\sum_{r\ permutation} seqR^2(\{x_k\}|r)$$ "