Three Essays on Hedge Funds:

Performance Fees, Tail Risk and Performance Diversification among Hedge Funds

by

Minli Lian

M.B.A., Simon Fraser University, 2001
B.B.A., Xiamen University, 1998

Thesis Submitted In Partial Fulfillment of the
Requirements for the Degree of
Doctor of Philosophy

in the
Segal Graduate School
Beedie School of Business Faculty

SIMON FRASER UNIVERSITY

Fall 2012

Approval

Name: **Minli Lian**

Degree: **Doctor of Philosophy (Finance)**

Title of Thesis: ***Three Essays on Hedge Funds: Performance Fees, Tail Risk and Performance Diversification among Hedge Funds***

Examining Committee: **Chair:** **Dr. Mila Lazarova**
Associate Professor, Beedie School of Business

Dr. Peter Klein
Senior Supervisor
Professor, Beedie School of Business

Dr. Dennis Chung
Supervisor
Professor, Beedie School of Business

Dr. Andrey Pavlov
Supervisor
Professor, Beedie School of Business

Dr. Amir Rubin
Internal Examiner
Associate Professor
Beedie School of Business

Dr. Douglas J. Cumming
External Examiner
Professor in Finance and Entrepreneurship
Schulich School of Business
York University

Date Defended/Approved: December 3, 2012

Abstract

Hedge funds are favoured by pension funds, institutional investors, and high wealth investors for their flexible investment trading strategies and possible diversification benefits with existing portfolios. The following three research papers help us understand certain hedge fund characteristics by examining fund performance and by making comparisons to other types of investments.

The first essay investigates the relationship between hedge fund performance fees and risk adjusted returns. The paper introduces an "effort" variable and reasons that the performance of hedge funds and the payoff of the performance fee contract are endogenously determined by the fund manager's effort. The paper concludes that the performance fee contract aligns the interest of the fund manager and the investor, and creates a win-win risk sharing instead of a risk shifting situation. Empirically, we find that performance fees are positively associated with risk adjusted returns. The second essay examines the hedge fund tail risk in terms of the Value at Risk (VaR) and Expected Shortfall and compares these measures with those of mutual funds. It also studies the hedge fund tail risk dependence on the stock market index and VIX index as well as the phase-locking effect. The third essay studies the cross-sectional difference between hedge fund style indexes and industry portfolios. It also examines the diversification benefit of investing in a pool of hedge funds.

Keywords: Performance Fee, Tail Risk, Expected Shortfall, Portfolio Diversification

To my parents Yazhen and Feizhe

my sisters Mary and Isabelle

my husband Justin

and my sons Kaison, Carter and Jaden

for their love, encouragement and support.

Acknowledgements

I would like to thank Dr. Peter Klein who introduced me to the research in finance and I am indebted to him for his years of supervision, encouragement and guidance throughout my academic years at Simon Fraser University.

I appreciate the valuable comments and suggestions from the faculty members of the Finance Department at Simon Fraser University, especially Dr. Andrey Pavlov, Dr. Amir Rubin, Dr. Dennis Chung and Dr. Jijun Niu and Dr. Douglas J. Cumming from York University..

I also thank Dr. Robert Grauer, Dr. George Blazenko, Dr. Avi Bick, Dr. Bleize Riech and Diane Miedema for their encouragement and support.

And, I thank the faculty at the Department of Finance and the support staffs at Beedie School of Business for their continuous support.

Last but not least, thank you all my friends.

Table of Contents

List of Tables

List of Figures

1. Introduction

Hedge funds are investment funds for wealthy investors or institutional investors such as pension funds, endowment funds and foundations. Hedge funds can adopt a wide range of trading techniques including short selling and leverage that are not available to mutual funds. Hedge funds are usually set up as a joint partnership and are limited to public selling. They typically charge a 10 to 25 percent performance fee, in addition to the annual management fees – the "two and twenty" structure. Although the origin of the first "hedge fund" is debatable, many investment "pools" were created in the 1920's. Alfred Jones is generally credited with creating the first hedge fund structure in 1949 by adding a 20% performance fee to the management compensation and allowing management ownership.

Hedge funds have experienced tremendous gains and have often out-performed the equity markets, but they have also had equally large losses. Despite the turbulent historic returns, hedge funds have gained popularity during the last decade due to market fluctuations stemming from global weather-related catastrophes, civil unrest, and economic distress. Investors are inevitably drawn to hedge funds for the potential to achieve stellar returns and for the varieties of funds and investment strategies. The hedge fund industry reached a high of over US$2 trillion in assets under management in early 2012.

Not only do the performances of hedge funds affect high-end investors, the related trading has a significant impact on the worldwide stock exchanges. Due to their structure, investment strategies and magnitude of investment dollars, hedge funds are now the most important investment vehicle under regulatory scrutiny.

This paper investigates three main characteristics of hedge funds: the option-like performance fee, the tail risk and the performance distribution of different hedge fund styles. We hope to shed some new light on the ever popular hedge fund industry.

2. Explaining Hedge Fund Performance Fees

2.1. Abstract

This paper investigates the relationship between hedge fund performance fees and risk adjusted returns. Existing literature argues that performance fees induce risk-taking behavior from fund managers because higher risk increases the value of the performance fee option. This paper argues that the relationship between the investor and manager is similar to the relationship between the shareholder and corporate manager in the corporate settings. Performance fees serve the same purpose as the employee stock options. They align the interest of the investor and manager and create a win-win risk sharing instead of a risk shifting situation. We introduce the “effort” in the model and apply principal-agent theory to this issue. We reason that the performance of hedge funds and the payoff of the performance fee contract are endogenously determined by the fund manager’s effort. The excess returns are shared among the investor and manager and there is a natural bound of risk. Empirically, we find that performance fees are positively associated with returns and risk adjusted returns in terms of the Sharpe ratio and Sortino ratio.

2.2. Introduction

Hedge funds provide high wealth investors the opportunity to adopt unconventional trading strategies and benefit from arbitrage opportunities. Fund managers are usually compensated with both a management fee and a performance fee. Typically, the management fee ranges from one to two percent of assets under management, while the performance fee usually ranges from ten to fifty percent of excess returns measured against benchmarks, such as yields on treasury bills. Most hedge fund performance fees have bonus-type characteristics where managers are rewarded for over-performance, but not penalized for under-performance. One of the most contentious debates on hedge fund compensation is the role that performance fees play in providing insurance and motivating management to achieve the goals of investors. According to Goetzmann, Ingersoll, and Ross (2003), the performance fee effectively costs ten to twenty percent of the portfolio returns. Therefore, it is important to examine whether the risk adjusted return of hedge funds is worth the performance fee.

Existing literature applies the option approach to evaluate the performance fee provision. They treat hedge fund performance fee contracts as a zero-sum game, where the risk is totally shifted from the manager to the investor. They argue that the optionality of the performance fee leads to unbounded risk shifting, as higher risk increases the value of the performance fee option.

We propose that the existing arguments on option-like performance fees are inaccurate and incomplete for three main reasons. First, the performance of hedge funds and the payoff of the performance fee contract are endogenously determined by the effort of the manager. Strategies with higher risk adjusted returns usually demand more effort from the manager. These investment opportunities are hard to spot and might require better management skills to setting up unconventional trading strategies. They also involve more due diligence from the managers. By exerting different levels of effort, the manager can potentially influence his own payoff from the performance fee contract. In contrast, the payoff of the call option is independent of the action of the option writers or holders. It was exogenously determined by the market. Unfortunately, the existing literature on hedge fund performance fee has not yet considered this issue that the performance fee might motivate more effort and therefore result in a bigger “pie”.

Second, with an incentive rate less than one, the excess returns are shared between the fund manager and investor. This is a “win-win” situation and is different from the “zero-sum” payoff function of a call option. The writer of a call option gives up the upside profit when the price of the underlying goes beyond the strike price in exchange for a premium. In other words, when the option is in the money, the option writer loses money as he/she needs to pay the option holder the difference between the spot price and the strike price. Meanwhile, the option holder pockets all the benefit. In comparison, the performance fee contract rewards the fund manager for additional effort and motivates him to strive for higher returns, which are shared between the fund manager and investor. These two important aspects are not captured in the option writer-holder relationship.

Third, we propose that under the performance fee contract, risk does not totally shift from the investor to the manager or vice versa. The resulting risk-taking behavior of the performance fee provision is jointly determined by the disutility of effort, the knockout effect, convexity effect, translation effect and magnification effect and there is natural bound of risk.

This paper reasons that the relationship between an investor and a hedge fund manager represents a principal-agent problem with hidden action, because the manager's effort is usually unobservable. Moreover, the performance of the investment not only reflects the manager's effort, but also depends on other factors such as the economy and macroeconomic shocks. This relationship is analog to the relationship between shareholders and corporate managers where the employee stock options are usually adopted to motivate the corporate managers. Hedge fund performance fee contact serves as the same role as the employee stock options. In general, there are four instruments that can mitigate the principal-agent problem: incentive contracts, ownership, regulation and market competition. The first two are more popular among hedge funds, while the latter two are relatively common among mutual funds. This is partially because hedge funds are historically less regulated and are exempt from standard disclosure requirements.

This paper examines the performance fee through the principal-agent framework and explains that the existence of performance fees satisfies the condition of Mas-Colell, Whinston and Green (1995) and can be economically justified. The performance fee reduces the moral hazard by aligning the interests of the fund manager and investor, thus creating a risk sharing mechanism. We introduce the "effort" factor and propose that the performance fee motivates the fund manager to exert more effort and create a bigger "pie." It motivates fund managers to pursue unconventional strategies that are riskier, but may have higher returns. We argue that the principal may embrace performance fees if they believe that the fee leads to higher risk adjusted returns, not just higher risk.

This paper also tests empirically the effect of the performance fee on the risk adjusted returns in terms of the Sharpe and Sortino ratios. Higher returns are usually associated with higher risk. Therefore, to objectively evaluate the effectiveness of the performance fee, we should investigate risk and return simultaneously. i.e., risk adjusted returns. Empirical tests using OLS and Maximum Likelihood Estimates (MLE) based on the skewed student's t-distribution are conducted following the methodology by Kouwenberg and Ziemba (2007). The approach incorporates the non-normality of distribution and provides more consistent results. We find empirically that performance fees are positively related to the risk adjusted returns in terms of both the Sharpe and Sortino ratios.

The main contribution of this paper introduces the "effort" factor and applies the principal-agent theory to explain the risk sharing prospect of the performance fee contract. The empirical test supports our explanation. In summary, we are not trying to derive the optimal solution to the performance fee problem, but to reconcile the difference in literature and understand the existence of prevailing performance fee structures.

This paper is organized as follows: Section one explains the motivation of the paper. Section two provides a brief literature review on the principal-agent model and the research on the performance fee. Section three presents the theoretical framework and discusses its implication. Section four presents the empirical test using individual fund data. And, section five summarizes the paper and discusses the implication for future studies.

2.3. Literature Review

In this section, we briefly review the principal–agent model and discuss the findings of risk-taking behavior from the existing literature. We also review the research on the performance fee in the mutual fund and hedge fund industry.

In the principal-agent literature, the principal is usually assumed to be risk neutral and the contract design problem is set up as a two-stage maximization problem. At stage one the principal characterizes the performance fee for each level of effort that the manager can choose, while at stage two the principal induces the desired effort level from the manager.

When the action is observable, the best solution is achieved where the principal specifies the desired effort level, the agent exerts the effort and is compensated correspondingly. When the action is unobservable and the agent is risk neutral, the best solution is still achievable where the principal receives a fixed rent and the agent acts as the residual claimant. The risk is entirely shifted from the principal to the agent. However, if the agent is risk averse, the principal needs to balance the trade-off between providing insurance and providing motivation for the agent to exert the desired effort level. The optimal solution requires risk sharing between the principal and the agent. To illustrate, let's assume that there are only two effort levels and that the principal is risk neutral. The contract design problem can be set up as follows (Mas-Colell, Whinston and Green, 1995):

$$max \int \ (\pi - w(\pi)) * f(\pi|e_h)\, d\pi$$

st:

$$\int v(w(\pi)) f(\pi|e_h) d\pi - g(e_h) \geq \bar{u}$$

$$\int v(w(\pi)) f(\pi|e_h) d\pi - g(e_h) \geq \int v(w(\pi)) f(\pi|e_l) d\pi - g(e_l)$$

Where "*v*" represents the utility function of the agent and it satisfies *v´>0, and v´´<0*. π is the outcome and $w(\pi)$ is the wage of the agent. The two effort levels are represented by: e_h for high effort level and e_l for low effort level. $g(e)$ is the disutility function of the fund manager due to the effort.

Condition (i) is the participation constraint and condition (ii) is the incentive constraint. Assuming that γ and μ are the Kuhn-Tucker multipliers for (i) and (ii) respectively, the first order condition at every $\pi \in [\underline{\pi}, \bar{\pi}]$, yields: $\frac{1}{v\prime(w(\pi))} = \gamma + \mu(1 - \frac{f(\pi|e_l)}{f(\pi|e_h)})$. This implies both the participation constraint and the incentive constraint bind *γ>0* and *μ>0* (for proof, please refer to Mas-Colell, Whinston and Green, 1995). The agent needs to be compensated more for the outcomes that are more likely to occur with a higher effort level. Given the diverse utility function of the agents, a universal optimal compensation scheme is undetermined.

The search for the optimal compensation fee is still ongoing and inconclusive. Starks (1997) showed that a linear compensation scheme is most efficient under some constraints. Li and Tiwari (2009) compared four types of compensation contracts: fixed payment, proportional asset-based fee, benchmark-linked fulcrum fee and the benchmark-linked option-type "bonus" performance fee. They showed that an option-type bonus performance fee is optimal with an appropriate benchmark.

The articles that examine the efficiency of the performance fee argue that option-like performance fees induce unbounded risk. Carpenter (2000) showed that hedge funds with returns below the benchmark seem to be motivated by excess risk-taking. He concluded that bonus type performance fees are risk inducing, because increasing risk increases the value of the call option of the performance fee. Richter and Brorsen (2000) used the look-back option to model the performance fee with the knockout feature and found that performance fees cause fund managers to adopt higher leverage.

Ross (2004) examined the risk-taking implication of performance fees. He showed that performance fees can be risk inducing or risk reducing depending on the interaction of the convexity effect, translation effect and magnification effect. The convexity effect refers to the effect that increasing volatility will increase the value of the option. The translation effect refers to the fact that the performance fee moves the agent to a regime with a different risk attitude. And, the magnification effect says that different incentive rates might magnify the incentive at different degrees. The combined impact of these three effects determines the result of performance fees. Our paper extends Ross' theory and proposes that the payoff function and the utility function, under the option type performance fee, can be divided into three regimes. The resulting risk-taking behavior depends on two other effects in additional to Ross' three effects: 1) the knockout effect; and 2) the disutility of effort. The knockout effect refers to the fact that when the return of the fund is far below the benchmark, there is a possibility that investors might withdraw their funds. As a consequence, managers may lose future administrative fees and their reputations might be damaged. This hinders the manager to take on too much risk. The knockout effect addresses the conflict between long term motivation and short term reaction. The disutility of effort says that when the effort increases, the marginal disutility of effort also increases. In addition, this disutility is increasing at an accelerating rate. The observed result is the interaction of these five effects instead of the three mentioned earlier.

Elton, Gruber and Blake (2003) examined the effect of performance fees on the behavior of mutual fund managers and found that funds with performance fees take on more risk than those without. And further, the same funds increase risk-taking after periods of poor performance. Drago, Lazzari and Navone (2010) investigated the Italian mutual fund industry with a free contracting environment. They surmised that proposed weakening price competition among managers and hedging cost structure are the main reasons for the existence of bonus plans and they found no support for risk inducing behavior.

Stracca (2006) surveyed the theoretical literature on delegated portfolio management under a principal-agent framework and found the result of the search for the optimal performance fee inconclusive. Liang (2001) found that funds with high-water marks significantly outperform those without. Brown, Goetzmann and Park (2001) found little evidence of increased risk-taking by fund managers below their high-water marks and claimed that career, reputation and the possibility of fund redemptions lessens the averse risk–taking behavior of fund managers. Anson (2001) examined the role of performance fees under a standard Black-Scholes model and argued that such structures encourage excess risk-taking behavior by the managers. Giuli, Maggi and Paris (2003) showed that a double contingency on fee payments does not remove managers from maximizing risks in order to increase the value of the option. They proposed that participation in the capital of the fund allowed investors to align their risk preferences with those of the shareholder-manager, thus mitigating the risk-taking behavior. Edwards and Caglayan (2001) examined fund managers' skills and hedge fund performance and found that funds with higher performance fees have higher excess returns.

Goetzmann, Ingersoll and Ross (2003) derived a close form solution to evaluate the high-water mark performance fees based on the option pricing model. They argued that hedge fund high-water mark performance fee contracts represent an option-like claim on the fund asset. Therefore, they adopted the option pricing method and derived the equilibrium value, based on Merton (1976) and Ingersoll (2002) to evaluate high watermark compensation fees. They estimated the model parameters under a continuous time framework and found that the trade-off between regular commission fees and high-water mark performance fees depended on the volatility of the portfolios as well as the withdrawal policy. The significant transfer of wealth under the high-water mark compensation contracts can be economically justified. Unfortunately, Goetzmann, Ingersoll and Ross (2003) assumed that hedge fund returns are normally distributed, which clearly contradicts with reality that hedge fund returns are non-normal with negative skewness and high kurtosis. Second, within the Black-Scholes option pricing framework, all factors are exogenous. While in reality the performance of hedge funds is highly dependent on the fund managers' effort, which is endogenously motivated by performance fees. Goetzmann, Ingersoll and Ross (2003) also considered the possibility of liquidation and concluded that it would lead to a decrease in volatility when the value of the fund fell below the boundary.

Clare and Motson (2009) found that fund managers adjust their risk profile based on the moneyness of the incentive option. Managers with incentive options in the money decrease their risk and managers also protect the value of the option at the end of the year. They argued that the risk-taking behavior depends on whether the high-water mark contract is in the money, at the money or out of money. The risk-taking behavior is most exaggerated when the performance fee option is out of money. In other words, the fund is way below the high-water mark.

Hodder (2007) extended Goetzmann et al. (2003) and investigated the effect of hedge fund compensation on manager risk-taking behavior in a multi-year setting under an assumption of constant relative risk aversion (CRRA). They argued that the short investment horizon increases risk-taking behavior as managers try to increase the value of the option. Their model also allowed for endogenous shut down, manager ownership and liquidation decisions by fund managers. They found similar results as Goetzmann, Ingersoll and Ross (2003). Panageas and Westerfield (2009) found that the high watermark effect will reduce excess risk-taking behavior under infinite horizon settings. Admati and Pfleierer (1997) pointed out that the benchmark is an irrelevant and distorting factor unless the benchmark itself is a conditional optimal portfolio.

Kouwenberg and Ziemba (2007) investigated the relationship between incentives, ownership and risk-taking in the hedge fund, based on the prospect theory. They found that if all other factors are the same, higher performance fees lead to mild risk-taking among individual funds and stronger risk-taking among funds of hedge funds. They also found that ownership reduced the risk appetite of the manager. Their empirical tests adopted the student's t-distribution to adjust for heteroscedasticity and non-normality in the OLS regression error term.

2.4. Theoretical Framework

This paper examines the investor-manager relationship and tries to reconcile the different implications of the performance fee in the existing literature. First, we introduce the factor “effort” and apply the principal-agent theory to explain the motivation of the hedge fund performance fee. We propose that the performance fee aligns the interest of the fund manager and the investor and creates a win-win situation. This paper posits that higher levels of effort do not imply more risk-taking, but result in higher risk adjusted returns. This paper also suggests that the payoff/expected utility function of the fund manager can be divided into three regimes with different risk-taking implications. There is a natural bound of risk because exerting effort induces disutility and high risk increases the possibility of potential loss of assets under management which could affect the manager’s reputation and potentially their future career. The resulting risk-taking behavior is the interaction of the convexity effect, translation effect, magnification effect, knockout effect and disutility of effort. Our approach adopts the principal and agent analyses by Mas-Colell, Whinston and Green (1995) and is similar to Giuli, Maggi and Paris (2003) and Kouwenberg and Ziemba (2007). The empirical analyses follow Kouwenberg and Ziemba (2007) and use the Maximum Likelihood Estimate based on the skewed student’s t-distribution to adjust for the non-normal distribution in risk adjusted return measures.

The performance fee contract is a mechanism designed by the principal to provide insurance and to motivate fund managers to exercise the principal’s desired effort level. In this section, we extend the traditional principal-agent model (Mas-Colell, Whinston and Green, 1995) and examine the implication on the performance fee. We also assume that the level of effort does not change the risk target of the fund manager. Allowing various risk targets is interesting but much more complicated and we will leave it to future studies. If the action of the manager is observable, the solution to the investor-manager problem is quite simple. The investor specifies the desired effort level while the agent is rewarded correspondingly. When the effort of the manager is un-observable, the optimal contract depends on the risk attitude of both the investor and agent and can be complicated. In the following section, we focus the discussion on the situation where the action is unobservable.

2.4.1. *Both Investor and Manager are Risk Averse*

First, we assume that both the principal and agent are risk averse. We set up the investor-manager contract design problem as a two-stage maximization problem. To simplify the discussion, we also assume that there are only two levels of effort: e_h and e_l. At the first stage, given each effort level, the investor selects the compensation scheme. At the second stage, he induces the desired effort level from the manager. The model can be set up similar to Mas-Colell, Whinston and Green(1995):

$$max \int \; u\big(\pi * NAV_{t-1} - w(\pi)\big) * f(\pi|e_h)\, d\pi$$

st.

$$\text{i).} \int v\big(w(\pi)\big) f(\pi|e_h) d\pi - g(e_h\,) \geq \bar{u}$$

$$\text{ii).} \int v\big(w(\pi)\big) f(\pi|e_h) d\pi - g(e_h\,) \geq \int v\big(w(\pi)\big) f(\pi|e_l) d\pi - g(e_l\,)$$

Where "*u*" represents the investor's utility function and "*v*" the fund manager's utility function, π is the outcome and $w(\pi)$ is the wage of the agent. The two effort levels are represented by: e_h for the high effort level and e_l for the low effort level. $g(e)$ is the disutility function of the fund manager due to the effort. NAV_{t-1} is the net asset value at the beginning of time t. Risk aversion requires that both u and v are concave. In other words, u´>0, u´´<0, v´>0, and v´´<0. $w(\pi)$ is the performance fee received by the manager. The two effort levels are represented by: e_h for high effort and e_l for low effort. $g(e)$ is the disutility of the fund manager due to the effort. NAV_{t-1} is the net asset value at the beginning of the t period. Condition (i) is the participation constraint and condition (ii) is the incentive constraint. Assuming that γ and μ are the Kuhn-Tucker multipliers for (i) and (ii) respectively, the first order condition at each level of $\pi, \pi \in \left[\underline{\pi}, \overline{\pi}\right],$ yields

$\frac{u\prime\left(\pi * NAV_{t-1} - w(\pi)\right)}{v\prime\left(w(\pi)\right)} = \gamma + \mu(1 - \frac{f(\pi|e_l)}{f(\pi|e_h)})$. The equilibrium contract is determined by the utility function of both the investor and agent. Similar to Mas-Colell, Whinston and Green (1995), we assume that the distribution of the return conditioning on the high effort level first order stochastically dominates the distribution conditioning on the lower effort level. This implies that the expected level of return is higher when the manager chooses a higher effort level and there exists some π where $(1-\frac{f(\pi|e_l)}{f(\pi|e_h)})$ is negative. Because both the investor and fund manager are risk averse $u'>0$, $u''<0$, $v'>0$, and $v''<0$, the left side is always positive. Therefore, γ must be strictly positive. In other words, the participation constraint always binds and there is a lower bound of compensation. However, it is possible that $\mu=0$. This is because under optimal risk sharing there may be excessive risk, such that there is no incentive for the manager to choose high effort. Therefore, when we examine the hedge fund performance fee structure, we should examine the risk adjusted returns instead of the return alone.

After reorganizing the incentive constraint, we yield

$$\int v\big(w(\pi)\big)f(\pi|e_h)d\pi - \int v\big(w(\pi)\big)f(\pi|e_l)d\pi \geq g(e_h) - g(e_l)$$

Because the disutility from effort is strictly convex, $g'(e) > 0$ *and* $g''(e) > 0$, it requires higher compensation to the agent for higher level of effort. In other words, the optimal performance fee must be non-decreasing in π. The incentive constraint also suggests that there might be a natural upper limit for the incentive fee, as a marginal benefit increases at the decreasing rate while the marginal disutility of effort increases at the increasing rate.

When the agent is risk averse, an optimal solution involves some form of risk sharing. The optimal compensation must relate the effort level to the investment outcome. This is because the distribution of the return conditioning on the high effort level first order stochastically dominates the distribution conditioning on the lower effort level. Therefore, the optimal compensation must be non-decreasing in π. A flat fee is not desirable because it fails to motivate managers to exert higher effort level. In addition, the participation constraint requires a lower limit for the performance fee because managers must be protected from averse situations. The first order condition also shows that optimal compensation is determined by the distribution of the return, given different effort levels and the utility functions of both the investor and manager.

Now we examine the prevailing compensation of the manager in the hedge fund industry. Typical compensation is composed of the management fee and performance fee. It takes the following form:

$$w = \max(\pi - H, 0) * NAV_{t-1} * incentive\ rate + MER * NAV_{t-1}$$

Where H is the high-water mark and π is the return on the fund. NAV_{t-1} is the net asset value at the beginning of the period and $incentive\ rate$ is the incentive payout ratio as a percentage of net asset value at the beginning of the period. This ratio is specified at the inception of the fund. MER is the management expense ratio. The first component, $\max(\pi - H, 0) * NAV_{t-1} * incentive\ rate,$ is the performance fee and the second component, $MER * NAV_{t-1}$, is the management fee. There are two possible outcomes depending on the realization of π. First, $\pi < H$. In this case, the performance fee equals zero and the fund manager earns the management fee only. This ensures that he receives at least his minimum level of utility. Second, $\pi \geq H$. In this case, the manager earns both the management fee and a performance fee. The amount of the performance fee can be calculated as $(\pi - H) * NAV_{t-1} * incentive\ rate$ where NAV_{t-1},H and the $incentive\ rate$ are positive and constant. Therefore, w is not decreasing in π . In other words, fund managers are rewarded for better returns. This satisfies the condition that we derived from the investor-manager model.

Next, we argue that this performance fee structure requires risk sharing instead of pure risk shifting because the $incentive\ rate$ is always less than one. The investor's payoff can be calculated as $\pi * NAV_{t-1} - max(\pi - H, 0) * NAV_{t-1} * incentive\ rate - MER * NAV_{t-1}$. After transformation, the investor's payoff function can be simplified to $(H - MER) * NAV_{t-1} * incentive\ rate + \pi * NAV_{t-1} * (1 - incentive\ rate)$, if $\pi > H$, and $\pi * NAV_{t-1} - MER * NAV_{t-1}$, if $\pi < H$. In either case, because $(H - MER) * NAV_{t-1} * incentive\ rate$ is a constant, the payoff function can be simplified into the format of $A + B \times \pi,$ where both A and B are constant and non-negative. Therefore, the investor's payoff strictly increases in π.

Both the fund manager's and investor's payoff function can be simplified to $y * NAV$ where $y = a + b\pi$ with 1> $b > 0$ and the sum of *b* for the fund manager and *b* for the investor equals one. Therefore, performance fees create a win-win situation where both the manager and investor benefit from over-performance.

Next we discuss why fixed rate management fees, which are widely adopted in the mutual fund industry, are not enough to motivate managers in the hedge fund industry. The management fees are solely based on the invested net asset value at the beginning of the year and the management expense ratio (MER), which is predetermined upon fund inception. In the single period model, this fee is fixed regardless of fund performance. This strictly violates the incentive constraints, as it fails to provide motivation for higher effort. When action is unobservable, the fund manager will choose lower effort because any additional effort will be a pure loss for him. In other words, insuring the agent against the risk by setting the compensation equal to a constant would leave him with no incentive to exert effort. In the multi-period condition the fund manager may implement higher effort, as the next period's income depends on the prior period's return or the net asset value at the end of prior period. However, the possibility of redemptions and the inability or unwillingness to raise new capital in the hedge fund industry might downplay this inter-temporary effect and render the management fee less effective than the option-like performance fee. Future fund flow is another factor that might influence fund management strategies. However, fund flows are convex functions of past performance, where good performance leads to potential inflow into the fund. Whereas poor performance might have a limited effect on outflows unless the result is extremely unexpected.

In summary, we propose that the effort level is endogenous and that it influences the payout of both the fund manager and investor. Therefore, the option-like performance fee aligns the incentives of the fund manager with those of the investor. It encourages risk sharing between the two parties and creates a win-win situation. We also reconcile different arguments about the risk-taking behavior of the fund manager. Literature surrounding the option-like features of the performance fee focuses on risk shifting characteristics. However, this problem is mitigated through the disutility of effort, the knockout effect, translation effect and magnification effect. Therefore, the risk is not unbounded. Other performance fee provisions, such as the high-water mark and hurdle rate provisions also help reduce the risk appetite of the manager. Investors should consider all these factors in the contract design and base their investment decisions on the risk adjusted returns.

2.4.2. Investor is Risk Neutral and Manager is Risk Averse

When the principal is risk neutral but the agent is risk averse, Mas-Colell, Whinston and Green (1995) found that the agent must be compensated more for the outcomes that are more likely to occur with a higher effort level due to disutility of effort. The optimal contract satisfies: $\frac{1}{v\prime(w(\pi))} = \gamma + \mu(1 - \frac{f(\pi|e_l)}{f(\pi|e_h)})$ for every $\pi \in [\underline{\pi}, \bar{\pi}]$. Let's illustrate this with the following example. Assume that the investor is risk neutral and that the manager has a preference defined over mean-variance of investment outcome as well as disutility of effort in terms of the following.

$$v(w) = E[w(\pi)] - c * var\big(w(\pi)\big) - g(e)$$

where $g(e)$ is the disutility due to effort. We also assume that the incentive fee takes the linear format as before. i.e., $w(\pi) = a + b * \pi$. When effort *e* is not observable, the first order condition yields: $g'(e) = \frac{1}{1+2*c*\sigma^2*g\prime\prime(e)}$ and the incentive constraint implies $b = g'(e)$. Because the denominator is greater than 1, we conclude that $0 < b$ <1. In other words, the optimal contract involves some form of risk sharing. If the manager is more risk averse in terms of higher value of *c*, the incentive rate *b* will be lower. If σ^2 increases, *b* also decreases. In other words, as the portfolio risk increases, the incentive rate should decrease.

2.4.3. Manager is Risk Neutral and Investor Is Risk Averse or Risk Neutral

Regardless of the investor's risk attitude, when the manager is risk neutral, the optimal contract involves the investor "renting" out the fund to the manager and receiving a fixed payment α^*, while the manager becomes the residual claimant and receives $w(\pi) = \pi - \alpha^*$. The risk is totally shifted from the investor to the manager. Assume that e^* is the optimal effort level that the investor desires and α is unique for each level of e, $\alpha^* = \int \pi f(\pi|e^*)\, d\pi - g(e^*) - \bar{v}$ is the solution to the investor-manager problem.

We illustrate this with an example. Assume that the agent is risk neutral with disutility from exercising effort, given by *g(e),* where *g'(e), g''(e), g'''(e)*>0. The principal has a risk-return preference defined over mean-variance of investment outcome in terms of: $u(w) = E[\pi - w(\pi)] - c * var\big(\pi - w(\pi)\big)$. Conditional on the effort level, we also assume that the investment return is normally distributed with a mean of *e* and a variance of σ^2. If we narrow our analysis to linear compensation schemes for the manager, $w(\pi) = a + b * \pi$, substituting this into the incentive constraint (ii) yields $b = g'(e)$. Because $g'(e)$>0 and $w'(\pi) = b = g'(e^*) = 1 > 0$, the optimal effort is induced when $b = 1$. Therefore, we conclude that the performance fee $w(\pi)$ increases when π increases and the risk is totally shifted from the investor to the manager.

In summary, the performance fee must be non-decreasing in the performance of the fund, regardless of the risk preference of the manager and investor. The participation constraint requires a floor on the performance fee.

2.4.4. Other Implications of Performance Fees

In this section, we discuss other implications of the performance fee. Similar to Ross (2004), we propose that the option type performance fee, the corresponding utilities and risk-taking behavior can be divided into three regimes as captured in Figure 1. In Regime (a), the performance fee is in the money. The translation effect and magnification effect dominate the other effects. Whether the performance fee is risk inducing or risk reducing depends on the risk attitude of the manager, as well as the marginal disutility of effort. Managers with increasing risk aversion will display totally different risk strategies from those with decreasing risk aversion or constant risk aversion. In Regime (b), the performance fee is at the money or slightly out of the money and the convexity effect dominates all other effects. Regardless of the manager's risk attitude, he opts to increase the volatility of the investment and the value of the performance fee contract. This phenomenon is well addressed in the literature. Regime (c) refers to the implicit floor on the performance fee, which is seldom discussed by the existing literature. The implicit floor occurs when the fund experiences a huge loss and the investor exercises his right to withdraw assets. When the fund hits the implicit floor, it is very detrimental to fund managers. Their performance fees for the current period are gone, future management fees are gone, and their reputations may be damaged. Therefore, managers are motivated to adopt more conservative risk approaches when faced with the threat of losing the base of assets under management, and the threat of damaging their reputation, which could curtail their future careers. Incorporating the disutility of effort, these five effects can either enhance or offset the result of each other in all three regimes. It is obvious that fund managers have the incentive to exert more effort and achieve Regime (a) because they are financially better off. Therefore, we propose that existing literature is inaccurate, based on the risk-shifting prospect of the optionality of the performance fee. It ignores the win-win aspect of performance fee contracts and misrepresents the relationships between fund managers and investors.

2.4.5. Other Performance Fee Features

In this section we discuss other performance fee provisions such as the hurdle rate and high-water mark (negative carry forward). The hurdle rate is another distinct feature of hedge fund performance fees. It stipulates that the performance fee can only be paid on the fund's performance in excess of a benchmark. This provision provides incentives for the manager to beat the benchmark, and the appropriate hurdle rate encourages greater effort and mitigates risk behavior. On the other hand, if the hurdle rate is not appropriate, the performance fee may discourage effort and distort incentives. Other performance fee provisions such as the “high-water mark” (“negative carry forward”) are in place to help smooth the return and reduce the risk faced by investors. A “high-water mark” usually requires fund managers to make up their previous losses before being rewarded for over-performance. The provision prevents managers from receiving fees for volatile performance and, to some extent, smooths the return of hedge funds. It also prevents the fund manager from writing off the loss in one year. Therefore, the manager also bears part of the downside risk. Moreover, if the performance is way below benchmark, investors may choose to withdraw their investments from the fund, causing fund managers to lose management fees and future performance fees. The fund manager may also place his reputation at risk, which can be very costly if prospective clients invest in other hedge funds instead. Thus, there are natural bounds of risk. We argue that because the high watermark provision requires fund managers to make up the prior loss before the performance fee kicks in, they are motivated to choose a high effort level even under poor market conditions to minimize losses.

2.5. Empirical Analyses

In this section, we present the results from the empirical tests and investigate whether performance fee contracts motivate hedge fund managers to achieve higher risk adjusted returns. We find a positive relationship between hedge fund performance fees and fund performance.

The risk adjusted returns are measured in terms of the Sharpe and Sortino ratios. The Sharpe ratio is the most popular measure for assessing risk adjusted returns. However, it penalizes both upside and downside risk despite the fact that upside variation is usually desirable. In contrast, the Sortino ratio only penalizes returns below the benchmark. Therefore, we believe that the Sortino ratio is a better measure between the two.

Our empirical tests follow Kouwenberg and Ziemba (2007) and adopt both the multiple linear regression approach (MLS) and Maximum Likelihood Estimate (MLE) approach. Because both the Sharpe and Sortino ratios fail the normality test, the Maximum Likelihood Estimates based on the skewed student's t-distribution and likelihood-ratio test are conducted to adjust for the non-normality.

The monthly return data is provided by www.hedgefundresearch.net (HFR), which is one of the biggest database providers of hedge fund data in North America. Over 7,000 hedge funds and funds of hedge funds are included in the database between January 1991 and December 2008. Our study includes funds with more than 12 months of data, with Table 2.1 summarizing the demographics of funds in the HFR database. The average monthly return of hedge funds is 0.35%, with mean live funds yielding 0.47%. This is 0.26% higher than the mean dead funds' yield of 0.21%. The risk-rate is downloaded from the Fama French data library. Live funds have an average return of 0.469% and graveyard funds have an average return of 0.209%. Live Funds' average performance fee in term of incentive rate is 15.88%, 3% higher than that of the graveyard funds (12.80%). This difference is statistically significant with t=17.31. The difference of the average management fee (rate) between the live funds and graveyard funds are minor (0.05%).

The average Sharpe ratio for the entire hedge fund universe is 0.08, with a standard deviation of 0.42. This includes a significantly higher average of 0.12 for live funds, compared to 0.05 for dead funds. The standard deviation of the Sharpe ratio among live funds is 0.39, which is lower than the standard deviation of the Sharpe ratio of 0.45 for dead funds. This shows that the distribution of the Sharpe ratio for live funds has a higher mean and lower variance. Therefore, it is more attractive.

The average Sortino ratio for the entire hedge fund universe is 0.18 and there is little difference among live and dead funds. In general, the average Sortino ratio is more favorable than the Sharpe ratio, as it only measures the downside movement. The first four moments of the Sharpe and Sortino ratios are reported in Table 2.5 and it is obvious that the distributions of both are non-normal. The distribution of the Sharpe ratio has positive skewness and moderate kurtosis, while the distribution of the Sortino ratio has positive skewness and high kurtosis. The kurtosis of the Sortino ratio of dead funds is extremely high. Therefore, the results from OLS might be biased and the use of a MLE test, based on the skewed student's t-distribution is recommended.

Charging a performance fee is the norm in the hedge fund industry. Out of 7,349 funds or funds of hedge funds in our study, only 14% do not charge performance fees. Among them, 12% of the live funds or funds of hedge funds have no performance fee provision. Of the dead funds, 17% charge no performance fees. In general, 52% of funds in the study follow the industry standard and charge a 20% performance fee. The rate is much higher among live funds at 63%, compared to 39% for dead funds. Meanwhile, 30% of hedge funds or funds of hedge funds have a performance fee below 20%, and four percent of them charge more than 20%. Among the live funds, 67% of the funds or funds or hedge funds charge 20% performance fees or more. In comparison, only 42% of dead funds or funds of hedge funds have performance fees more than 20%. The average age of live funds in the study is 72.6 months, while the average life span of dead funds is just over four years. We conclude from these statistics that higher performance fees could potentially contribute to the longevity of the funds. The average performance fee among all funds is 14.5% with a standard deviation of 7.7%. The average performance fee is higher among live funds (15.9%) than among the dead funds (12.8%). This is consistent with our expectation that performance fees might be higher among live funds because their Sharpe ratios are higher. There is no significant difference between the average management fees among live funds and those among dead funds. The average management fee of live funds is 1.46%, compared to 1.41% for dead funds. The average management fee for the entire hedge fund universe is about 1.44% per year (Table 2.1).

Table 2.2 compares the performance of hedge funds with and without performance fees. It also examines the difference in performance for hedge funds that charge below or above the median performance fees (20%). In general, hedge funds with performance fee provision display higher average returns and risk adjusted returns. Hedge funds with performance fee provisions provide an average rate of return of 0.41%, while those without the performance fee provision only score 0.02%. The average Sharpe ratio for the hedge funds with performance fee provisions is three times higher than the average Sharpe ratio for those without. The average Sortino ratio is also higher for the hedge funds with the performance fee provision. The differences are all statistically significant. Table 2.2 shows that hedge funds that charged more than 20% performance fees usually perform better than those charged less than 20% performance fee in terms of average monthly returns, Sharpe ratios and Sortino ratios.

Tables 2.3 to 2.5 report the regression results on returns from the OLS method and the Maximum Likelihood Estimates based on the skewed student's t-distribution. Table 2.3 is based on the entire hedge fund universe, Table 2.4 is based on the live funds and Table 2.5 is based on the dead funds. The results from the OLS regression are reported because it is easier to understand and it provides a general picture of the size and direction of the effects. The more consistent estimates are derived from the skewed student's t-distribution, which is recognized as a better approach for capital market analyses. Our conclusion is therefore based on the results of the maximum likelihood analyses. Consistently, performance fees are positively related to the returns with coefficient estimates ranging between 0.02 and 0.04 in all three tables.

Tables 2.6 to 2.8 report the test results for risk adjusted returns. Table 2.6 displays OLS regression result and the Maximum Likelihood Estimate based on the skewed student's t-distribution for the whole hedge fund universe. The first two rows report the OLS estimates and the third and fourth rows report the MLE results. We propose that performance fees motivate the fund manager to exert more effort and explore higher risk opportunities which lead to higher risk adjusted returns. As expected, both the OLS and the MLE estimates based on the student's t-distribution show that performance fees are positively related to the Sharpe ratio and that the effect is statistically significant in all analyses. In the single linear model, the coefficient estimate yields 0.009 for the Sharpe ratio and 0.017 for Sortino ratio. Both values decrease under the MLE estimation but are still statistically significant. On average, as performance fees increase by 1%, the Sharpe ratio increases by 0.006 to 0.01. The increase in the Sharpe ratio is desirable for fund managers because the ratio describes the amount of reward per unit of risk. The higher the coefficient estimate on the Sharpe ratio, the better. Meanwhile, the performance fee is also positively and statistically significant relative to the Sortino ratio. The coefficient estimates based on the OLS is 0.02 and reduces to 0.006 when adopting the MLE approach. However, it is still statistically significant even after controlling for other factors.

The effect of management fees is negligible based on the OLS analysis. In some cases, the management fee contributes negatively to the Sharpe ratio and this might be due to the fact that the MER reduces the total return of the investment. In the MLE analysis, the t-values for the coefficient on the management fees are much less than those of performance fees. This again is consistent with our expectations and hypothesis.

Results showing the effect of the performance fee, age and management fees for live funds and graveyard funds are displayed in Tables 2.7 and 2.8. The first two rows report the OLS estimates, while the third and fourth rows report the MLE results. Results for both the live funds and dead funds are similar to the results based on the hedge fund universe and are very robust. Both the Sharpe ratio and Sortino ratio are positively related to the performance rates. In other words, performance fees motivate fund managers to pursue better risk-return investment opportunities. These results are consistent with our theory and we concur that the performance fee provision creates a good risk sharing mechanism that improves the welfare of both investors and fund managers.

In summary, the empirical results verify our proposition and are consistent with the claim that higher performance fees motivate fund managers to pursue aggressive strategies and both the fund investor and fund manager benefit from such a compensation scheme.

2.6. Conclusion

In conclusion, this paper provides a theoretical framework for the hedge fund performance fee provision. It shows empirically that performance fees can be economically justified because fund managers must be compensated for their effort. The performance fee aligns the interest of the fund manager and investor and creates a win-win risk-sharing position. The higher the performance fee, the higher the risk adjusted returns. The goal of this paper was not to search for an optimal contract, but to explain the existence of the prevailing option-like performance fee contract. The results from the empirical testing are consistent with our explanation. A comparison between mutual funds and hedge funds might shed more light on the trade-offs between different compensation schemes and is recommended for future study.

2.7. References

Admati and Pfleierer. 1997. Does it all add up? Benchmarks and the compensation of active portfolio managers. Journal of Business, 70, 323-350

Anson. 2001. Hedge fund performance fees and the “free option”. The Journal of Alternative Investments, 14(2), 43-48.

Brooks, Clare, and Motson. 2007. The gross truth about hedge fund performance and risk: The Impact of Performance fees. SSRN working paper. Nov 2007.

Brown, Goetzmann and Park. 2001. Careers and survival: competition and risk in the hedge fund and CTA industry. Journal of Finance, 56(5) 1969-1886.

Carpenter. 2000. Does option compensation increase managerial risk appetite. The Journal of Finance, 55, 2311-2331.

Clare and Motson. 2007. Locking in the profits or putting it all on black? An investigation into the risk-taking behavior of hedge fund managers. Journal of Alternative Investment. 12(2), 7-25

Drago, Lazzari and Navone. 2010. Mutual fund incentive fees: determinants and effects. Financial Management, 39, 365–392

Edwards and Caglayan. 2001. Hedge fund performance and management skills. Journal of Futures Markets, 21(11), 1003–1028.

Elton, Gruber and Blake. 2003. The Journal of Finance. 58(2), 779–804.

Giuli, Maggi and Paris. 2003. Pricing performance fee of hedge fund managers: a discussion of moral hazard. Italy, working paper

Goetzmann, Ingersoll and Ross. 2003. High-water marks and hedge fund management contracts. Journal of Finance, 58(4), 1685-1718.

Grinblatt and Titman. 1989. Averse risk incentives and the design of performance based contracts. Management Science, 35, 807-822.

Hodder and Jackwerth. 2007. Incentive Contracts and Hedge Fund Management. Journal of Financial and Quantitative Analysis, 42, 811-826.

Holmstrom. 1979. Moral hazard and observability. The Bell Journal of Economics, 10 (1): 74- 91.

Ineichen. 2003. Absolute returns: the risk and opportunities of hedge fund investing. Wiley Finance. New Jersey.

Ingersoll. 2000. Digital contracts: Simple tools for pricing complex derivatives. Journal of Business 73, 67-88.

Ingersoll. 2002. The subjective and objective evaluation of compensation stock options. Working paper. International Center for Finance. Yale School of Management.

Kouwenberg and Ziemba. 2007. Incentives and risk-taking in hedge funds. Journal of Banking & Finance, 31(11), 3291-3310.

Li and Tiwari. 2009. Incentive contracts in delegated portfolio management. Review of Financial Studies, 22 (11), 4681-4714.

Liang B. 2001, Performance of hedge funds: 2001-2009. Financial Analyst Journal, 57, 11-19.

Mas-Colell, Whinston and Green. 1995. Microeconomic Theory. Oxford University Press.

Merton. 1976. Option pricing when the underlying stock returns are discontinuous. Journal of Financial Economics, 3, 125-144.

Panageas and Westerfield. 2009. High-water marks: high risk appetites? Convex compensation, long horizon and portfolio choice. Journal of Finance, 64, 1589-1622.

Richter and Brorsen. 2000. Estimating fees for managed futures: a continuous-time model with a Knockout Feature. Applied Mathematical Finance, 7(2), 115-125.

Ross. 2004. Compensation, incentives, and the duality of risk aversion and riskiness. The Journal of Finance, 59(1), 207–225.

Starks. 1997. Performance incentive fees: an agency theoretic approach. Journal of Financial and Quantitative Analysis, 22(1), 17-32.

Stracca. 2006. Delegated portfolio management: a survey of the theoretical literature. Journal of Economic Surveys, 20(5), 823–848.

2.8. Tables and Figures

Table 2.1 Hedge Funds – Summary Statistics

This table presents summary statistics on the seven features of hedge funds between January 1991 and December 2008. Features include: mean monthly returns, volatilities, Sharpe ratio, performance and management fees, and Sortino ratio. We also report the results for live funds and dead funds.

		Live	Dead	Overall
Mean Monthly Return	Mean	0.469	0.209	0.353
	Stdev	1.188	1.045	1.134
Volatility	Mean	3.983	3.295	3.677
	Stdev	2.998	2.571	2.838
Sharpe Ratio	Mean	0.115	0.045	0.084
	Stdev	0.389	0.451	0.419
Sortino Ratio	Mean	0.176	0.177	0.177
	Stdev	0.934	0.916	0.926
Performance fee	Mean	15.877	12.805	14.512
	Stdev	7.372	7.793	7.714
Management Fee	Mean	1.461	1.413	1.439
	Stdev	0.666	0.691	0.691
Funds with Performance Fees of:	=0	483	549	1032
	<20%	854	1344	2198
	=20%	2589	1262	3851
	>20%	158	110	268
	Total	4084	3265	7349
	=0	12%	17%	14%
	<20%	21%	41%	30%
	=20%	63%	39%	52%
	>20%	4%	3%	4%
	Total	100%	100%	100%

Table 2.2 Performance Comparison of Hedge Funds with Different Performance Fees

This table compares the returns, Sharpe ratios and Sortino ratios of hedge funds with and without performance fees, and hedge funds that charged below 20% performance fees with those charged above 20% performance fees.

	With	Without	t	Below 20%	Above 20%	t
Return	0.41	0.02	9.90	0.11	0.85	-9.08
Sharpe Ratio	0.09	0.03	3.88	-0.02	0.23	-6.16
Sortino Ratio	0.20	0.03	7.59	0.00	0.32	-4.41

Table 2.3 Hedge Fund Universe – Regression Results for Returns

This table presents the estimation results of the cross-sectional regression for the entire hedge fund universe. Each set of regression comprises four rows.The results for the multiple linear regressions are reported in the first and second row of each measure, where the first row provides the estimates and the second row presents the t-statistics. The MLE estimates based on skewed student's t-distribution are presented in the third and fourth row, where the third row reports the estimates and the fourth row reports the t-statistics. LR is the likelihood ratio and DoF is the estimated degree of freedom. The cross-sectional model is as follows:

$Returns\ = \alpha + \beta_1 * \text{Age} + \beta_2 * \text{Performance fee} + \ \beta_3 * \text{Management fee} + \varepsilon.$

Intercept	Age	Performance Fee	Management Fee	R Squared	DoF	LR
-0.678	**0.007**	**0.031**	**0.051**	0.13		
-16.93	**27.39**	**18.98**	**2.76**			
-0.338	**0.005**	**0.022**	**0.080**		1.74	-8273.84
-12.74	**35.93**	**26.45**	**6.76**			
-0.616	**0.007**	**0.032**		0.13		
-18.64	**27.25**	**20.07**				
-0.240	**0.005**	**0.023**			1.75	-8296.71
-10.87	**35.87**	**28.55**				
-0.319	**0.007**		**0.127**	0.09		
-8.83	**25.91**		**6.94**			
-0.207	**0.005**		**0.152**		1.83	-8612.54
-7.94	**33.92**		**15.06**			
-0.124	**0.007**			0.08		
-5.45	**25.29**					
-0.023	**0.005**				1.84	-8693.72
-0.98	**33.40**					
-0.072		**0.029**		0.04		
-2.61		**17.45**				
0.268		**0.023**			1.92	-8907.28
13.24		**25.64**				
0.234			**0.083**	0.00		
7.66			**4.35**			
0.352			**0.145**		2.00	-9168.06
14.53			**12.93**			

Table 2.4 Live Funds – Regression Results for Returns

This table presents the estimation results of the cross-sectional regression for the live funds. The first two rows report the OLS results and the third and fourth rows report the MLE results. The first row provides the estimates and second row presents the t-statistics. The MLE estimates based on skewed student's t-distribution are presented in the third and fourth row, where the third row reports the estimates and the fourth row reports the t-statistics. LR is the likelihood ratio and DoF is the estimated degree of freedom. The cross-sectional model is as follows: $Returns = \alpha + \beta_1 * \text{Age} + \beta_2 * \text{Performance fee} + \beta_3 * \text{Management fee} + \varepsilon$.

Intercept	Age	Performance Fee	Management Fee	R Squared	DoF	LR
-0.720	**0.007**	**0.036**	**0.086**	0.12		
-11.93	**19.19**	**14.62**	**3.15**			
-0.277	**0.005**	**0.021**	**0.096**		1.73	-4881.84
-7.23	**24.70**	**17.46**	**5.96**			
-0.619	**0.007**	**0.038**		0.12		
-12.12	**18.95**	**15.94**				
-0.167	**0.004**	**0.023**			1.73	-4900.64
-5.03	**24.74**	**19.79**				
-0.27	**0.01**		**0.19**	0.07		
-5.03	**17.60**		**6.95**			
-0.052	**0.004**		**0.162**		1.83	-5026.18
-1.42	**22.23**		**12.67**			
0.030	**0.006**			0.06		
0.94	**16.78**					
0.158	**0.004**				1.84	-5089.17
4.72	**21.43**					
-0.054		**0.033**		0.04		
-1.25		**13.35**				
0.361		**0.021**			1.89	-5190.93
11.57		**15.73**				
0.280			**0.129**	0.01		
6.26			**4.64**			
0.464			**0.148**		1.93	-5271.11
14.37			**10.87**			

Table 2.5 Graveyard Funds – Regression Results for Returns

This table presents the estimation results of the cross-sectional regression for the dead funds. The results for the multiple linear regressions are reported in the first and second row of each measure, where the first row provides the estimates and second row presents the t-statistics. The MLE estimates based on skewed student's t-distribution are presented in the third and fourth row, where the third row reports the estimates and the fourth row reports the t-statistics. LR is the likelihood ratio and DoF is the estimated degree of freedom. The cross-sectional model is as follows: $Returns\ =\ \alpha + \beta_1 * \text{Age} + \beta_2 * \text{Performance fee} +\ \beta_3 * \text{Management fee} + \varepsilon$.

Intercept	Age	Performance Fee	Management Fee	R Squared	DoF	LR
-0.619	**0.008**	**0.023**	0.007	0.126		
-11.66	**19.66**	**10.14**	0.28			
-0.312	**0.005**	**0.018**	**0.058**		1.73	-3314.18
-8.36	**24.32**	**15.83**	**3.24**			
-0.610	**0.008**	**0.023**		0.126		
-14.07	**19.68**	**10.35**				
-0.240	**0.005**	**0.019**			1.75	-3319.14
-8.01	**24.10**	**16.75**				
-0.377	**0.008**		**0.049**	0.10		
-7.83	**18.96**		**2.03**			
-0.238	**0.005**		**0.105**		1.75	-3443.44
-6.48	**23.65**		**5.85**			
-0.305	**0.008**			0.10		
-9.44	**18.86**					
-0.113	**0.005**				1.76	-3459.38
-3.74	**23.37**					
-0.053		**0.020**		0.02		
-1.53		**8.83**				
0.265		**0.020**			1.91	-3604.70
10.74		**15.88**				
0.180			0.021	0.00		
4.47			0.82			
0.305			**0.096**		1.94	-3718.07
8.75			**4.68**			

Table 2.6 Hedge Fund Universe – Regression Results on Risk Adjusted Returns

This table presents the estimation results of the cross-sectional regression for the entire hedge fund universe. The results for the multiple linear regressions are reported in the first and second row of each measure, where the first row provides the estimates and the second row presents the t-statistics. The MLE estimates based on skewed student's t-distribution are presented in the third and fourth row, where the third row reports the estimates and the fourth row reports the t-statistics. LR is the likelihood ratio and DoF is the estimated degree of freedom. The cross-sectional model is as follow: $Sharpe\ ratio\ =\ \alpha+\beta_1*\mathrm{Age}+\beta_2*\mathrm{Performance\ fee}+\ \beta_3*\mathrm{Management\ fee}+\varepsilon$; $\mathrm{Sortino\ ratio}\ =\ \alpha+\beta_1*\mathrm{Age}+\beta_2*\mathrm{Performance\ fee}+\ \beta_3*\mathrm{Management\ fee}+\varepsilon$.

	Intercept	Age	Performance Fee	Management Fee	R Squared	LR	DoF
Sharpe Ratio	**-0.134**	**0.001**	**0.010**	-0.003	0.04		
	-8.61	**11.69**	**14.92**	-0.38			
	-0.295	**0.002**	**0.006**	**0.014**		297.52	2.50
	-28.16	**39.47**	**19.65**	**3.20**			
Sortino Ratio	**-0.157**	**0.001**	**0.017**	0.009	0.02		
	-4.51	**4.51**	**11.91**	0.58			
	-0.400	**0.003**	**0.006**	**0.016**		-1932.41	1.85
	-37.23	**48.74**	**17.04**	**2.96**			
Sharpe Ratio	**-0.137**	**0.001**	**0.009**		0.04		
	-10.71	**11.76**	**15.21**				
	-0.279	**0.002**	**0.006**			292.55	2.51
	-30.18	**39.41**	**20.73**				
Sortino Ratio	**-0.146**	**0.001**	**0.017**		0.02		
	-5.07	**4.48**	**12.35**				
	-0.381	**0.003**	**0.006**			-1936.53	1.86
	-44.33	**48.80**	**17.73**				
Sharpe Ratio	**-0.046**		**0.009**		0.03		
	-4.48		**14.33**				
	-0.052		**0.007**			-392.89	2.62
	-5.26		**20.92**				
Sortino Ratio	**-0.068**		**0.017**		0.02		
	-2.97		**12.08**				
	-0.165		**0.008**			-2866.73	2.17
	-15.77		**18.65**				

Table 2.7 Live Funds – Regression Results on Risk Adjusted Returns

This table presents the estimation results of the cross-sectional regression for the live funds. The results for the multiple linear regression is reported in the first and second row of each measure where the first row provides the estimates and the second row presents the t-statistics. The skewed student –t MLE estimates are presented in the third and fourth row where the third row reports the estimates and the fourth row reports the t-statistics. LR is the likelihood ratio and DoF is the estimated degree of freedom. The cross-sectional model is as follows: $\text{Sharpe ratio} = \alpha + \beta_1 * \text{Age} + \beta_2 * \text{Performance fee} + \beta_3 * \text{Management fee} + \varepsilon$; $\text{Sortino ratio} = \alpha + \beta_1 * \text{Age} + \beta_2 * \text{Performance fee} + \beta_3 * \text{Management fee} + \varepsilon$.

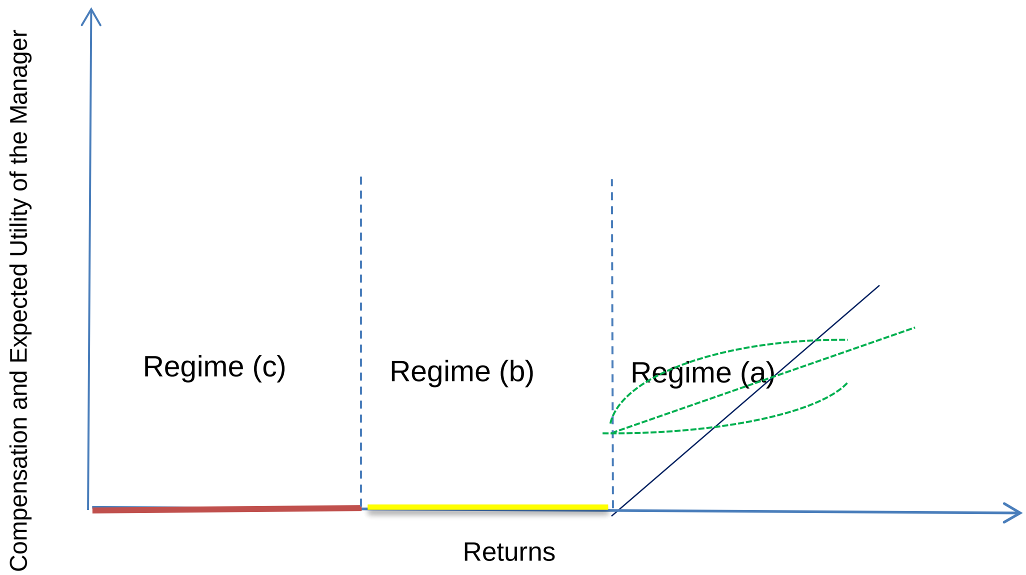
	Intercept	Age	Performance Fee	Management Fee	R Squared	LR	DoF
Sharpe Ratio	**-0.107**	**0.001**	**0.008**	0.011	0.04		
	-5.15	**8.11**	**9.98**	1.22			
	-0.229	**0.002**	**0.005**	**0.018**		148.09	2.53
	-15.29	**23.51**	**12.64**	**3.40**			
Sortino Ratio	**-0.161**	**0.001**	**0.018**	0.000	0.02		
	-3.47	**4.04**	**9.08**	0.01			
	-3.920	**0.003**	**0.006**	0.011		-1230.53	1.81
	-26.51	**35.69**	**13.20**	1.52			
Sharpe Ratio	**-0.093**	**0.001**	**0.009**		0.04		
	-5.33	**8.03**	**10.65**				
	-0.209	**0.002**	**0.006**			142.36	2.52
	-15.29	**23.47**	**13.69**				
Sortino Ratio	**-0.161**	**0.001**	**0.018**		0.02		
	-4.18	**4.06**	**9.34**				
	-0.379	**0.003**	**0.006**			-1231.64	1.81
	-31.65	**35.76**	**13.66**				
Sharpe Ratio	-0.011		**0.008**		0.02		
	-0.79		**9.74**				
	0.020		**0.006**			-113.80	2.50
	0.15		**12.64**				
Sortino Ratio	**-0.066**		**0.017**		0.02		
	-2.16		**8.98**				
	-0.158		**0.008**			-1745.24	2.11
	-11.14		**13.18**				

Table 2.8 Graveyard Funds – Regression Results on Risk Adjusted Returns

This table presents the estimation results of the cross-sectional regression for graveyard funds. The results for the multiple linear regression are reported in the first and second row of each measure, where the first row provides the estimates and the second row presents the t-statistics. The skewed student –t MLE estimates are presented in the third and fourth row, where the third row reports the estimates and the fourth row reports the t-statistics. LR is the likelihood ratio and DoF is the estimated degree of freedom. The cross-sectional model is as follows: $\text{Sharpe ratio} = \alpha + \beta_1 * \text{Age} + \beta_2 * \text{Performance fee} + \beta_3 * \text{Management fee} + \varepsilon$; $\text{Sortino ratio} = \alpha + \beta_1 * \text{Age} + \beta_2 * \text{Performance fee} + \beta_3 * \text{Management fee} + \varepsilon$.

	Intercept	Age	Performance Fee	Management Fee	R Squared	LR	DoF
Sharpe Ratio	**-0.153**	**0.002**	**0.010**	-0.017	0.04		
	-6.40	**8.22**	**9.54**	-1.58			
	-0.334	**0.002**	**0.005**	0.004		236.99	2.43
	-22.89	**31.33**	**11.68**	0.56			
Sortino Ratio	**-0.154**	**0.001**	**0.017**	0.023	0.02		
	-2.90	**2.12**	**7.76**	0.94			
	-4.120	**0.003**	**0.005**	**0.021**		-694.29	1.92
	-26.56	**33.47**	**10.63**	**2.75**			
Sharpe Ratio	**-0.175**	**0.002**	**0.009**		0.04		
	-8.93	**8.31**	**9.40**				
	-0.330	**0.002**	**0.005**			236.81	2.43
	-26.23	**31.34**	**11.98**				
Sortino Ratio	**-0.125**	**0.001**	**0.017**		0.02		
	-2.89	**2.08**	**8.11**				
	-0.387	**0.003**	**0.006**			-697.74	1.93
	-31.46	**33.46**	**11.07**				
Sharpe Ratio	**-0.069**		**0.009**		0.02		
	-4.58		**8.89**				
	-0.092		**0.006**			-195.32	2.66
	-6.20		**12.20**				
Sortino Ratio	**-0.071**		**0.017**		0.02		
	-2.05		**8.08**				
	-0.175		**0.009**			-1115.79	2.26
	-11.37		**13.25**				

Figure 2.1 Utility and Risk Attitude of the Manager



This figure displays the compensation of a fund manager and his corresponding expected utility based on an option-like performance fee. The dotted lines indicate the expected utilities and the solid line represents the total compensation. In Regime (a), the performance fee is in the money, and the utility and risk appetite of the manager depends on his utility function. In Regime (b), the performance fee is out of the money and the investor still keeps his investment in the fund. The manager receives a flat management fee. In Regime (c), the investor withdraws his investment from the fund and the manager's future compensation is zero.

3. Understanding Hedge Fund Tail Risk

3.1. Abstract

Hedge fund returns have fat tails and high kurtosis, but the severity of this issue compared to mutual funds is still unaddressed in the academic and practitioner literature. This paper examines the hedge fund tail risk in terms of the Value at Risk (VaR) and Expected Shortfall and compares these measures with those of mutual funds. We find that hedge fund tail risk is relatively comparable to that of mutual funds. We also evaluate hedge fund tail risk dependence on the stock market index and VIX index. We find that the VIX is a good indicator of hedge fund Expected Shortfall and that the relation between the two strengthens during market turbulence, displaying the phase-locking effect.

3.2. Introduction

Hedge funds are favored by institutional investors, pension funds and high wealth investors for their flexible investment trading strategies and possible diversification benefit with existing portfolios. Existing literature shows a low correlation between stock market returns and hedge fund returns during normal market conditions. However, during the 1998 and 2008 financial crises, hedge funds failed to provide loss protection and incurred unprecedented losses as the stock market plummeted. Are hedge funds still a good portfolio diversification instrument?

This paper addresses this question by comparing the tail risk between mutual funds and hedge funds. Hedge funds are perceived to have higher tail risk than mutual funds because hedge funds can adopt highly sophisticated investment strategies with trading flexibilities and high leverage. We expect that hedge funds have a moderately higher tail risk compared with mutual funds. We also examine the correlation between the tail risk of mutual funds and hedge funds. If the correlation is high, it will raise the question about the diversification benefit of including hedge funds into mutual fund portfolios for institutional investors.

Second, this paper examines the tail risk dependence between hedge funds and the stock market in terms of market returns. It helps us understand how hedge funds react to market conditions and compares the severity of the tail risk of hedge funds with those of the stock market.

Third, we also study the relationship between the tail risk of hedge funds and the VIX. A high VIX value is usually associated with a bear market. We expect that the tail dependence between hedge funds and the VIX will be relatively moderate during normal market conditions, and strengthened when markets decline due to lack of liquidity and excessive leverage implemented by hedge funds. During market catastrophes, liquidity spirals cause tail risk of different hedge fund strategies to correlate to the VIX, thus displaying the phase-locking effect. Existing literature uses quartile analyses to examine the phase-locking effect, which we test empirically through the interaction effect. If the phase-locking effect is observed, the diversification benefit of including hedge funds in the portfolio would decrease, which would have practical implications on portfolio management.

This paper is organized as follows: Section 2 is a brief literature review on hedge fund risk and tail risk; Section 3 provides an empirical design model; Section 4 discusses the source of the data; Section 5 presents the analyses and test results on the tail risk model; and Section 6 concludes the paper.

3.3. Literature Review

This section briefly reviews the literature on hedge fund systematic risk and tail risk. Systematic risk and tail risk are the two most important topics in hedge fund risk management. Papers that investigate hedge fund systematic risk usually examine the beta and source of alpha. Fung and Hsieh (2004a) found that by using an arbitrage pricing theory, the asset-based style (ABS) factors can explain eighty percent of the variation of hedge fund returns. Fung and Hsieh (2001) regressed the excess return of the Primitive Long/Short Equity funds on the Fama-French-Carhart four-factor model and found that it explained the majority of excess returns even after controlling for different liquidity factors. Their 2001 paper showed that look-back straddles did a better job of modeling trend-following strategies. In Fung and Hsieh (2004b), they found that when hedging out the systematic risk factors, the resultant alternative alpha returns were independent of systematic risks and were portable.

Chan, Getmansky, Haas, and Lo (2005) examined the systemic risk of hedge funds and developed measures to investigate them. These measures include: illiquidity risk exposure, banking-sector indexes, and aggregate measures of volatility and distress based on regime-switching models. They also adopted a non-linear factor model and a logistic regression analysis to test for hedge fund liquidation probabilities. They found that the hedge fund industry may be heading into a period of lower expected returns and higher systemic risk. Agarwal and Naik (2004) characterized the systematic risk exposure of hedge funds and demonstrated that the traditional mean-variance framework underestimates the tail risk.

Expected Shortfall measures the average loss when the portfolio value falls below the benchmark. This concept was first introduced by Artzner et al (1999) who argued that Expected Shortfall satisfies four requirements of a coherence measure in terms of monotonicity, translation invariance, positive homogeneity, and sub-additivity. Thus, Expected Shortfall is a better risk measure than Value at Risk (VaR). Acharya (2010) introduced systemic Expected Shortfall and used it to predict a system failure during the 2007-2009 financial crises. Brown, Hwang, In and Kim (2011) used the Marginal Expected Shortfall (MES) to measure the systemic risk of an individual hedge fund and found a robust and positive relationship between MES and returns, even after controlling fund characteristics such as age, asset size, and liquidity.

Adrian and Brunnermeier (2009) introduced the Conditional Value at Risk (CoVaR) measure. Adrian, Brunnermeier and Nguyen (2011) used the hedge fund style indices compiled by Credit Suisse/Tremont to examine the q-quantile dependence between hedge funds under stress and normal market conditions. They noticed an increase in dependence during times of crisis and identified seven factors that explain tail dependence: (i) CRSP market return in excess of the 3-month bill rate, (ii) VIX straddle excess returns, (iii) variance swap return, (iv) short-term liquidity spread, (v) carry-trade excess return, (vi) slope of yield curve, and (vii) credit spread. The volatility index (VIX) is a popular measure of implied volatility of the S&P 500 index options. However, averaging coefficient estimates across multiple strategies may cancel the positive and negative coefficient estimates among different strategies. It may also underestimate the dependence of some strategies – the smoothing effect.

Bacmann and Gawron (2004) suggested that hedge funds can provide diversification benefits because they found no dependence between hedge funds and bonds. They found some dependence between hedge funds and the stock market using the multivariate extreme value theory. Kang, In, Kim and Kim (2010) applied the Copula Theory to examine the asymmetric dependence between hedge fund returns and market returns under a range of time horizons. They found that as the investment horizon increased, the asymmetric dependence weakened. Both the extreme value and copula theories involve fitting a distribution to the data and were usually criticized for data mining. As pointed out by Dacorogna et al. (2001), the convergence of fourth moment may not exist in financial data and the test results derived from the Extreme Value Theory or Copula Theory are difficult to interpret and may be inaccurate.

Lo (2001) proposed the phase-locking effect in hedge funds. He used the two-factor model – the market factor (S&P index value) and the phase-locking factor to elaborate the phase-locking effect theoretically. The model is as follows:

$$R_{it} = \alpha_i + \beta_i \wedge_t + I_t Z_t + \varepsilon_{it}$$

Where $R_{it}$is the return on fund i at time t, α_i is the fund intercept, $\wedge_t$ is a “market” component, β_i is fund sensitivity to the market, and $I_t Z_t$ captures the phase-locking component or catastrophic market event. I_t takes only two values, 0 and 1. I_t equals “1,” which indicates the catastrophic market event and takes a value of “0” otherwise. ε_{it} is non-systematic (idiosyncratic) risk of fund i at time t. He also assumed that $\wedge_t$, I_t, Z_t and ε_{it} are mutually i.i.d.. This model explicitly allowed for the catastrophic event and helped estimate situations where otherwise uncorrelated actions suddenly became synchronized. The empirical test of the phase-locking effect was first carried out by Boyson, Stahel, and Stulz (2006) who used a logit model to test for contagion across hedge fund styles. They investigated the daily and monthly returns of hedge funds and documented contagion across hedge fund styles. Adrian, Brunnermeier and Nguyen (2011) studied the hedge fund tail dependence across different styles using q-quantile analyses and found an increase in tail dependence in times of crisis – a contagion effect. They also found that the dependence does not affect the fund flow.

The award winning paper by Papageorgiou et al. (2010) showed that “Firstly, most significant market corrections have been preceded by an increase in market volatility. By conditioning one’s exposure to the level of volatility in the market, the impact of the market correction will be significantly dampened. Secondly, empirical evidence shows that asset returns tend to be greater during periods of low volatility.” In other words, the correlation between different investment vehicles weakens in bull markets and strengthens in bear markets.

This paper examines the tail risk of hedge funds and proposes that the tail dependence between hedge funds and the stock market strengthens during market downturns and weakens during normal market conditions. Instead of using returns as a dependent variable, we use Expected Shortfall as a dependent variable and introduce the interaction effect. This allows us to estimate the non-linear relationship demonstrated in the phase-locking effect. The short horizon effect reported by Kang, In, Kim and Kim (2010) was observed because the severe correlation during the bear market was smoothed out by normal market conditions over a long horizon. Therefore, we disagree with Kang, In, Kim and Kim (2010) and agree with Lo (2001) and Adrian, Brunnermeier and Nguyen (2011) that phase-locking effects exist.

3.4. Empirical Design

Tail risk generally refers to the possibility of experiencing extreme negative or positive returns that are higher than predicted by the normal distribution. Papers that investigate tail risk usually study the Value at Risk (VaR), downside risk, and Expected Shortfall. The VaR is a popular risk measure and evaluates the value at risk when the stock falls below a certain percentile. Expected Shortfall is also known as conditional VaR and measures the average loss when the portfolio value falls below a certain benchmark. Expected Shortfall is calculated as follows:

$$Expected\ Shortfall = E[R_t|R_t < VaR_t]$$

Where VaR_t is the value at risk at time t, R_t is the rate of return over the period. According to Artzner et al (1999), Expected Shortfall is preferable to VaR because it is a coherent measure. A coherent measure satisfies properties of monotonicity, sub-additivity, homogeneity, and translational invariance. To measure VaR and Expected Shortfall, we use the historical return to proxy for the return distribution. We calculate VaR and Expected Shortfall based on one-month, 12-month (one-year) and 36-month (three-year) rolling windows. We choose the 5th percentile for the threshold, as it is commonly adopted in the literature. It also simplifies the calculation because the value at the bottom 5th percentile is the value for VaR and the average return of the bottom 5% measures the Expected Shortfall.

Our first agenda is to examine the difference of tail risk between mutual funds and hedge funds and test for the significance of the difference using the t-test. We expect hedge funds to have moderately higher tail risk than mutual funds. If the difference is not significant, an investment in hedge funds is recommended as it provides higher risk adjusted returns.

We are also interested in the correlation of tail risks between hedge funds and mutual funds. If the correlation is low, including hedge funds into the portfolio, it provides diversification benefits. Whereas if the correlation is high, the inclusion of hedge funds is not recommended.

Second, we compare the difference of tail risks between hedge funds and the stock market in terms of market returns and the volatility index (VIX). VIX, also known as the "investor fear gauge," is a measure of perceived market risk in either direction. Copeland and Copeland (1999) found that the VIX is a good indicator of market performance.

Third, we test the phase-locking effect between hedge funds and the stock market. Existing literature finds phase-locking effects and contagion effects among different hedge fund strategies. Our study focuses on individual funds and tests for the phase-locking effect between hedge funds and the volatility index. We estimate the regression equation through the GMM Newey-West test and the MLE based on the skewed student's t-distribution. The MLE, based on the skewed student's t-distribution, accounts for the non-normal distribution and fits the characteristics of hedge fund return distributions.

Lo (2001) adopted the catastrophic market dummy. Improving upon his model, we introduced the interaction effect in our regression. The interaction effect allows for a nonlinear relationship between independent and dependent variables. It enables us to estimate the relationship during normal market situations and catastrophes simultaneously. It captures the phase-locking behavior and measures the magnitude of such behavior. A similar approach was observed in Agarwal and Naik (2004) with different variables and research focus.

Our model is as follows.

$$ES_{HF} = \alpha + \beta_1 * VIX + \delta_1 * Down_{mkt} + \delta_2 * Down_{Mkt} * VIX + \beta_2 * (Mkt - Rf) + \beta_3 * SML + \beta_4 * HML + \beta_5 * R_f + \varepsilon \ldots \quad (3)$$

Where VIX is the volatility index – a measure for market uncertainty, Mkt is the market return, R_f is the risk-free rate, $Mkt - Rf$ is the equity risk premium, and $Down_{Mkt}$ is the market timing dummy. $Down_{Mkt}$ takes the value of "1" in times of crisis and "0" during normal market situations. SML and HML are the Fama-French factors. R_f is the risk-free rate. We incorporate the Fama-French factors following Fung and Hsieh (2001, 2002, and 2003) and Hasanhodzic and Lo (2007). R_f is also included because it reflects the cost of borrowing and macro-economic conditions. The coefficient estimate (β_1) for VIX evaluates the relationship during normal market conditions. The coefficient (δ_1) on $Down_{Mkt}$ helps capture the change in the intercept from normal market conditions to bear market conditions. The coefficient estimate (δ_2) of the interaction factor tests the phase-locking effect. $\beta_1 + \delta_2$ measures the relation between VIX and the tail risk of hedge funds during a catastrophe. We expected that: 1. Both the VIX and market return would have a significant impact on the Expected Shortfall of hedge funds; 2. As market returns rise, the Expected Shortfall decreases and as the VIX increases, the Expected Shortfall increases; 3. The coefficient estimates of the interaction effect are statistically and economically significant, thus supporting the presence of a phase-locking effect. In other words, when markets are uncertain, the probability of a potential loss increases as well as the Expected Shortfall of hedge funds. We hope to observe significant coefficients on both the “Down” factor and the interaction factor.

This paper studies the Expected Shortfall and VaR as did Adrian, Brunnermeier and Nguyen (2011), but with different approaches and focuses. First, Adrian, Brunnermeier and Nguyen (2011) used the q-quantile analyses to examine the correlation and tail dependence among different hedge fund strategies. This paper compares the severity of tail risk between hedge funds and mutual funds and investigates the relation between the hedge fund tail risk and the return on the market, as well as the VIX. Second, this paper analyses the individual hedge fund data instead of index data. Third, this paper captures the phase-locking effect of the tail risk through the creation of dummy variables and the interaction effect. The interaction effect allows us to estimate tail dependence in normal market situations and in times of distress simultaneously. It also provides a direct test on the phase-locking effect. Fourth, instead of q-quantile analyses, we used the MLE estimates based on the skewed student’s t-distribution defined by Fernandez and Stell (1998). The skewed student’s t-distribution takes into account that the distribution of variables may not be normally distributed and provides more consistent results. It has three parameters: the skewness parameter, the degree of freedom and the degree of volatility. The degree of freedom, based on the skewed student t-distribution, is usually a non-integer greater than two. Past empirical studies that used linear regression analyses to explain alphas, systematic risk or source of hedge fund returns can be misleading. This is because hedge fund returns are highly skewed with positive kurtosis and these characteristics violate assumptions of linear regression. This paper fills in the gap and offers insight on hedge fund tail dependence and its diversification benefit.

3.5. Data

Data for the monthly hedge fund returns is provided by the hedge fund research database (HFR). Although data is reported voluntarily, they have maintained data on dead funds since 1992. As HFR's data has minimum survivorship bias compared with other data sources, we include both live funds and graveyard funds in our analysis to minimize the survivorship bias.

The value-weighted S&P 500 returns include dividends from the Wharton Research Data Services website and are used as the proxy for market returns. The monthly data for market risk premium, SMB, HML, and risk-free rates are downloaded from the Kenneth French data library. The VIX data is available on the Chicago Board Options Exchange's website.

The historical monthly mutual fund returns are calculated from the monthly net asset value per share of the funds downloaded from the CHASS database. The CHASS mutual fund data includes more than 4000 active funds from almost 200 sponsor companies. We examined the period between January 1994 and February 2009 to match the available data period for hedge funds.

3.6. Analyses and Test Results

In this section, we present the test results for comparison of the tail risk between mutual funds and hedge funds, the correlation between tail risk of hedge funds and the market, and for the phase-locking effect through the interaction effect.

3.6.1. Comparison of Tail Risk between Mutual Funds and Hedge Funds

First, we compare the tail risk between mutual funds and hedge funds in terms of VaR and Expected Shortfall using the bottom 5^{th} percentile as a benchmark and the return distribution of one-month, one-year and three-year rolling windows. The results are reported in Table 3.1.

The average VaR for mutual funds at the 5th percentile between January 1994 and February 2009 is 4.0%, while hedge funds averaged 4.5% for the same period. Therefore, based on the one-month return distribution, the average VaR for hedge funds is about 0.5% more than that for mutual funds, although the difference is not statistically significant. Meanwhile, if using one or three-year rolling windows as the proxy for the return distribution, the average VaR for hedge funds is smaller than that for mutual funds. The average VaR for hedge funds based on the return distribution of a one-year rolling window is 4.9%, while mutual funds averaged 5.5%. This is about 0.6% higher than hedge funds, which is statistically significant. The tail risk based on the return distribution of a three-year rolling window displays similar results. The statistics are presented in Table 3.1 and the information is graphically presented in Figures 3.1 and 3.2.

The summary statistics for the Expected Shortfall are reported in Table 3.2. The average monthly Expected Shortfall of hedge funds at the 5th percentile is 8.0%, with a standard error of 0.36 based on the distribution of one-month returns. In comparison, the average Expected Shortfall for mutual funds is 6.3%, with a standard error of 0.33 for the same study period. The difference of 1.7% is statistically significant using the t-test for equal mean. However, if we use the return distribution of one or three-year rolling windows, the differences in the Expected Shortfall between mutual funds and hedge funds are greatly diminished. Based on the return distribution of a one-year rolling window, the Expected Shortfall for mutual funds at the 5th percentile is 8.4% and that for hedge funds is 8.5% – a difference of 0.1%. Similarly, using the return distribution of a three-year rolling window, the Expected Shortfall for mutual funds is 8.4% and that for hedge funds is 8.5% – again a minor difference of only 0.1%.

Figure 3.3 shows the historical Expected Shortfall of mutual funds from January 1994 to February 2009. The maximum monthly Expected Shortfall is 25.8%, while the minimum monthly Expected Shortfall is 0.1%. Compared with hedge funds, the Expected Shortfall of mutual funds fluctuates more during the study period, with the two biggest spikes occurring August 1999 and October 2008.

The maximum monthly Expected Shortfall for hedge funds over the entire study period is 35.8%, compared to the minimum monthly Expected Shortfall of 1.9%. We observed two spikes in the Expected Shortfall during January 1994 to February 2009 – one in October

1998 and another in August 2008. The first incident corresponded with the closure of Long-Term Capital Management and the default of Russian government debt, which triggered a global flight to quality in 1998. The second spike occurred during the 2008 financial crisis, which originated in the USA. This information is graphically presented in Figure 3.4.

The maximum VaR and Expected Shortfall for hedge funds is bigger than those of mutual funds at the 5th percentile using the return distribution of one-month, one-year and three-year rolling windows. The difference is 1.8% based on one-month returns, 4.0% based on a one-year rolling window and 5.0% based on a three-year rolling window. Therefore, hedge funds are riskier than mutual funds in the worst case.

The correlation between the hedge fund tail risk and mutual fund tail risk are relatively high (0.7), based on one-month return data. As the time horizon increases, the correlation decreases to 0.5 using the return distribution of both one-year and three-year rolling windows. This result is reported in Table 3.3. Note that we need to be cautious about the results based on one-year and three-year rolling windows because of overlapping information.

3.6.2. Comparison between Hedge Funds and the Stock Market

In this section, we examine the relation between the tail risk of hedge funds and the stock market. We use the value weighted S&P 500 returns, including dividends as the proxy for market returns, and compare its return distribution with that of hedge funds. Between January 1994 and February 2009, the mean monthly return of the market was 0.5% with a standard deviation of 4.4%. The market return distribution is slightly non-normal with a maximum monthly return of 9.8% and a maximum loss of 16.7%, as evidenced in Table 3.4.

To compare tail risk, we evaluate the percentage frequency and VaR of market returns and hedge fund returns at the bottom 5^{th} and 1^{st} percentile levels over the entire study period. The VaR for market returns at the 5^{th} percentile is 8.1%, compared to 5.6% for hedge funds, which is 2.5% less than the market. Overall, only 2.8% of hedge funds had monthly returns below -8.1%. At the 1^{st} percentile, the VaR for market returns is -11.30%, compared to 13.3% for hedge funds, which is 2.0% below the stock market. Of all hedge funds, 1.43% of the monthly returns are below -11.3%. Therefore, tail risks for hedge funds are worse than the market at the 1st percentile level. The correlation between hedge fund Expected Shortfall and market returns is 0.59 based on a one-month rolling window. To further evaluate the relationship, we regressed the hedge fund returns on the market risk premium. The test results are incorporated into Tables 3.7 and 3.8 and will be discussed in the following section.

3.6.3. Tail Dependence

This section presents the test results of hedge fund tail dependence with the VIX and market returns. We incorporated the interaction effect of the market timing factor to test the phase-locking effect.

Table 3.6 presents the descriptive summary of the volatility index (VIX). As demonstrated, the average VIX is 20.2 with a standard deviation of 7.9, while the interquartile range is 10. Although the VIX generally remains around 20, it fell to a low of 10.42 in January 2007 and reached a high of 59.9 during the October 2008 financial crises. Figure 3.4 shows the fluctuation of the historical VIX from January 1994 to February 2009.

Tables 3.7 to 3.10 report the GMM Newey-West estimates and MLE estimates based on the skewed student's t-distribution. As expected, test results show a significant correlation between the VIX index and the tail risk (VaR and Expected Shortfall) of hedge funds.

Tables 3.7 and 3.8 present the test results for the VaR. Table 3.7 reports the GMM Newey-West estimates and Table 8 shows the MLE results based on the skewed student's t-distribution. The VIX is positively related to the VaR in all cases, which indicates that when market fears increase, the VaR increases. This relation is amplified during market turmoil, as demonstrated through the positive statistically significant coefficient estimates on the interaction factor. The GMM Newey West estimator for the VIX is 0.27. And, when incorporating the market timing effect and interaction effect, the Newey-West coefficient estimate on the VIX yields 0.19 during normal conditions and increases to 0.55 during bear markets. If controlling for the risk-free rate and Fama-French factors, the coefficient estimate on the VIX remains statistically significant. The

Newey-West coefficient estimates on the VIX yield 0.13 and 0.37 during normal conditions and bear markets respectively. Among Fama-French's three factors, the equity risk premium factor and SMB are consistently significant, while the coefficient estimates on market premium are all negative. This implies that when the market risk premium increases, the VaR decreases. This is reasonable, as the equity risk premium measures the excess return investors are rewarded with when investing in risky assets. The risk premium is usually high in bull markets and low in bear markets. Meanwhile, the tail risk is lower when markets are booming and higher when markets plummet. Therefore, equity risk premium and VaR are negatively related. The adjusted R-squared for the equation is 0.63 in the all-factor model. Therefore, the model is a good fit to the data. The results based on the return distribution of a one-year rolling window are reported at the bottom of Tables 3.7 and 3.8. It shows similar results as those based on a one-month return distribution. Table 3.8 presents the MLE estimates based on the skewed student's t-distribution and also displays consistent results with the GMM Newey-West estimates. The VIX shows a positive correlation with the VaR and the overall effect is amplified during bear markets. The market risk premium is again negatively related to the VaR.

Tables 3.9 and 3.10 report the test results for Expected Shortfall. In one factor model, the GMM Newey-West estimator for the VIX is 0.38. This implies that when the VIX increases by one, the Expected Shortfall in hedge funds increases by 0.38%. The magnitude of dependence is further amplified when we control for market timing. Not only is the coefficient on the dummy factor statistically significant, but also the coefficient on the interaction factor. Compared with the single factor model, the coefficient estimate on the VIX decreases from 0.38 to 0.29. Meanwhile, the coefficient estimate on the interaction factor yields 0.42. They are both statistically significant. When we aggregate both the VIX and interaction effect, the coefficient estimates on the VIX in times of crises are more than double those during normal market conditions. The aggregated coefficient estimate between the VIX and Expected Shortfall during market turmoil is 0.71. This provides strong evidence for the "phase-locking" effect – situations wherer otherwise uncorrelated actions suddenly become synchronized. When including the Fama-French factors into the regression, the coefficient of both the VIX and the interaction factor remain statistically significant. The adjusted R-squared increases to 0.58 from 0.45. These results are presented in Table 3.9.

For a robustness check, the MLE test, based on the skewed student's t-distribution, was used to rerun the tests, with results presented in Table 3.10. Test results are consistent with those of the GMM Newey-West estimators. Again, the VIX has a statistically significant correlation with the Expected Shortfall. The magnitude is lower during normal market situations and higher when market fears increase, thus showing a phase-locking effect.

We also conducted a robustness check for the time period specificity for the period after 2000. Similar results are observed. We then adopt the random resampling with replacement approach to rerun the robustness check. Thirty random samples with half of the sampling periods were created. The MLE parameter estimates for Expected Shortfall based on the skewed student's t-distribution were reported in Table 3.11. The results are consistent with those reported for the entire data set. Both the VIX and interaction effect are positively related to the Expected Shortfall. All the sub-sample estimates for VIX are positive with an average of 0.20. There are only two cases where the estimates for the interaction effect are negative with the minimum of -0.21. The average estimate for the interaction effect is 0.44. This confirms the phase-locking effect that Expected Shortfall and the VIX are positively correlated, and this relationship strengthens during bear markets.

3.7. Conclusion

In conclusion, this paper compares the tail risk of hedge funds with mutual funds and stock markets. As hedge funds can implement trading strategies with higher leverage and risk, our empirical tests show that they had a slightly larger Expected Shortfall relative to mutual funds and the stock market based on the distribution of one month returns. Therefore, investors should allocate their investments based on their risk tolerance and investment objectives. We also found strong tail dependence between the VaR, Expected Shortfall and the VIX index. The correlation is higher in times of market distress, which demonstrates the phase-locking effect as mentioned in the existing literature. This implies that the ability of hedge funds to provide loss protection is limited. Tail dependence between hedge funds and capital markets casts doubt on the ability of hedge funds to provide diversification benefits into traditional investment vehicles.

Similar arguments apply to the use of the VIX as a component of hedge fund diversification. Further study is needed to investigate the optimum level of allocation.

3.8. References

Acharya, V.V., Pedersen, L.H., Philippon, T., Richardson, M.. 2010. Measuring systemic risk. Working paper. New York University No.10-02.

Adrian, T., and Brunnermeier, M. K. 2009 .CoVaR,.Federal Reserve Bank of New York Staff Reports, 348.

Adrian, T., Brunnermeier M. K. and Nguyen H. 2011. Hedge fund tail risk. Chapter in NBER Book: Quantifying Systemic Risk

Agarwal, V. and Naik, N. 2004. Risks and portfolio decisions involving hedge funds. The Review of Financial Studies, 17, 63-98.

AIMA. 2004. AIMA Canada Hedge fund Premier, AIMA, June 2004

Artzner, P., Delbaen, F., Eber, J.-M., and Heath, D. 1999. Coherent measures of risk. Mathematical Finance, 9, 203-228.

Bacmann, J.F. and Gawron, G. 2004. Fat tail risk in portfolios of hedge funds and traditional investments. RMF Investment Management, EFMA 2004 Basel Meetings Paper

Boyson, N. M., Stahel C. W., and Stulz R. M. 2006. Is there hedge fund contagion. NBER Working Paper 12090.

Brown, S., Hwang, I., Inc, F. and Kim, T. 2011. Systemic risk and cross-sectional hedge fund returns. Unpublished working paper, New York University.

Brunnermeier M. K. and S. Nagel. 2004. Hedge funds and the technology bubble. Journal of Finance, 59(5), 2013-2040.

Chan, N., Getmansky M., Haas, S. and Lo, A. W. 2006. Systemic risk and hedge funds, in The Risks of Financial Institutions and the Financial Sector, edited by M. Carey, and R. M. Stulz. The University of Chicago Press: Chicago, IL

Copeland, M. and Copeland, T. 1999. Market timing: style and size rotation using VIX. (Financial Analyst Journal, 55(2), 73-81

Dacorogna, M.M., Gencay, R., Muller, U., Olsen, R.B. & Picktet, O.V. 2001. An introduction to high frequency finance, Academic Press 2001

Fernandez, C. and Stell, M. 1998. On Bayesian modeling of fat tails and skewness. Journal of the American Statistical Association, 93, 359-371

Fung, W., and Hsieh, D.A. 1997. Empirical Characteristics of Dynamic Trading

Strategies: The Case of Hedge. Review of Financial Studies, 10(2), 275-302.

Fung, W. and Hsieh, D.A. 2001. The risk in hedge fund strategies: theory and evidence from trend followers. Review of Financial Studies, 14(2), 313-341.

Fung, W., and Hsieh, D.A. 2004-a. Hedge fund benchmarks: A risk-based approach. Financial Analyst Journal, 60(5), 65-80.

Fung, W. & Hsieh. D.A. 2004-b. Extracting portable alphas from equity long-short hedge funds. Journal of Investment Management, 2(4)

Getmansky, M., Lo A. W., and Makarov, I. 2004. An econometric model of serial correlation and illiquidity in hedge fund returns. Journal of Financial Economics, 74(3), 529 -609.

Hill, J.M. 2009. A perspective on liquidity risk and horizon uncertainty. The Journal of Portfolio Management, 35(4), 60-68.

Hasanhodzic, J., and Lo, A. W. 2007. Can Hedge-Fund Returns be Replicated.

The Linear Case,.Journal of Investment Management, 5(2), 5-45.

Ineichen, A. 2002. Absolute returns: the risks and opportunities of hedge fund investing by A. M. John Wiley & Sons

Bacmann, J.M. and Gawron, G. 2004. Fat tail risk in portfolios of hedge funds and traditional investments, RMF Investment Management, RMF Investment Products January 2004 EFMA 2004 Basel Meetings Paper

Kang, F., In, F., Kim, G., and Kim, T. 2010. A longer look at the asymmetric dependence between hedge funds and the equity market. Journal of Financial and Quantitative Analysis, 45(3), 763-789.

Liang, B., and H. Park. 2007: .Risk Measures for Hedge Funds. European Financial Management, 13(2), 333-370.

Lo, A. 2001. Risk management for hedge funds: introduction and overview. Financial Analyst Journal, Vol. 57, No. 6:16-33.

Papageorgiou, N., Reeves, J. and Xie, X. 2010. A constant volatility framework for managing tail risk. CBV Best paper Award 2010.

Sadka, R. 2006. Momentum and post-earnings-announcement drift anomalies: the role of liquidity risk. Journal of Financial Economics 80, 309–349.

Sadka, R. 2010. Liquidity risk and the cross-section of hedge fund returns. Journal of Financial Economics, 98, 54–71.

Whaley, R. 2000. The investor fear gauge. Journal of Portfolio Management, 26(3), 12-17.

Welton, P. and Keenan, C. 2010. Tail risk, about 5x worse than you may think. Hedge Fund Journal, October 2010.

3.9. Tables and Figures

Table 3.1 Comparison of Tail Risk between Mutual Funds and Hedge Funds – VaR

This table compares the VaR of mutual funds and hedge funds. It presents the summary statistics of VaR based on the bottom 5th percentile and bottom 1st percentile. The first two columns are based on the distribution of one-month returns. Results in the third and fourth columns are based on the return distribution using one-year and three-year rolling windows respectively at the 5th percentile.

	5^{th} percentile	*Prior 1 year 5^{th} percentile*	*Prior 3 year 5^{th} percentile*
	MF VaR		
Mean	4.04	5.53	5.42
Stdev	3.47	2.33	1.38
Median	3.34	4.77	5.04
Maximum	21.55	12.76	8.73
Minimum	-0.04	1.98	3.30
	HF VaR		
Mean	4.50	4.90	4.84
Stdev	3.52	1.81	1.15
Median	3.71	4.82	4.88
Maximum	26.55	11.56	7.16
Minimum	0.01	1.86	2.82
	Difference (MF-HF)		
Mean	-0.45	0.63	0.58
Stdev	-0.05	0.52	0.23
Median	-0.37	-0.05	0.17
Maximum	-4.99	1.20	1.57
Minimum	-0.04	0.12	0.48
t	-1.24	2.89	4.39

Table 3.2 Comparison of Tail Risk between Mutual Funds and Hedge Funds – Expected Shortfall

This table compares the Expected Shortfall of mutual funds and hedge funds. It presents the summary statistics of Expected Shortfall based on the bottom 5th percentile and bottom 1st percentile. The first section is based on a one-month return distribution. The results in the second and third columns are based on return distributions using one-year and three-year rolling windows respectively at 5th percentile.

	5th percentile	*Prior 1 year 5th percentile*	*Prior 3 year 5th percentile*
	MF ES		
Mean	6.26	8.41	8.35
Stdev	0.33	0.31	0.25
Median	5.27	7.60	8.06
Minimum	0.15	0.00	0.00
Maximum	25.76	33.38	22.37
	HF ES		
Mean	8.00	8.53	8.47
Stdev	0.35	0.21	0.15
Median	6.83	8.30	8.41
Minimum	1.91	3.96	4.98
Maximum	35.80	19.51	14.80
	Difference (MF-HF)		
Mean	-1.73	-0.12	-0.12
Stdev	-0.03	0.10	0.10
Median	-1.56	-0.70	-0.35
Minimum	-1.77	-3.96	-4.98
Maximum	-10.04	13.87	7.57
t	-3.59	-0.33	-0.40

Table 3.3 Correlation of Expected Shortfall between Mutual Funds and Hedge Funds

This table presents the correlation of expected shortfall between mutual funds and hedge funds based on the return distribution of one-month, one-year and three-year rolling windows.

	Mutual Funds		
Hedge Funds	*Current Month*	*1-year rolling window*	*3-year rolling window*
Current Month	0.74		
1-year rolling window		0.54	
3-year rolling window			0.35

Table 3.4 Summary Statistics for Stock Market Returns

The following table presents the summary statistics of the value-weighted return on the S&P 500 companies, including dividends, between January 1994 and February 2009. The data is provided by Wharton Data Research Service (WRDS).

S&P 500 Value-Weighted Return - incl. dividends	
Mean	0.005
Standard Deviation	0.044
Kurtosis	1.22
Skewness	-0.795
Minimum	-0.167
Maximum	0.098

Table 3.5 Summary Statistics for VIX

The following table presents the summary statistics of the VIX index value between January 1994 and February 2009. The data is downloaded from the Chicago Board Options Exchange website.

	VIX
Mean	20.58
Median	19.51
Standard Deviation	8.22
Kurtosis	4.39
Skewness	1.67
Minimum	10.42
Maximum	59.89

Table 3.6 Summary Statistics for Fama-French Factors

The following table presents the summary statistics of equity risk premium, *SMB, HML* and R_f between January 1994 and February 2009. The data is downloaded from the Fama-French data library.

	Mkt-RF	*SMB*	*HML*	*RF*
Mean	0.21	-0.09	0.37	0.31
Median	0.97	-0.23	0.33	0.37
Standard Deviation	4.56	3.76	3.52	0.14
Kurtosis	1.59	8.01	2.65	-1.15
Skewness	-0.97	-1.16	0.40	-0.46
Minimum	-18.54	-22.06	-9.93	0.00
Maximum	8.18	13.74	13.88	0.56

Table 3.7 Regression Results – VaR

The following results are based on the estimated equation: $VaR_{HF} = \alpha + \beta_1 * VIX + \delta_1 * Down_{mkt} + \delta_2 * Down_{Mkt} * VIX + \beta_2 * (Mkt - Rf) + \beta_3 * SML + \beta_4 * HML + \beta_5 * Rf + \varepsilon$ where VIX is the volatility index – a measure for market uncertainty, Mkt is the market return, $Mkt - Rf$ a is the risk premium, and $Down_{Mkt}$ is the market timing dummy. $Down_{Mkt}$ takes the value of "1" in times of crisis and "0" during normal market situations. SML and HML are the Fama-French factors. Rf is the risk free rate.

	Intercept	VIX	Down	Interaction	Mkt-RF	SMB	HML	Rf	R Squared
	Based on one-month return distribution								
VaR	-1.07	**0.27**							0.39
t	-1.16	**5.55**							
VaR	-0.86	**0.26**	0.48						0.39
t	-0.89	**5.01**	0.34						
VaR	0.44	**0.19**	**-12.22**	**0.36**					0.44
t	0.72	**5.77**	**-2.08**	**2.24**					
VaR	**4.33**				**-0.55**	**-0.22**	**-0.22**	1.10	0.50
t	**9.12**				**-6.45**	**-3.99**	**-2.93**	0.85	
VaR	0.30	**0.17**			**-0.38**	**-0.15**	-0.09	**2.69**	0.60
t	0.44	**5.45**			**-6.53**	**-2.96**	-1.33	**2.44**	
VaR	0.88	**0.13**	-8.43	0.24	**-0.34**	**-0.13**	-0.04	**2.98**	0.63
t	1.33	**4.12**	-1.87	1.97	**-7.16**	**-2.51**	-0.60	**2.69**	
	Based on one-year rolling window								
VaR	**2.00**	**0.14**							0.41
t	**6.32**	**8.71**							
VaR	**1.69**	**0.16**	-0.72						0.41
t	**4.77**	**8.29**	-1.20						
VaR	**1.89**	**0.15**	-2.71	0.06					0.41
t	**4.99**	**7.12**	-1.27	0.92					
VaR	**4.63**				**-0.10**	-0.04	**-0.17**	1.14	0.08
t	**12.94**				**-2.74**	-1.03	**-2.72**	1.19	
VaR	0.52	**0.17**			**0.07**	0.03	-0.03	**2.77**	0.48
t	1.32	**10.04**			**2.27**	0.86	-0.75	**4.27**	
VaR	0.60	**0.17**	-3.66	0.09	**0.08**	0.03	-0.02	**2.76**	0.49
t	1.41	**8.30**	-1.85	1.61	**2.61**	0.90	-0.49	**4.51**	

Table 3.8 MLE based on Skewed Student's t-Distribution – VaR

The following results are the MLE estimates using the skewed student's t-distribution and are based on the equation: $ES_{HF} = \alpha + \beta_1 * VIX + \delta_1 * Down_{mkt} + \delta_2 * Down_{Mkt} * VIX + \beta_2 * (Mkt - Rf) + \beta_3 * SML + \beta_4 * HML + \beta_5 * Rf + \varepsilon$ where VIX is the volatility index – a measure for market uncertainty, Mkt is the market return, $Mkt - Rf$ is the risk premium, and $Down_{Mkt}$ is the market timing dummy. $Down_{Mkt}$ will take the value of "1" in times of crisis and "0" during normal market situations. SML and HML are the Fama-French factors. Rf is the risk free rate.

	Intercept	VIX	Down	Interaction	Mkt-RF	SMB	HML	Rf	LR
	Based on one-month return distribution								
VaR	**-1.24**	**0.11**							-419.08
t	**-2.79**	**4.83**							
VaR	**-1.55**	**0.13**	-0.49						-418.60
t	**-2.80**	**4.46**	-0.97						
VaR	**-1.08**	**0.10**	**-11.75**	**0.34**					-408.81
t	**-2.18**	**3.95**	**-7.93**	**7.96**					
VaR	**1.49**				**-0.45**	**-0.15**	**-0.10**	1.07	-389.68
t	**5.50**				**-10.67**	**-4.05**	**-2.06**	1.14	
VaR	-0.79	**0.10**			**-0.34**	**-0.09**	-0.04	**2.69**	-376.74
t	-1.54	**5.53**			**-9.29**	**-3.01**	-1.06	**2.99**	
VaR	-0.66	**0.10**	**-8.04**	**0.22**	**-0.29**	**-0.05**	0.06	1.36	-369.93
t	-1.71	**6.65**	**-4.23**	**4.21**	**-9.05**	**-2.23**	1.86	1.97	
	Based on one-year rolling window								
VaR	**0.97**	**0.12**							-310.64
t	**2.92**	**10.49**							
VaR	**0.77**	**0.14**	-0.72						-309.43
t	**2.12**	**8.68**	-1.56						
VaR	**0.85**	**0.13**	-1.52	0.02					-309.24
t	**2.22**	**7.34**	-1.08	0.61					
VaR	**2.01**				0.02	0.04	0.06	**2.09**	-342.32
t	**9.59**				0.47	1.21	1.05	**3.24**	
VaR	-0.24	**0.15**			**0.07**	**0.06**	0.05	**3.02**	-292.88
t	-0.71	**12.97**			**3.20**	**2.46**	1.53	**5.66**	
VaR	-0.23	**0.15**	-1.94	0.05	**0.08**	**0.06**	0.05	**2.92**	-291.86
t	-0.66	**9.79**	-1.40	1.30	**3.25**	**2.29**	1.41	**5.25**	

Table 3.9 Regression Results – Expected Shortfall

The following results are based on the regression equation: $ES_{HF} = \alpha + \beta_1 * VIX + \delta_1 * Down_{mkt} + \delta_2 * Down_{Mkt} * VIX + \beta_2 * (Mkt - Rf) + \beta_3 * SML + \beta_4 * HML + \beta_5 * Rf + \varepsilon$ where VIX is the volatility index – a measure for market uncertainty, Mkt is the market return, $Mkt - Rf$ is the risk premium, and $Down_{Mkt}$ is the market timing dummy. $Down_{Mkt}$ will take the value of "1" in times of crisis and "0" during normal market situations. SML and HML are the Fama-French factors. Rf is the risk free rate.

	Intercept	VIX	Down	Interaction	Mkt-RF	SMB	HML	Rf	R Squared
	Based on one-month return distribution								
ES	0.20	**0.38**							0.42
t	0.17	**6.07**							
ES	0.28	**0.37**	0.17						0.42
t	0.23	**5.87**	0.09						
ES	**1.83**	**0.29**	**-14.96**	**0.42**					0.45
t	**2.15**	**6.52**	**-2.06**	**2.14**					
ES	**7.22**				**-0.67**	**-0.29**	**-0.32**	3.27	0.41
t	**10.69**				**-5.55**	**-3.93**	**-3.02**	1.70	
ES	0.35	**0.29**			**-0.39**	**-0.18**	-0.01	**5.99**	0.56
t	0.34	**6.61**			**-4.85**	**-2.65**	-0.97	**3.65**	
ES	1.15	**0.23**	**-11.46**	**0.33**	**-0.33**	**-0.15**	-0.02	**6.39**	0.58
t	1.18	**5.24**	**-2.01**	**2.11**	**-4.98**	**-2.20**	-0.22	**3.80**	
	Based on one-year rolling window								
ES	**3.54**	**0.24**							0.50
t	**9.59**	**13.21**							
ES	**3.01**	**0.27**	-1.24						0.50
t	**6.62**	**11.11**	-1.40						
ES	**3.37**	**0.25**	**-4.76**	0.10					0.51
t	**6.24**	**8.60**	**-2.62**	1.97					
ES	**7.85**				**-0.17**	-0.08	-0.25	2.61	0.09
t	**15.12**				**-2.88**	-1.36	-3.07	1.82	
ES	**0.70**	**0.30**			**0.12**	0.04	-0.02	**5.43**	0.60
t	**1.35**	**12.43**			**2.91**	1.00	-0.34	**6.49**	
ES	**0.93**	**0.28**	**-6.61**	**0.17**	**0.14**	0.05	0.01	**5.50**	0.61
t	**1.64**	**10.05**	**-3.72**	**3.36**	**3.31**	1.07	0.12	**7.23**	

Table 3.10 MLE based on Skewed Student's t-Distribution – Expected Shortfall

The following results are the MLE estimates using the skewed student's t-distribution based on the equation: $ES_{HF} = \alpha + \beta_1 * VIX + \delta_1 * Down_{mkt} + \delta_2 * Down_{Mkt} * VIX + \beta_2 * (Mkt - Rf) + \beta_3 * SML + \beta_4 * HML + \beta_5 * Rf + \varepsilon$ where VIX is the volatility index - a measure for market uncertainty, Mkt is the market return, $Mkt - Rf$ is the risk premium, and $Down_{Mkt}$ is the market timing dummy. $Down_{Mkt}$ will take the value of 1 in times of crisis and "0" during normal market situations. SML and HML are the Fama-French factors. Rf is the risk free rate.

	Intercept	VIX	Down	Interaction	Mkt-RF	SMB	HML	Rf	LR
	Based on one-month return distribution								
ES	-0.66	**0.21**							-474.11
t	-0.51	**2.17**							
ES	-0.68	**0.20**	**-1.58**						-471.15
t	-1.03	**5.86**	**-2.48**						
ES	-0.20	**0.18**	**-14.80**	**0.40**					-462.48
t	-0.37	**6.33**	**-6.67**	**6.65**					
ES	**3.23**				**-0.55**	**-0.23**	**-0.15**	**2.76**	-459.90
t	**7.95**				**-8.82**	**-3.62**	**-2.01**	**2.09**	
ES	-0.52	**0.17**			**-0.38**	**-0.13**	-0.05	**5.38**	-440.77
t	-0.72	**7.06**			**-7.27**	**-3.26**	-0.91	**4.14**	
ES	-0.58	**0.18**	**-8.21**	**0.20**	**-0.34**	**-0.11**	-0.01	**4.80**	-435.46
t	-0.89	**6.52**	**-2.90**	**2.39**	**-6.31**	**-2.84**	-0.20	**3.98**	
	Based on one-year rolling window								
ES	**1.88**	**0.23**							-377.56
t	**4.09**	**12.13**							
ES	**1.42**	**0.26**	-1.29						-375.74
t	**2.68**	**10.25**	-1.89						
ES	**1.88**	**0.23**	**-5.26**	**0.12**					-373.49
t	**3.46**	**8.51**	**-2.77**	**2.24**					
ES	**4.22**				-0.02	0.01	0.01	**2.57**	-421.35
t	**12.36**				-0.31	0.12	0.08	**2.23**	
ES	-0.04	**0.28**			**0.07**	0.05	-0.01	**5.69**	-355.73
t	-0.07	**13.30**			**2.09**	1.51	-0.17	**6.55**	
ES	0.13	**0.27**	**-6.26**	**0.16**	**0.09**	0.05	0.01	**5.55**	-349.55
t	0.23	**10.93**	**-3.51**	**3.14**	**2.52**	1.57	0.12	**6.52**	

Table 3.11 Results from Robustness Test - Random Resampling using MLE and Skewed Student's t-Distribution – Expected Shortfall

The following table reports the random resampling robustness test results of the MLE estimates based on the skewed student's t distribution. The estimated equation is : $ES_{HF} = \alpha + \beta_1 * VIX + \delta_1 * Down_{mkt} + \delta_2 * Down_{Mkt} * VIX + \beta_2 * (Mkt - Rf) + \beta_3 * SML + \beta_4 * HML + \beta_5 * Rf + \varepsilon$ where VIX is the volatility index - a measure for market uncertainty, Mkt is the market return, $Mkt - Rf$ is the risk premium, and $Down_{Mkt}$ is the market timing dummy. $Down_{Mkt}$ will take the value of "1" in time of crisis and "0" during normal market situation. SML and HML are the Fama-French factors. Rf is the risk free rate. The results are based on a total of 30 random samples with replacement and the sample size is 91 months.

	Intercept	VIX	Down	Interaction	MktRF	SMB	HML	RF
Entire Sample								
	-0.58	0.18	-8.21	0.20	-0.34	-0.11	-0.01	4.80
Ramdon Resampling Results								
Mean	-0.50	0.20	-15.57	0.44	-0.32	-0.14	-0.03	4.19
Max	1.52	0.30	10.12	1.94	-0.10	0.10	0.39	8.63
Min	-2.35	0.10	-64.06	-0.21	-0.62	-0.31	-0.36	0.31
Standard Deviation	1.02	0.05	15.38	0.44	0.11	0.09	0.14	2.13

Figure 3.1 Mutual Fund VaR

This figure presents the historical VaR for mutual funds based on the return distribution of one-month, one-year and three-year rolling windows.

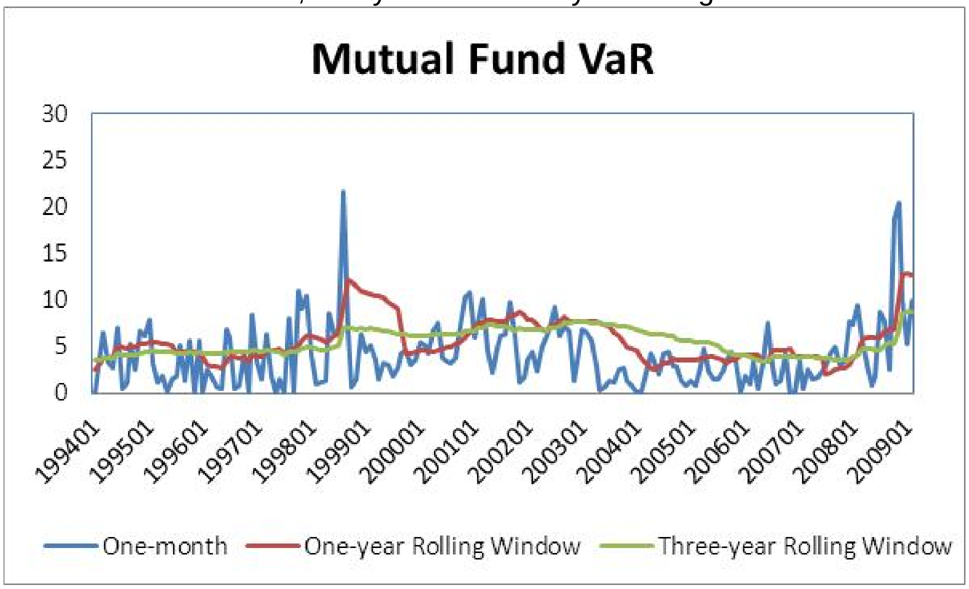


Figure 3.2 Hedge Fund VaR

This figure presents the historical VaR for hedge funds based on the return distribution of one- month, one-year and three-year rolling windows.

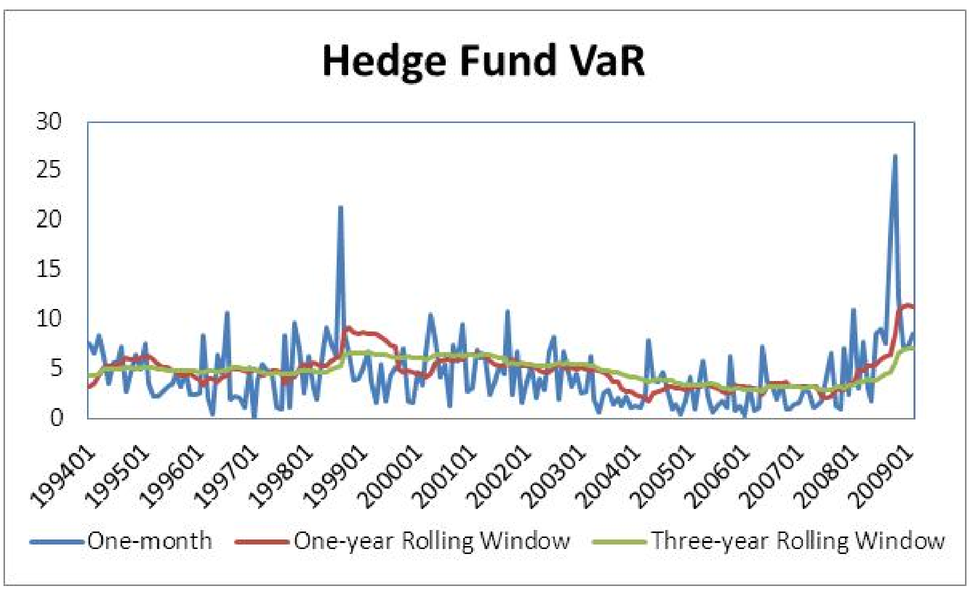


Figure 3.3 Mutual Fund Expected Shortfall

This figure presents the historical Expected Shortfall for mutual funds based on the return distribution of one-month, one-year and three-year rolling windows.

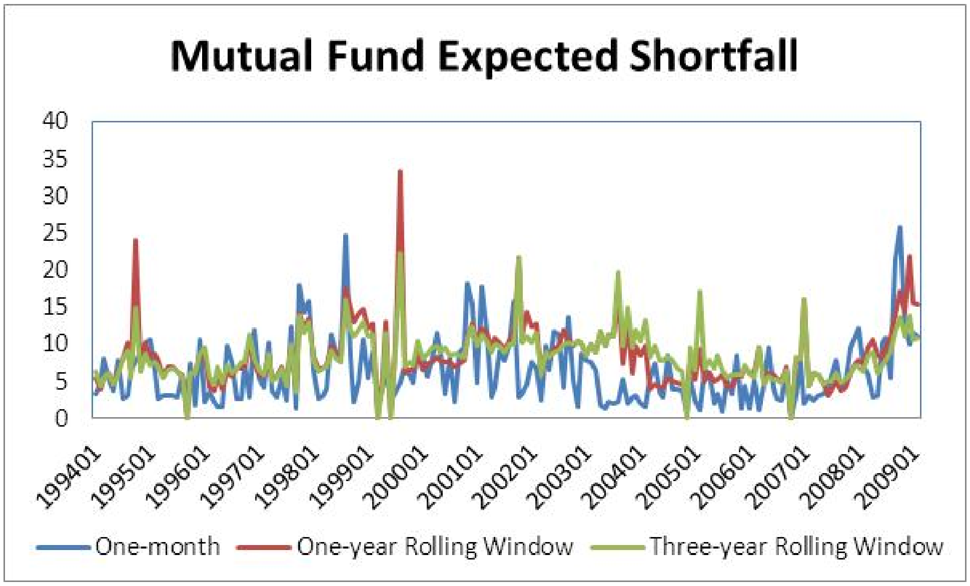


Figure 3.4 Hedge Fund Expected Shortfall

This figure presents the historical Expected Shortfall of hedge funds based on the return distribution of one-month, one-year and three-year rolling windows.

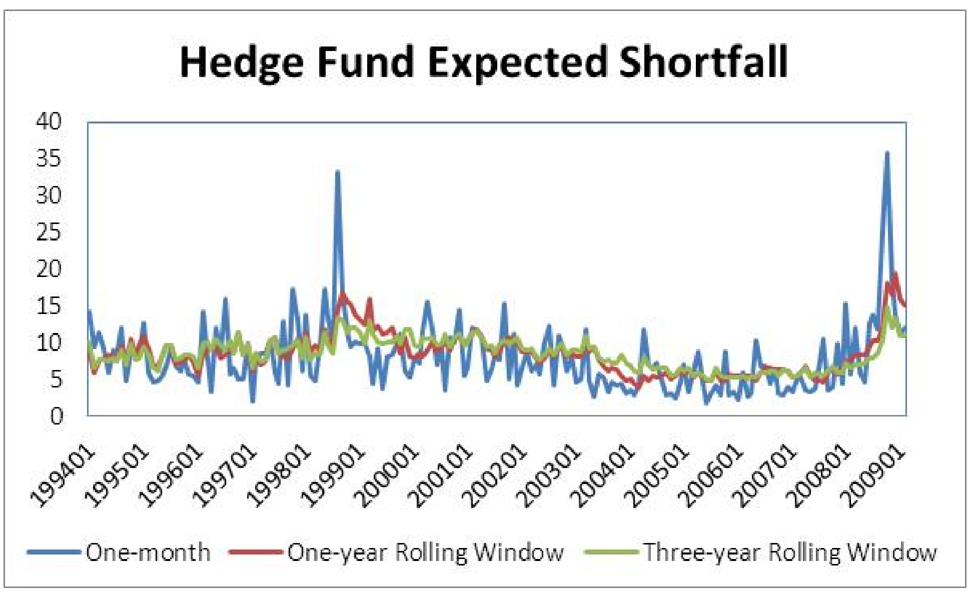


Figure 3.5 Historical Stock Market Returns

This figure presents the historical returns on the S&P 500 value-weighted index, including dividends, during January 1994 and February 2009. The data is downloaded from the Wharton Research Data Service.

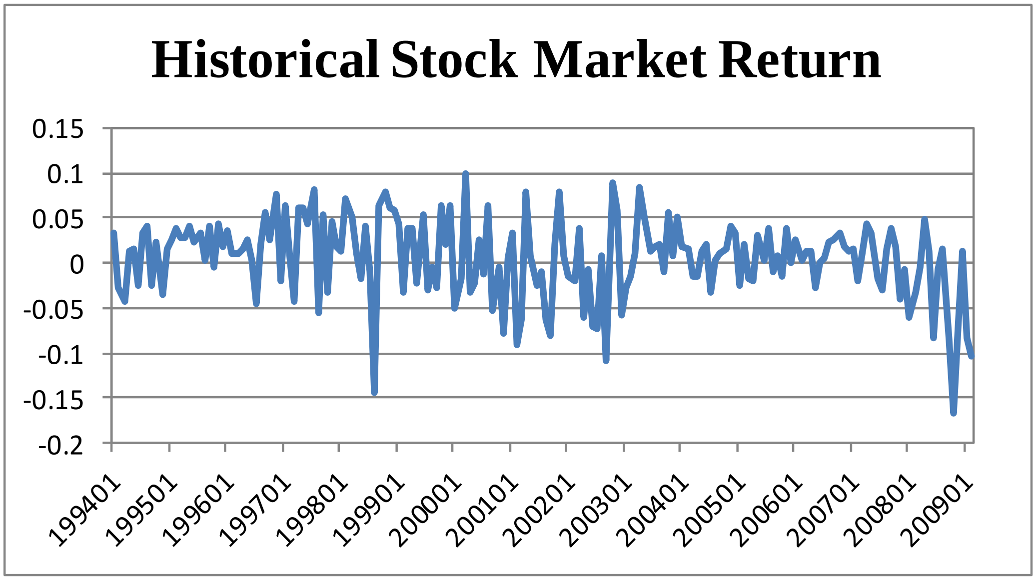
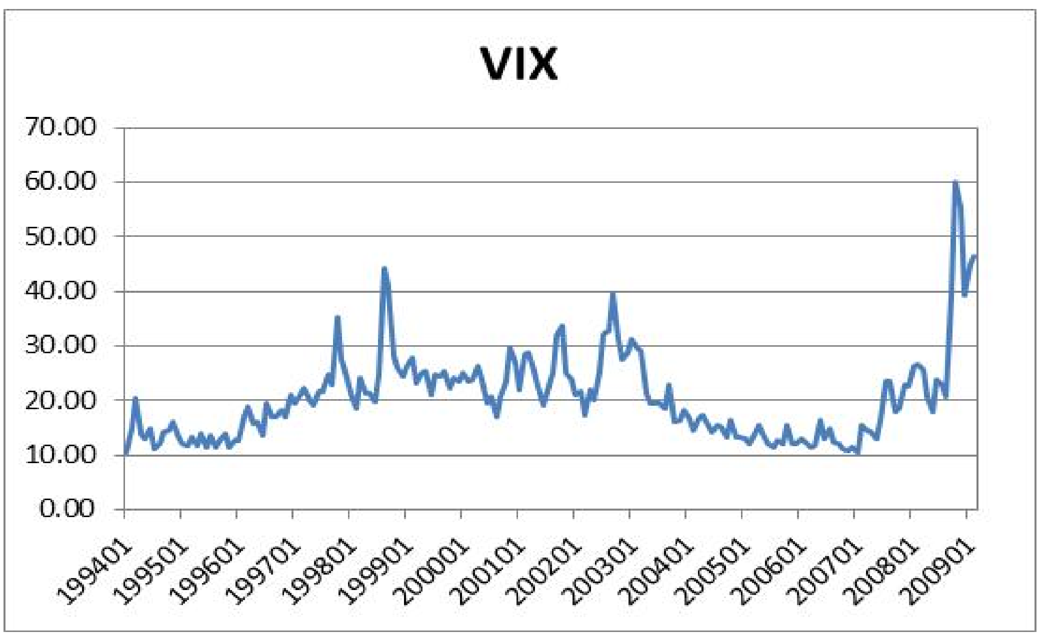


Figure 3.6 Historical VIX

This figure presents the historical VIX during January 1994 and February 2009. The data is downloaded from the Chicago Board Options Exchange website.



4. Are Hedge Funds Strategic Style Indexes That Much Different From Industry Portfolios?

4.1. Abstract

This paper studies the cross-sectional difference between hedge fund style indexes and industry portfolios. We examine the diversification benefit of investing in a pool of hedge funds in lieu of one single hedge fund, and compare the results with those of industry portfolios. To our surprise, we find that industry portfolios perform better on the absolute return measure during the study period between January 1994 and February 2006. However, the volatility of industry portfolios is comparatively higher than those observed in hedge fund style indexes. Therefore, hedge fund style indexes consistently outperform industry portfolios on risk-return basis in terms of the Sharpe ratios, Omega ratio, Sortino ratio and up/down ratio. In addition, the correlation matrix and the Principal Component Analysis show that hedge fund style indexes are more diverse than the industry portfolio. If investors are advised to diversify their investment among different industry groups, the same logic should be applied to hedge funds. We also notice that some industry groups display high levels of skewness that have been overlooked by the existing literature. While researchers tend to emphasize the higher third and fourth moments of hedge funds, attention should also be directed to industry portfolios.

4.2. Motivation

Hedge fund investors usually “put all their eggs in one basket” and invest in only one or two funds. Should investors be more prudent and diversify their investments in a pool of funds instead of just a couple? To answer this question, we investigate the cross sectional difference among the performance of hedge fund style indexes and compare it with industry portfolios. Results show that the performance of hedge funds varies from style to style and that diversification among hedge fund styles is beneficial to investors.

Therefore, we recommend that investors invest in funds of hedge funds to gain exposure and diversification to the hedge funds market.

4.3. Introduction

The hedge fund industry has grown tremendously during the last few years. In the USA alone, it has reached over US$1 trillion. Over 2000 hedge funds were reportedly started in 2005 with approximately 1,400 more added in 2004. Not only has the number of hedge fund grown dramatically, but so has its impact on the capital market. It is estimated that more than 75 percent of quoted convertible bonds are now held by hedge funds. In fact, around 20 percent of the trading on the New York Stock Exchange and 33 percent on the London Stock Exchange are hedge fund related.

Hedge fund trading involves three main strategies - Convertible Arbitrage, Event Driven and Tactical. Convertible Arbitrage involves purchasing convertible bonds and simultaneously short-selling common stocks from the same issuer. It is most effective when the market is volatile. If the stock price goes up, Convertible Arbitrage benefits from the increase in a bond's yield. Whereas, the stock price drops, this strategy makes money from the short sale. However, if stock price movements and bond prices are uncorrelated, the convertible arbitrage strategy can be detrimental. The Event Driven strategy tries to take advantage of transaction announcements and other one-time events such as mergers and acquisitions. While the Tactical or Directional strategy usually includes market neutral, dedicated short, and long/short strategies.

Hedge funds are unique in the following senses. First, hedge funds have mandates to seek positive, absolute returns and positive alphas regardless of the performance of the benchmarks. Second, most funds use hedging strategies and derivative instrument to generate favorable returns. Third, hedge funds are exempted from registering with any regulatory body. Therefore, have the flexibility to explore better risk reward opportunities that are difficult to mimic. For the same reason, hedge funds are prohibited from soliciting and advertising to the general public. Fourth, hedge funds are "the mutual funds for wealthy investors" because of the minimum contribution requirement and the one to three-years lock-up window. Last, but not least, the return distribution of hedge funds is asymmetric and they usually demonstrate negative skewness and high kurtosis.

The correlation between hedge fund strategies and the S&P 500 varies widely. Hedge fund investment can be complicated and has survival bias. Institutional investors, who intend to gain exposure to this market, are often hindered by the lack of accurate data and lack of understanding of hedge fund performance. As Lo (2005) states, there is "a need for a new set of dynamic risk analytics specifically targeted for hedge fund investment. The standard tools and lexicon of the industry currently provide only an incomplete characterization of such risk."

This paper intends to investigate the performance of the hedge fund industry and compare them to industry portfolios. Previous studies do not investigate the difference between investing in equity markets and investing in hedge funds, except for Fung and Hiesh (1997) who discuss the difference between hedge funds and mutual funds. This is the first paper that investigates the similarities and differences between hedge fund investment and industry portfolios empirically.

The difference between our study and Brown, Goetzmann and Ibbotson (1997, thereafter referred to as BGI) is that BGI emphasizes fund returns and the performance persistence prospective. While our study captures a more complete and detailed analyses of risk measurement, such as the Maximum Drawdown ratio, Omega ratio and Sortino ratio. Our data set is also different. We examine the monthly return data from www.hedgefund.net while BGI studies off-shore hedge funds. In brief, we find that hedge fund performance varies widely depending on styles. The performance of some hedge fund styles is quite stable and predictable, while others are surprisingly volatile and asymmetric. Similar patterns are observed in the industry portfolios.

This paper is organized as follows: Section 2 briefly reviews the literature on hedge fund research, the portfolio theory, and the international diversification effect. It then presents the analytical framework in Section 3, followed by empirical evidence on the performance characteristics of hedge funds and performance of the industry portfolios in Section 4. Section 5 summarizes the findings from performance evaluation and addresses the survivorship bias problem. Section 6 discusses the implication of the results and provides direction for future research.

4.4. Literature Review

This section provides a brief review of the existing literature on portfolio management, international diversification and hedge fund research.

Investigation on diversification effects was started by Grubel (1968) and Levy and Samat (1970), who show that a low correlation between foreign investment and domestic stocks is the key to the international investment benefit. In the 1980s and 1990s, more researchers took a closer look at such benefit. Grauer and Hakansson (1987), De Santis and Gerard (1997) and Levy and Leman (1988) find that even with increasing integration of global markets, the diversification benefits persist. However, as globalization evolves, the country diversification benefits are gradually diluted by industry diversification.

Academic research on hedge funds started in the late 1990s and gradually gained popularity in recent years. The main stream of hedge fund research focuses on the performance distribution and return characteristics of hedge funds. Returns are non-normal and asymmetric. Brulhart and Klein (2005) showed higher moment hedge fund returns are significantly different from those of the traditional market index. Asness, Krail and Liew (2001) and Liang (2003) examine the return and risk characteristics of hedge funds and suggest some ways to adjust hedge fund returns for market exposure. Brooks and Kat (2001) study the statistical properties of hedge fund index returns and their implications for investors.

Edwards and Cagayan (2001) analyze the performance of 16 different investment styles find that commodity funds provide greater downside protection than hedge funds. Four hedge fund styles also perform reasonably well: market neutral, event driven, global macro and short selling. Fung and Hsieh (1997) show that hedge funds investment styles are dramatically different from those of mutual funds. And further, that the five dominant investment styles can provide an integrated frame-work for style analysts of buy-and-hold and dynamic trading strategies when added to Sharpe's (1992) asset class factor model. Fung and Hsieh (2001) use the look-back straddle to model trend-following investment strategies and discover that hedge fund performance resembles the straddles and delivers positive return when markets are at extremes.

Merger arbitrage and convertible arbitrage with clear beta agenda demonstrate high realized risk-adjusted returns. Weisman (2002) shows that fund managers can use non-information based investment strategies to generate spectacular returns without specific manager skills.

In addition, hedge fund performance varies widely depending on the strategies. For example, Convertible Arbitrage did well in 2000-2002 when the equity market struggled. A typical Convertible Arbitrage fund can provide more than 10 percent rate of return per year. However, this strategy did not work in 2005 as interest rates increased and the equity market rebounded. Fung and Hsieh (1997a) and Brown, Goetzmann, and Park (1997b) report that hedge fund styles exhibit different return characteristics. According to Brown (2003), the distinct management styles account for about 20 percent of the cross-sectional variability in performance between 1989 and 2000. Therefore, style analysis and style management are critical in hedge fund investments. Kat and Palaro (2005) find that out of 485 funds of hedge funds, most fail to add value using hedge fund return replication techniques**.**

Asness (2004a), Liew and French (2005), Nishiyama (2001) and Conners (2003) also find that some hedge fund strategies demonstrate serial correlation, mainly due to the illiquid asset holdings and untimely reporting. Hedge funds may provide disappointing results in market downturns.

Previous research also shows that hedge fund strategies have a low correlation either with economic conditions or among themselves. This makes hedge funds a good candidate for diversification, especially during market down turns. Various researches have been conducted to investigate the effectiveness of incorporating hedge funds into the investment portfolio. Amin, Gaurav and Kat (2003) deal with diversification effects that occur when hedge funds are combined with stocks and bonds. They show that, although including hedge funds in a traditional investment portfolio may significantly improve the portfolio's mean-variance characteristics, it can also lead to significantly lower skewness and higher kurtosis. Therefore, the benefit of adding hedge funds to portfolios is less straightforward than often suggested and requires investors to make a trade-off between profit and loss potential. In addition, older funds may be closed to new investments. Investors who are relatively new to hedge fund investing are often forced to invest in funds with little or no track record. If so, selecting funds on the basis of track record is not an option. As a result, reviewing fund prospectus and interviewing with managers is recommended, even though this information will be sketchy and may add more confusion than actual value.

Lochoff (2002) addresses several issues on constructing a meaningful allocation of hedge funds in a portfolio. His research justifies the qualification of hedge funds as an asset class, and discusses the reliability of published data on hedge fund returns. Liu and French (2005) discuss issues that are important for clients to consider when making investment decision in USA hedge funds. They argue that alternative investments have historically benefited traditional portfolios through risk reduction and stable historical returns. Funds of hedge funds become the institutional vehicle of choice to gain exposure to hedge funds. With institutional aversion to headline risk and the need for experienced and trained staff to properly execute a sound investment process, the pendulum has swung away from direct investments toward institutional-quality funds of hedge funds.

Ennis and Sebastian (2003) report that most institutional investors diversify their investment in hedge funds as they do with other types of investments through investing in fund of funds or selecting a handful of funds with different styles. They evaluate the institutional investment in hedge fund as a matter of portfolio policy. To their surprise, the Effective Style Mix Analysis (ESM) displays a high degree of variability in factor exposure over 36-month rolling windows. Therefore, they conclude that investment in hedge funds is not market neutral and style selection is important.

Liew and French (2005) claim that if hedge fund monthly returns suffer from positive serial correlation, then the true diversification benefits will be overestimated.

Rudin and Morgan (2006) use a Portfolio Diversification Index (PDI) to measure the number of unique investments in a portfolio and present a new way to understand the diversification in portfolio construction. PDI is useful in assessing marginal and cumulative diversification benefits across asset classes and across time. Rudin and Morgan (2006) find that hedge funds offer less diversification than expected, and that the diversification benefit from investing in hedge funds has decreased in the last few years.

Fung and Hsieh (2004) address the difficulties of applying conventional data and methodological models to hedge funds. They propose a model based on an arbitrage pricing theory to capture hedge fund returns with dynamic risk-factor coefficients. The paper shows that for diversified hedge fund portfolios (as proxies by indexes of hedge funds and funds of hedge funds), the seven ABS factors can explain up to 80 percent of monthly return variations. Because ABS factors are directly observable from market prices, this model provides a standardized framework for identifying differences among major hedge fund indexes that is free of the biases inherent in hedge fund databases.

Asness (2004b) summarizes the major characteristics of hedge funds and drew the attention to the drawback of hedge funds, such as some potential dangers and potential for fraud. Examples included: mis-marked portfolios that caused the risk of hedge fund investing to be understated by standard statistical tests, and hedge fund practices that were not straightforward to implement basic buying and holding stocks. The acts of shorting and levering and the understanding of complex derivatives are skills needed to implement these strategies, and can vary widely from manager to manager.

Pohlman, Ang, and Hollinger (1978) discuss measurement issues on institutional portfolio performance. They argue that the periods over which performance is measured should coincide with the planning horizons of the funds concerned. If the period selected is too long, the positive and negative effect during shorter time periods will be lost because of a canceling out effect. The time periods used must then be flexible to cover the approximated planning horizons of the funds. They also propose a method to evaluate portfolio performance that reduced the severity of these two problems. The method is then applied to a sample of publicly traded hedge funds over four sub-periods of two advancing markets and two declining markets.

Lo (2005) examines the investment process of fund of funds and he recommends an integrated approach that blends qualitative judgment with quantitative analyses. He also investigates the implications of hedge fund performance on the efficient market hypothesis theory. He finds that markets have to be inefficient to justify the existence of excess hedge fund returns.

Dopfel (2005) summarizes the difference between hedge funds and traditional investments, including benchmarks, investment processes, fees, and regulatory environment. Traditionally, active managers are usually benchmarked to a well-understood market index. Hedge funds, however, are often claimed as absolute return strategies, implying that their performance should be compared with a reference return of zero. Aside from benchmarks and fee structures, hedge funds are capable of holding securities long or short, while traditional strategies are long-only. Therefore, additional investment skill is required to evaluate the quality of hedge funds and to know how a hedge fund fits into the portfolio. He notes that one should think of hedge fund returns as composed of systematic and idiosyncratic components, even though both components may be more complex for hedge funds than for traditional products.

Recently, researchers start to examine the data quality of hedge funds. Malkiel and Saha (2005) discuss the survivorship bias and backfilled bias which inflated the returns of hedge funds.

In summary, each hedge fund style has its own unique characteristics and deserves a detailed independent investigation. However, most research papers treat them as one single portfolio group. All the literature mentioned above fails to examine the difference between hedge funds and equity market investment.

4.5. Methodology

In this section, we present the methodological framework for the empirical test. To address the question of how unique a hedge fund strategy can be, we examine different prospects of hedge funds based on their reported strategies. Our criteria include the first four moments of the performance distribution, the maximum drawdown, and the performance consistency measure. For performance consistency, we consider the up/down ratio. This is the ratio that divides the frequency that funds outperform the S&P500 by the number of times funds under-perform the market. The higher the ratio, the more attractive are the funds. Another test for persistency of hedge fund performance is to test the auto-correlation. Funds with high performance persistency demonstrate high auto-correlation. However, some researchers criticize this measure because some hedge fund instruments are illiquid. In order to report their performance, analysts usually apply some interpolation to the existing data, which introduces, if not magnifies, the autocorrelation within hedge funds. In this paper, we temporarily ignore this measure to avoid getting into the debate. Instead, we provide the test results for the traditional evaluation of funds such as the Sharpe ratio and the information ratio. Given that the tracking error is not as important for hedge fund evaluation and there is ambiguity about the correct measure of alphas and betas, the tracking errors will not be reported in this paper.

4.5.1. Descriptive Statistics

To compare the performance of a single hedge fund, it is important not only to show their mean absolute returns but also to test whether the difference is statistically significant. Secondly, although an efficiency portfolio frontier based on mean-variance has been well examined in the academic research, studies show that such a frontier is no longer sufficient for funds that demonstrate higher moment asymmetric characteristics. Kraus and Litzenberger (1976) identify such a problem and incorporate skewness into their portfolio evaluation framework.

Skewness and kurtosis can be calculated using the following formula

$$skewness = \frac{\sum (y_i - \overline{y})^3}{(n-1)s^3}$$

$$kurtosis = \frac{\sum (y_i - \overline{y})^4}{(n-1)s^4}$$

Hedge fund returns usually display negative skewness and high kurtosis. Negative skewness indicates heavier left tail, and higher kurtosis implies higher tendency for a bigger surprise. Such features may not be attractive to an investor. However, Brulhart and Klein (2005) suggest that skewness and kurtosis are inaccurate, as it is hard to tell whether the difference in measure comes from standard deviation or higher moment. Therefore, they recommend an adjustment to the third and fourth moments. That is to take the third and fourth root of the third and fourth moment respectively. The formula for the third and fourth moment are $\frac{\sum (y_i - \overline{y})^3}{n-1}$ and $\frac{\sum (y_i - \overline{y})^4}{n-1}$ respectively. As suggested by Brulhart and Klein, we take the corresponding roots of the moments to normalize the measure. All these descriptive measures are reported later on.

4.5.2. Risk Measure

The second most important aspect about investment is risk. Hedge fund returns tend to have fat tails, "left skewed". Therefore, the traditional mean variance analyses would not be enough to examine a hedge fund performance. In this paper, we apply the maximum drawdowns, Sharpe ratio, Sortino ratio, and Omega measure to evaluate the differences between hedge fund styles and industry portfolios.

The most intuitive measure of risk is the maximum drawdown value. It calculates the loss that can possibly occur to an investment. Sometimes, a big investment loss can be very costly to a short term investor who is forced to liquidate his/her position in an unfavorable market situation. The maximum drawdown captures such risk and it is calculated as

$$MaximumDrawdown = \underset{i=1...t,t=1..n}{Min}(\underset{j=1...t}{sum}(r(j)))$$

The maximum drawdown value can overstate the severity of the loss, as it overlooks the probability of such an event occurring. Nevertheless, it provides some useful information and is a very important input for decision making, if investors are quite risk adverse and the main objective is to protect the original principal. However, for the majority of investors, maximum drawdown is not a sufficient measure, because achieving a positive return is as important as avoiding shortfalls. A balanced approach is called for, such as the risk to reward ratio. One commonly used ratio is the Sharpe ratio, which measures how much excess return an investor is rewarded per unit of risk. The Sharpe ratio is defined as:

$$SharpeRatio = \frac{R_p - Rf}{\sigma_p}$$

Because most hedge funds are evaluated on their absolute returns, we will calculate the pseudo-Sharpe ratio where the risk-free rate is assumed to be zero. The higher the Sharpe ratio, the higher the reward per unit of risk. Therefore, a higher ratio is preferable to lower ones. However, the Sharpe ratio penalizes over-performance relative to the mean as much as underperformance. There are some ways to improve on the Sharpe ratio. For example some researchers recommend replacing standard deviation with semi-variance. In this paper, we adopt the Omega and Sortino ratio, which will be discussed in detail later on.

The Omega function was first introduced by Keating and Shadwick (2002) to capture the risk return trade-off based on the gain and loss. It is defined as

$$\Omega(r) := \frac{\int_r^b [1 - F(x)]\, dx}{\int_a^r F(x) dx}$$

Or in discrete terms:

$$\Omega(r) = \frac{\frac{1}{n}\sum_i \max(0, R_i - r)}{\frac{1}{n}\sum_i \max(0, r - R_i)}$$

where r is the threshold of return. The Omega ratio can be used to calculate the probability of extreme events happening. A high Omega ratio is desirable, as it implies more favorable outcomes than unfavorable ones. Or that the average magnitude of favorable outcome outweighs the average magnitude of unfavorable events.

Recognizing that only downside risk is undesirable, Sortino came up with a measure that captures whether a portfolio return in excess of a benchmark is enough to compensate for the undertaking downside risk. Therefore, the Sortino ratio can be viewed as an extension of the Sharpe ratio. It is calculated as:

$$S = \frac{\mu - \tau}{\sqrt{\int_{-\infty}^{\tau} (\tau - R)^2 \partial F(R)}}$$

If the benchmark return or MAR is set to zero, the Sortino ratio will indicate whether the portfolio’s positive returns are sufficient to cover the risk of negative returns. Therefore, it is viewed as an indicator of capital preservation in nominal terms. Both the Omega ratio and the Sortino ratio are gaining popularity among researchers.

4.5.3. Diversification

To investigate the diversification effect, we first study the correlation coefficient matrix of the hedge funds styles index and that of industry portfolios. The lower the correlation, the higher the potential gain from diversifying among hedge funds. De Souza and Gokcan (2004) and Lo (2004) warned that correlations between hedge fund strategies are “unstable” and that overlooking this issue will have a detrimental effect on portfolio investment. A better approach is to examine the mean correlation matrix based on 60-month rolling windows, as it provides a more consistent picture of the relationship among hedge funds.

In addition, we conduct a principal component analysis (PCA), which is commonly used in the study of the international portfolio diversification effect. We also study the existence of general movements in the returns of common stocks. This approach dates back to Farrar (1962), King (1966) and Hester (1967) and it is recently introduced to the hedge fund research by Fung and Hsiesh (1997, 2001). Rudin and Morgan (2006) extend PCA approach and derive the Portfolio Diversification Index (PDI), which is easier to interpret. The PCA approach is a good way to evaluate the dimensions of hedge fund returns. It assumes that the returns on the stocks or hedge funds are linear functions of several underling independent components, which are complex linear combinations of original returns. To run the PCA analyses, we first demean the returns, and then we run the eigen value and vector test on the transferred data. The components are selected in a way that each successive component explains a maximum of the remaining variance. Usually a few components are enough to explain a large percentage of the total variance. However, results obtained from PCA are usually hard to interpret intuitively.

To offset this drawback, we explore the potential diversification benefits by simulating the possible portfolio allocation among hedge fund styles and industry portfolios separately, and by summarizing the ex-ante statistics. It is essentially a “brute force” approach to portfolio optimization. However, instead of crunching through all feasible portfolio combinations based on a small increment in portfolio weights, we assume an equal weighted portfolio. We then summarize the aggregate statistics instead of conducting a portfolio optimization. It is also related to thee Empirical Probability Assessment Approach of Grauer and Hakansson (1998)’s, where coincident historical returns on all assets are combined and then aggregated on a portfolio level over time. For the twelve existing industry portfolios, there are 66 possible combinations of two 50/50 split industry portfolios and 924 possible allocations of six equally weighted portfolios. For the existing 10 hedge funds styles, we examined every possible combination of equally weighted allocations to two, three, and up to six hedge fund styles. In other words, there are 45 possible 50/50 allocations to two different hedge fund style indexes under the two-fund-style diversification scenario. There are 120 possible 33.3/33.3/33.3 allocations to the three fund styles and 210 possible combinations of six equal weighted hedge fund styles. The approach includes all alternatives under consideration and provides us a complete picture of diversification benefit.

4.6. Data and Analysis

The monthly hedge fund indexes data for the period of January 1994- February 2006 are obtained from the Credit Suisse/Tremont Hedge Fund index website. The Credit Suisse/Tremont database tracks more than 4500 funds and the Index Universe includes only the funds with a minimum of US $50 million assets under management ("AUM"), a minimum one-year track record, and current audited financial statements. Hedge funds are grouped together into ten primary subcategories based on their investment style. Each style index represents at least 85 percent of the AUM in each respective Index Universe category. The Index is calculated and rebalanced monthly. Funds are reselected on a quarterly basis as necessary.

The descriptive statistics – mean, standard deviation, third moment and fourth moment - of the index are summarized in Tables 4.1 and 4.2. Interestingly, hedge fund indexes achieve a positive monthly return of 72 basis points. Out of 10 style indexes, only one strategy style (dedicated short bias) had an insignificant negative average return over the investigated period, -0.07%. And only two hedge indexes, equity market neutral and managed futures, follow a normal distribution. Most hedge indexes displays positive kurtosis, with the Event Driven index demonstrates the highest positive kurtosis (24.06), followed by the Fixed Income Arbitrage (19.03).

To our surprise, the average mean monthly return of the industry portfolios over the investigating period is 0.97%, about 25 basis points higher than the hedge fund indexes.

The range of mean returns (0.52% to 1.34%) is narrower than that of hedge funds (-0.07% to 1.13%). In addition, the hedge fund indexes had a lower average standard deviation (0.0256) than the industry portfolios (0.0518), indicating lower risk and better Sharpe ratios for hedge fund indexes. The average adjusted Sharpe Ratio for the hedge fund index is 0.41 while that for industry portfolio is 0.19. The maximum Sharpe ratio for the hedge fund index is 0.941 – much higher than its best competitor from industry portfolios (0.26). Among all hedge fund indexes and industry portfolios, the dedicated short bias hedge fund index had the lowest mean return, while its standard deviation is the highest among all the hedge fund indexes and second highest if including the industry portfolios.

Contrary to our expectation, some industry portfolios display small negative skewness. But the degree of skewness is very similar among industry portfolios than among the hedge fund indexes. Most of the skewness of industry portfolio clusters around -0.3, while that of the hedge fund index varied from 0.84 to -3.36. All hedge fund indexes and industry portfolio demonstrate positive kurtosis, with the Event Driven hedge fund index taking the lead (26.09). Similar results are observed in the third and fourth moments. On average, industry portfolios have a higher negative third moments and higher positive fourth moment. Therefore, we have to question previous research on the mean-variance analyses on industry portfolios and further examination on the cross-sectional evaluation of industry portfolios is required. However, we will leave this to a future paper.

Hedge funds provide better downside protection as advertised. On average, industry portfolios have relatively higher downside risk, with the average minimum return of -15.8%. Whereas, the average minimum return for the hedge fund index is -9.4%, about 6.4% higher than that of industry portfolio. Contrary to our expectation, the mean maximum return of industry portfolios is higher (15.4%) despite the fact that the Dedicated Short Bias style index had achieved highest possible returns (22.7%) among all alternatives.

Figures 4.1 and 4.2 show that industry portfolios display volatile returns during the study period, while volatilities of hedge fund indexes remain stable over time except for a spike in late 1998. Secondly, the ranges of industry portfolio returns are very similar within groups, while those of hedge funds indexes vary widely as showed in Figure 4.2.

Figures 4.3 and 4.4 provide the mean - standard deviation plot of both industry portfolios and hedge fund indexes. Apparently, most hedge fund style indexes cluster around low standard deviation area except for the Dedicated Short Bias hedge fund index. If we consider the first two moments only, the Dedicated Short Bias style index is strongly dominated by the rest of the hedge fund indexes, as it offers the lowest mean return of -0.1 % and highest standard deviation of 5%. However, because of its potential for creating the highest returns, this index survived. This suggests that mean-variance consideration is not enough in investment practice. Figure 3.4 presents the combination of the first four moments of all industry portfolios and hedge fund indexes. Obviously, hedge fund indexes have higher positive kurtosis than its counterpart.

Figures 4.5 and 4.6 present the first four moments of hedge fund returns and industry portfolio returns. Apparently, hedge funds have higher third and fourth moments.

Figure 4.7 compares the historical returns within industry portfolios and hedge fund strategy indexes. Surprisingly, average returns of hedge fund indexes did not fluctuate as much as industry portfolios. However, within industry portfolios, some are consistently more volatile than the others. For instance, the business equipment portfolio shows a wide spread of its returns over the years. Small global macro and distressed hedge fund indexes provide the highest mean returns among all the hedge fund indexes. Equity Market Neutral hedge fund index consistently has small positive monthly returns as well as fixed income arbitrage index. The dedicated bias hedge fund index is most volatile.

4.6.1. Risk Measure

The results for the risk measures are reported in Tables 4.4 and 4.5. In general, hedge fund style indexes provide a better risk return trade-off as indicated by the Sharpe ratios, Omega value, Sortino ratios and the up/down ratios. Cross-sectionally, the Equity-Market Neutral has the highest Sharpe ratio, Omega value and up/down ratio. However, the Long-Short Equity Style ranks the highest on Sortino ratio, followed by Global Macro.

The average Sharpe ratio among the hedge fund style index is 0.41, whereas that of industry portfolio is only 0.19. This implies that for the same amount of risk, hedge funds style indexes reward more than twice the excess return than the industry portfolios. We also notice that the Dedicate Bias Style had a minimum Sharpe ratio among all indexes and portfolios, which was driven by its low average return over the study period of January 1994 to February 2006.

Secondly, hedge fund style indexes outperform industry portfolios on the Omega measure. The average Omega value for hedge fund style indexes is 3.89 as compared with 1.66 of industry portfolios. This means thathedge fund style indexes tend to provide more positive returns than industry portfolios. However, cross-sectionally, the Omega measures of industry portfolios are more clustered than hedge fund style indexes. The range of Omega value for industry portfolios is between 1.28 and 1.99, whereas, that for hedge fund style indexes varies from a low of 0.97 to a peak of 12.89.

Similar patterns are observed in the Sortino ratios and up/down ratios. Again, we found that for the same amount of downside risk, hedge fund style indexes provide better average returns. However, their range of reward is wider than that of industry portfolios. Similarly, based on the up/down ratios, hedge fund style indexes provide more frequent positive return than industry portfolios. Figures 4.8 and 4.9 show these four risk measures.

4.6.2. Diversification Benefit

Table 4.6 presents the pair-wise correlation between industry portfolios. All the correlation coefficient estimates are positive and the highest correlation coefficient estimate is 0.778 between the manufacturers and durable good portfolios. The lowest estimate is 0.007 between the business equipment portfolio group and the utility portfolio. This makes sense as utility portfolios are acyclical while stocks in business equipment are usually pro-cyclical. The average correlation coefficient is 0.494. Such a high average shows limited diversification capabilities if leverage is not allowed.

Table 4.7 provides the pair-wise correlation coefficients of hedge fund indexes. Of these, 85.7 percent of the correlation coefficients are positive and 14.3 percent are negative. The correlation coefficient between hedge funds style indexes (excluding Credit Suisse/Tremont index) can reach 0.676 (between Emerging Market and Event Driven) whereas the lowest correlation coefficient (-0.716) is between the Long/Short Equity index and the Dedicated Short Bias index. The average correlation coefficient of hedge fund indexes is 0.254. If a short sell is not allowed, investment within hedge fund indexes provides better diversification potential, as the lower the correlation coefficient, the less likely that the funds would lose money at the same time.

The average 5-year pair-wise correlation among industry portfolios and hedge fund styles are presented separately in Table 4.8 and 4.9. Compared with the static calculation method, the correlation remains in the similar range. The correlation between industry portfolios can reach as high as 0.78 and as low as -0.06. In comparison, the correlation among the hedge fund style index ranges from -0.72 to 0.84. The narrower range of a 5-year average correlation between industry portfolios indicates a limited diversification benefit within this group. Therefore, if investors are advised to diversify among industry portfolios, the same action should be taken with respect to investment in hedge funds.

To further illustrate this point, we perform the principal component analyses (PCA), as recommended by Rudin and Morgan (2006). The results are presented in Tables 4.10 and 4.11. Obviously, hedge fund indexes are more diverse than the industry portfolios. The first component contributes 39 percent of the total variance and four principal components are constructed to explain 75 percent of the total variations. In comparison, industry portfolio seems to be affected by a common market factor. The first component explains up to 55 percent of the total variance and only two unique components are extracted.

Figures 4.10 and 4.11 present the eigen values of the extracted components. The analyses reveal that industry portfolios are more related than the hedge fund style indexes. Only two components extracted from the 12 industry portfolios have an eigen value greater than one and these two components explain up to 67.39 percent of the total variance displayed by 12 industry portfolios. The first component alone contributes 55.06 percent of the total variance. In comparison, four components are constructed out of 10 hedge fund styles indexes with an eigen value greater than one, although, the first component can only explain about 37.04 percent of the total variance displayed by the hedge fund style indexes.

We also estimate the potential benefit of diversification by simulating the possible combination of equal weighted hedge fund styles and those of industry portfolios. The results are provided in Tables 4.12 and Table 4.13. The analysis shows that combining hedge funds from different styles reduces the magnitude of the average standard deviation and the higher moments. The range of possible returns narrows down. The average minimum returns have increased, while the maximum returns have decreased. As expected, the Sharpe ratios improved as we increased the number of styles in the portfolio. For instance, the average Sharpe ratio for hedge fund style index is 0.41. When we combined six hedge fund styles into a portfolio, the average Sharpe ratio reached 0.58. The portfolios of hedge fund style indexes also outperform singular hedge fund styles on the Omega and Sortino ratios, while the average up/down ratio remains stable. Figure 4.13 presents the diversification benefits on the risk and return measures. As suspected, diversification among hedge fund styles improves the risk-return performance as the industry portfolios do.

4.7. Conclusion

To our surprise, industry portfolio performed better on absolute return measures during the study period of January 1994 to February 2006. However, based on risk-return trade off measures, such as the Sharpe ratios, Omega, Sortino and up/down ratios, hedge fund style indexes consistently outperform industry portfolios. Secondly, the levels of volatility of hedge fund style indexes are comparatively lower than those observed in industry portfolios, despite the fact that hedge funds style indexes tend to have high fourth moments. However, if we only consider the mean-variance frontier, hedge funds style indexes outperform industry portfolio. In addition, the maximum drawdowns for hedge funds are much lower than those of industry portfolio. Therefore, it is not obvious whether hedge funds are riskier than industry portfolios. Cross-sectionally, not only does the performance of hedge funds vary widely, the correlations between hedge fund styles indexes are also smaller than those of industry portfolios. This implied better potential diversification benefits.

As expected, the performance of hedge funds varies from strategy to strategy. The Dedicated Short Bias appeared to be a loser in the study period with negative average returns and highest volatility. On the other hand, there is not a single winner among the hedge fund style indexes. The Distress Style index provides highest absolute returns over the last 12 years but the Equity Market Neutral ranks the top of the Omega and up/down ratios. In other words, the performance distribution of each hedge fund strategic style is so unique that each style should probably deserve its own investigation.

Theoretically, we can also conclude that the capital market is in-efficient. As Lo (2005) mentioned, the continuous growth and the existence of the unique distribution of hedge fund is difficult to justify by the capital market efficient hypothesis, as hedge funds derive from market anomalies.

The performance of hedge funds may be overstated due to the survivorship bias. However, some researchers have argued that hedge fund index data does not include some well-established funds, which voluntarily discontinued reporting to hedge fund indexes such as Soro's Quantum Fund. Therefore, the degree of overestimation or understatement is ambiguous. Due to time constraints, we will leave this question for another paper and use the hedge fund indexes for our analyses as they are available and commonly used by other researchers.

4.8. Future Studies

This paper provides a cross-section comparison of the performance of hedge funds strategy styles and that of the industry portfolios. The findings prompt us to question efficient market hypothesis (EMH) and to wonder whether the conventional analyses on equity market can be applied to the hedge fund strategy style indexes. The first interesting question is whether some style indexes display leading or lagging indicator characteristics. As we know, equity market can be categorized into stocks that are cyclical, countercyclical and acyclical. The cyclical stocks can further divide into groups that lead the economy. It will be interesting to find out if such a pattern also exists in hedge funds indexes. We wonder whether we can obtain better performance result through strategy rotation over time, similar to the industry rotation theory. As many researchers have dug into factor analyses of hedge funds, we are curious to find out whether factors such as interest rates and many other macro-economic factors play a role in the performance of hedge fund strategies. Fourth, we also recognize that hedge funds invest in a much wider universe of securities while industry portfolios invest only in stocks. Therefore, it will be interesting to compare the diversification benefits between hedge funds style indexes and the investment in derivatives and alternative investments.

Previous research has successfully compared the risk measure of industry portfolios with that of mutual funds. It will be interesting to see if such tools can or cannot be applied to hedge fund indexes.

The characteristics that we identified earlier in this paper may evolve with time and rely on the formation of the strategy indexes. If we can access the individual fund data, we would like to examine whether our test results are robust, regardless of the index formation.

We believe that the direction of cash flow would affect hedge fund performance. Therefore, it will be interesting to investigate whether this prediction is correct. We would also like to examine whether hedge fund indexes follow short-term momentum and long-term reversal as those observed in equity markets.

4.9. References

Adachi J. and Gupta A.(2005), “Simulation-Based Parametric Optimization for Long-Term Asset Allocation Using Behavioral Utilities”, Applied Mathematical Modeling 29 (4), pp.309-320.

Amin, G., Gaurav S. and Kat, H.(2003), “Stocks, Bonds, and Hedge Funds”, Journal of Portfolio Management, Summer2003, Vol. 29 Issue 4, pp.113-120.

Asness, C.; Krail, R. and Liew, J.(2001). “Do Hedge Funds Hedge?”, Journal of Portfolio Management, Vol. 28 Issue 1, pp.6-19.

Asness, C. (2004). “An Alternative Future: Part II”, Journal of Portfolio Management, Fall2004, Vol. 31 Issue 1, pp.8-23.

Brulhart, T. and Klein, P.(2005), “Are extreme hedge fund returns problematic?” Working paper.

Budhraja, V., De Figueiredo, R., and Malik, A.(2005), “How Risky Are Illiquid Investments? - A Practical Approach to Estimating Volatilities and Correlations for Non-Traded Assets”, Journal of Portfolio Management 31 (2): 83 pp.

Basak, S.(2000), “A Model of Dynamic Equilibrium Asset Pricing With Heterogeneous Beliefs and Extraneous Risk”, Journal Of Economic Dynamics & Control 24 (1), pp.63-95.

Brandt M., Goyal A., Santa-Clara P., and Stroud J.(2005), “A Simulation Approach To Dynamic Portfolio Choice With An Application To Learning About Return Predictability”, Review Of Financial Studies 18 (3), pp.831-873.

Brandt et al. (2003), “A Simulation Approach to Dynamic Portfolio Choice with an Application to Learning about Return Predictability.” Working Paper.

Bekaert, G., Erb,C.B., Harvey, C.R., and Viskanta, T. (1988), “Distributional Characteristics of Emerging Market Returns and Asset Allocations”, Journal of Portfolio Management, Winter 1988, pp. 102-116.

Bekaert, G. and Harvey, C.(2003), “Emerging Markets Finance, Journal of Empirical Finance”, Volume 10, pp.13-55.

Kat, H. and Brooks, C. (2001), “The Statistical Properties of Hedge Fund Index Returns and Their Implications for Investors”, ISMA Centre, Working Paper.

Brown S. (2003), “Hedge Funds With Style - Style Analysis And Management Are Crucial To Success”, Journal of Portfolio Management 29, pp.101.

Brown, S and Goetzmann, W.(2003), “Hedge Funds With Style”, Journal of Portfolio Management, Vol. 29 Issue 2, pp.101-112.

Campbell J., Chacko G., Rodriguez J., and Viceira L.(2004), “Strategic Asset Allocation In A Continuous-Time Var Model”, Journal Of Economic Dynamics & Control 28 (11), pp.2195-2214.

Chordia T., Sarkar A., and Subrahmanyam A.(2005), “An Empirical Analysis Of Stock And Bond Market Liquidity”, Review Of Financial Studies 18 (1), pp.85-129.

Jose M. and Simi K. (2002), “Explaining the Diversification Discount”, The Journal of Finance, Volume 57 Issue 4, pp.1731.

Chacko G. and Viceira L. (2005), “Dynamic Consumption and Portfolio Choice with Stochastic Volatility in Incomplete Markets”, Review Of Financial Studies 18 (4), pp.1369-1402.

Chao X., Lai K.K., Wang S.Y.(2005), “Optimal consumption portfolio and no-arbitrage with nonproportional transaction costs”, Annals of Operations Research, 135 (1), pp.211-221.

Chun G, Sa-Aadu J, and Shilling J.(2004), “The Role Of Real Estate In An Institutional Investor's Portfolio Revisited”, Journal of Real Estate Finance and Economics 29 (3), pp.295-320.

Cremers, J.; Kritzman, M.; and Page, S.(2005), “Optimal Hedge Fund Allocations”, Journal of Portfolio Management, Vol. 31 Issue 3, pp.70-81.

Coen-Pirani D. (2005), “Margin Requirements and Equilibrium Asset Prices”, Journal of Monetary Economics 52 (2), pp. 449-475.

Detemple J., Garcia R., and Rindisbacher M. (2005), “Intertemporal Asset Allocation: A Comparison of Methods”, Journal Of Banking & Finance 29 (11), pp.2821-2848.

DeLint C. and Stolin D. (2003), “Predictive Power o Yield Curve: A Theoretical Assessment”, Journal of Monetary Economics 50 (7), pp.1603-1622.

Detemple E. (2003), “A Monte-Carlo Method for Optimal Portfolios”, Journal of Finance 58, pp.401-406.

Dopfel F.(2003), “Asset Allocation in A Lower Stock-Bond Correlation Environment - How Lower Correlation Would Impact Investor Decisions and Welfare”, Industry & Market Reports.

Dopfel, F.(2005), “How Hedge Funds Fit”, Journal of Portfolio Management; Vol. 31 Issue 4, pp.9-20

Dyl, E.(2003), “Negative Betas: The Attractions of Selling Short”, Journal of Portfolio Management, Spring75, Vol. 1 Issue 3, pp.74-76.

Edwards, F., Caglayan, M.(2001), “Hedge Fund And Commodity Fund Investments In Bull And Bear Markets”, Journal of Portfolio Management, Summer2001, Vol. 27 Issue 4, pp.97-108.

Ennis, R. and Sebastian, M.(2003), “A Critical Look At The Case For Hedge Funds”, Journal of Portfolio Management, Vol. 29 Issue 4, pp.103-112

Farrar, D.(1962), “The Investment Decision Under Uncertainty", Engliwoood Cliff, New Jersey; Prentice-Hall.

Arditti. F.(1967), “Risk and the Required Return on Equity”, Journal of Finance, Vol. 22, No. 1, pp. 19-36.

Fung W. (2002), “Asset-Based Style Factors For Hedge Funds”, Financial Analysts Journal 58: 16, pp.16-27.

Fung W, and Hsieh D.(2004), “Hedge s of Dynamic Trading Strategies: The Case of Hedge Funds”, Review of Financial Studies 10 (2), pp.275-302.

Gomes J., Yaron A., and Zhang L. (2003), “Asset Prices And Business Cycles With Costly External Finance”, Review Of Economic Dynamics 6 (4), pp.767-788.

Grauer, R. and Hakansson, N.(1998), "On Naive Approaches to Timing the Market: The. Empirical Probability Assessment Approach With an Inflation Adapter” in World Wide Asset and Liability Modeling, edited by Ziemba, W. and Mulvey, J., Cambridge University Press, pp.149-181.

Domowitz I., Hansch O., and Wang X. (2005), “Liquidity Commonality and Return Co-Movement”, Journal of Financial Markets 8 (4), pp.351-376.

Harry M. and Helder P.(2006), “Replication and Evaluation of Fund of Hedge Fund Returns Alternative” Investment Research Centre Working Paper No. 28.

Feeney D. and Hester D.(1967), “Stock Market Indices: A Principal Components Analysis, Risk Aversion and Portfolio Choice”, Cowles Foundation Monograph, No. 19. New York.

Hou K., and Moskowitz T.(2005), “Market Frictions, Price Delay, and the Cross-Section of Expected Returns”, Review of Financial Studies 18 (3), pp.981-1020.

Hirshleifer J.(1966), “Investment Decision under Uncertainty - Applications of State-Preference Approach”, Quarterly Journal of Economics 80, pp.252.

Huang H.(2005), “Asset Pricing Under Progressive Taxes and Existence of General Equilibrium”, Journal of Global Optimization 31 (3), pp.471-491.

Ineichen, A. (2005), “The Critique of Pure Alpha”, UBS Investment Research.

King, B.(1966), “Market and Industry Factors in Stock Price Behavior”, Journal of Business, 39, pp.139-190.

Klos A.(2004), “The Investment Horizon and Dynamic Asset Allocation - Some Experimental Evidence”, Economics Letters 85 (2), pp.167-170.

Kubler I. and Schmedders K. (2005), “Approximate Versus Exact Equilibria in Dynamic Economies”, Econometrica 73 (4), pp.1205-1235.

Kubler F. and Schmedders K.(2003), “Generic Inefficiency Of Equilibria In The General Equilibrium Model With Incomplete Asset Markets And Infinite Time”, Economic Theory 22 (1), pp.1-15.

Kung, E. and Pohlman, L.(2004), “Portable Alpha”, Journal of Portfolio Management, Spring2004, Vol. 30 Issue 3, pp.78-87.

Lessard, D. (1970), “Multinational Portfolio Diversification for Developoing Countries, Unpublished dissertation”, Stanford University.

Longstaff, F, Mithal, S, and Neis E.(2005), “Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market”, Journal of Finance 60 (5), pp.2213-2253.

Liang, B.(2003), “The Accuracy Of Hedge Fund Returns”, Journal of Portfolio Management, Vol. 29 Issue 3, pp.111-122.

Liew, J.(2003), “Hedge Fund Index Investing Examined”, Journal of Portfolio Management, Vol. 29 Issue 2, pp.113-123.

Lochoff, R.(2002). “Hedge Funds and Hope”, Journal of Portfolio Management, Vol. 28 Issue 4, pp.92-99.

Liew, J. and French, C.(2005). “Quantitative Topics in Hedge Fund Investing”, Journal of Portfolio Management, Vol. 31 Issue 4, pp.21-32.

Lo (2005), A.(2003). “The Dynamics of the Hedge Fund Industry”, Research Foundation of CFA Institute.

Malkiel and Saha(2005), “Hedge Funds: Risk and Returns”, Financial Analyst Journal Volume 61, number 6.

Michael L., and Ronald C.(1974). “Diversification, Systematic Risk, and Shareholder Return: A Capital Market Extension of Rumelt's 1974 Study”, Academy Of Management Journal, and Vol. 32, No. 2, 1989), pp.454-465.

Gibbons, M., Ross, S. and Shaken, J (1989), “A Test of the Efficiency of A Given Portfolio”, Econometrica, Vol. 57, No. 5, pp. 1121-1152.

Munk C, and Sorensen C. (2004), “Optimal Consumption and Investment Strategies with Stochastic Interest Rates”, Journal of Banking & Finance 28 (8), pp.1987-2013.

Nishiyama(2001), “One idea of Portfolio Risk Control for Absolute Return Strategy Risk Adjustments by Signals from Correlation Behavior”, Physicia 301, pp.457-472.

Peng H, Tamura Y, Gui W, and Ozaki T.(2005), “Modelling And Asset Allocation For Financial Markets Based On A Stochastic Volatility Microstructure Model”, International Journal Of Systems Science 36 (6), pp.315-327.

Pohlman, R., Ang, J. and Hollinger, R.(2003), “Performance And Timing: A Test Of Hedge Funds”, Journal of Portfolio Management, Spring78, Vol, 4 Issue 3, pp.69-72.

Davis, R. and Thomas, L.(1995). “Direct Estimation of Synergy: A New Approach to the Diversity-Performance.” Management Science, Vol. 39, No. 11, pp.1334-1346.

Richard S. (1977). “An Empirical Test of the Alternative Hypotheses of National and International Pricing Of Risky Assets”, Journal Of Finance, Vol. 32, No. 2, Papers And Proceedings Of The Thirty-Fifth Annual Meeting Of The American Finance Association, Atlantic City, New Jersey, pp. 493-502.

Roll R.(1971), “Investment Diversification and Bond Maturity”, Journal of Finance 26 (1), pp.51-66.

Rudin A., and Morgan J.(2006). “A Portfolio Diversification Index and Systematic Risks of Hedge Fund Investment Styles”, Journal of Portfolio Management 32 (2): 81.

Sortino, F. and Hal J.(1996), “On The Use and Misuse of Downside Risk”, Journal of Portfolio Management, v22, pp.35-42.

Sortino, F.(2001), “From Alpha to Omega, in Managing Downside Risk in Financial Markets”, Frank A. Sortino and Stephen E. Satchell, eds., Reed Educational and Professional Publishing Ltd.

Sortino, F. and Van Der Meer R. (1991), “Downside Risk”, Journal of Portfolio Management, v17 (4), pp.27-32.

Stephen, M.(1973), “A Re-Examination Of Market And Industry Factors In Stock Price Behavior”, Journal of Finance, Vol. 28, No. 3, pp. 695-705.

Solnik, B. (1973). “The International Pricing Of Risk: An Empirical Investigation of the World Capital Market Structure”, Journal Of Finance, Vol. 29, No. 2, Papers and Proceedings Of The Thirty-Second Annual Meeting Of The American Finance Association, New York, New York, December 28-30, pp.365-378.

Stutzer M.(2004), “Asset Allocation Without Unobservable Parameters”, Financial Analysts Journal 60 (5), pp.38-51.

Villalonga B. (2004), “Does Diversification Cause The Diversification Discount”, Financial Management-Tampa, Afajof.Org.

Weisman, A.(2002). “Informationless Investing and Hedge Fund Performance Measurement Bias”, Journal Of Portfolio Management, Summer2002, Vol. 28 Issue 4, pp.80-91.

Wu, W. and Wang, Y.(2005), “Investment With Restricted Stock and The Value Of Information”, Applied Mathematics And Computation 163 (2), pp.811-824.

4.10. Tables and Figures

Table 4.1 Comparison of Performance and Risk: Industry Portfolios vs. Hedge Fund Style Indexes

This table compares the performance and risk measure of industry portfolios and hedge fund style indexes. The average, maximum and minimum value of each measure are calculated. The value weighted industry portfolio returns are from the Fama-French data library website and the hedge fund style indexes data are from www.hedgefund.net.

		Industry Portfolios	Hedge Fund Indexes
Mean	Average	0.97	0.72
	Min	0.52	-0.07
	Max	1.34	1.13
Standard deviation	Average	5.18	2.56
	Min	3.86	0.85
	Max	8.72	4.98
Skewness	Average	-0.24	-0.81
	Min	-0.53	-3.36
	Max	0.49	0.84
Kurtosis	Average	3.81	8.86
	Min	3.17	3.35
	Max	5.73	26.09
Third Moment	Average	-39.57	1.59
	Min	-206.69	-70.83
	Max	73.59	103.55
Fourth Moment	Average	3829.70	865.77
	Min	803.74	1.74
	Max	19615.00	3720.10
Max	Average	15.44	8.89
	Min	10.97	2.00
	Max	21.92	22.70
Min	Average	-15.83	-9.36
	Min	-26.59	-23.00
	Max	-11.39	-1.20
Sharpe Ratio	Average	0.19	0.41
	Min	0.09	-0.01
	Max	0.26	0.94
Omega	Average	1.66	3.89
	Min	1.28	0.97
	Max	1.99	12.86
Sortino	Average	0.30	0.56
	Min	0.13	-0.03
	Max	0.51	2.16
Up/Down Ratio	Average	1.55	3.15
	Min	1.25	0.85
	Max	1.92	5.45

Table 4.2 First Four Moments of Industry Portfolios

This table reports the descriptive statistics of 12 industry portfolios with data obtained from Fama-French data library. The periods between January 1994 and February 2006 is examined. The formula for the third and fourth moments, as well as the Maximum Drawdown is provided in the methodology section.

	Non-durable	Durable	Manu-facture	Energy	Chemistry	Business Equipment	Tele-communi-cation	Utilities	Shops	Health	Money	Other
Mean	0.864	0.607	0.971	1.338	0.940	1.310	0.518	0.865	0.897	1.136	1.310	0.883
Standard Deviation	3.856	6.109	4.772	5.307	4.389	8.715	5.611	4.326	4.692	4.359	4.981	5.058
Skew-ness	-0.391	-0.304	-0.531	0.492	-0.043	-0.312	-0.023	-0.320	-0.263	-0.317	-0.480	-0.357
Kurtosis	3.637	3.597	4.425	3.654	3.691	3.400	4.231	3.218	3.368	3.166	5.733	3.576
Third Moment	-22.382	-69.202	-57.718	73.591	-3.591	-206.686	-4.036	-25.937	-27.181	-26.223	-59.272	-46.146
Fourth Moment	804.000	5011.000	2294.000	2898.000	1370.000	19615.000	4194.000	1127.000	1632.000	1143.000	3528.000	2340.000
Max	10.970	15.440	14.320	19.130	15.680	21.920	21.200	11.560	13.610	11.730	16.730	12.950
Min	-12.970	-19.510	-16.740	-11.770	-11.390	-26.590	-15.030	-12.340	-13.760	-11.900	-22.060	-15.860

Table 4.3 First Four Moments of Hedge Fund Style Indexes

This table reports the descriptive statistics of hedge fund style indexes with data obtained from hedgefund.net. The periods between January 1994 and February 2006 are examined. The formulas for the third and fourth moments as well as maximum drawdown are provided in the methodology section.

	Credit Suisse/ Tremont	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long/ Short Equity	Managed Futures	Multi-Strategy
Mean	0.893	0.721	-0.068	0.827	0.796	0.934	0.519	1.127	1.000	0.572	0.757
Stdev	2.271	1.380	4.976	4.734	0.848	1.647	1.082	3.203	2.963	3.475	1.254
Skewness	0.094	-1.280	0.840	-0.668	0.333	-3.356	-3.078	0.010	0.213	0.040	-1.169
Kurtosis	5.803	5.803	5.020	7.410	3.371	26.094	19.034	5.699	6.678	3.352	6.173
Third Moment	1.101	-3.360	103.549	-70.826	0.203	-14.991	-3.903	0.325	5.532	1.678	-2.303
Fourth Moment	137.395	21.000	3078.200	3720.100	1.700	192.000	26.100	599.900	514.600	488.700	15.200
Max	8.500	3.60	22.70	16.40	3.30	3.70	2.00	10.60	13.00	10.00	3.6
Min	-7.600	-4.70	-8.70	-23.00	-1.20	-11.80	-7.00	-11.60	-11.40	-9.40	-4.8

Table 4.4 Risk Measure of Industry Portfolios

This table reports the risk measure of 12 industry portfolios with data obtained from the Fama-French data library. The periods between January 1994 and February 2006 is examined. The formula for maximum drawdown, Sharpe ratio, Omega and Sortino ratios are provided in the methodology section. The up/down ratio is the number of positive returns divided by the number of negative returns. We also assume that the riskfree rate is zero.

	Non-durable	Durable	Manufacture	Energy	Chemistry	Business Equipment	Tele-communication	Utilities	Shops	Health	Money	Other
Max DrawDown	-0.501	-0.505	-0.492	-0.479	-0.496	-0.517	-0.513	-0.500	-0.487	-0.490	-0.496	-0.486
Sharpe Ratio	0.224	0.099	0.204	0.252	0.214	0.150	0.092	0.200	0.191	0.261	0.263	0.175
Omega	1.767	1.291	1.683	1.957	1.745	1.479	1.282	1.654	1.616	1.925	1.985	1.558
Sortino	0.333	0.147	0.292	0.512	0.337	0.220	0.134	0.310	0.303	0.400	0.382	0.260
Up/down	1.824	1.318	1.433	1.475	1.517	1.246	1.355	1.808	1.475	1.920	1.704	1.561

Table 4.5 Risk Measure of Hedge Fund Style Indexes

This table reports the risk measure of the hedge fund style indexes with data obtain from www.hedgefund.net. The periods between January 1994 and February 2006 is examined. The formulas for maximum drawdown, Sharpe ratio, Omega and Sortino ratio are provided in the methodology section. The up/down ratio is the number of positive returns divided by the number of negative returns. We also assume that the risk-free rate is zero.

	Credit Suisse/ Tremont	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long/ Short Equity	Managed Futures	Multi-Strategy
Max Drawdown	-0.076	-0.0876	-0.1156	-0.23	-0.063	-0.118	-0.07	-0.116	-0.114	-0.094	-0.07
Sharpe Ratio	0.393	0.522	-0.014	0.175	0.939	0.567	0.480	0.352	0.338	0.165	0.604
Omega	3.042	3.529	0.965	1.605	12.857	4.920	3.422	2.710	2.590	1.543	4.733
Sortino	0.556	0.576	-0.027	0.222	2.159	0.404	0.370	0.470	0.508	0.272	0.602
Up/down	2.600	3.500	0.846	1.704	5.455	4.500	4.143	2.744	2.085	1.250	5.318

Table 4.6 Correlation Coefficient Matrix of Industry Portfolios

This table provides the correlation among 12 the industry portfolios with data obtained from Fama-French data library. The period between January 1994 and February 2006 is examined.

	Non-durable	Durable	Manufacture	Energy	Chemistry	Business Equipment	Tele-communication	Utilities	Shops	Health	Money	Other
Non-durable	1.000											
Durable	0.425	1.000										
Manufacture	0.573	0.778	1.000									
Energy	0.375	0.384	0.553	1.000								
Chemistry	0.672	0.557	0.747	0.422	1.000							
Business Equipment	0.228	0.534	0.620	0.252	0.299	1.000						
Tele-communication	0.419	0.551	0.535	0.235	0.358	0.650	1.000					
Utilities	0.472	0.276	0.306	0.528	0.289	0.007	0.181	1.000				
Shops	0.561	0.669	0.685	0.339	0.556	0.580	0.620	0.188	1.000			
Health	0.560	0.321	0.395	0.247	0.452	0.399	0.485	0.346	0.379	1.000		
Money	0.707	0.654	0.674	0.440	0.652	0.445	0.588	0.438	0.690	0.552	1.000	
Other	0.498	0.693	0.746	0.439	0.581	0.722	0.722	0.302	0.767	0.514	0.752	1.000

Table 4.7 Correlation Coefficient Matrix of Hedge Fund Style Index

This table provides the correlation between hedge fund style indexes with data obtained from www.hedgefund.net. The period between January 1994 and February 2006 is examined.

	Credit Suisse/ Tremont	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long/ Short Equity	Managed Futures	Multi-Strategy
Credit Suisse/ Tremont	1										
Convertible Arbitrage	0.411	1									
Dedicated Short Bias	-0.482	-0.246	1								
Emerging Markets	0.65	0.306	-0.553	1							
Equity Market Neutral	0.335	0.337	-0.327	0.223	1						
Event Driven	0.67	0.568	-0.633	0.676	0.365	1					
Fixed Income Arbitrage	0.45	0.538	-0.08	0.279	0.109	0.392	1				
Global Macro	0.856	0.292	-0.132	0.412	0.214	0.377	0.454	1			
Long/ Short Equity	0.79	0.284	-0.716	0.592	0.353	0.666	0.216	0.429	1		
Managed Futures	0.136	-0.142	0.138	-0.09	0.116	-0.152	-0.064	0.249	-0.003	1	
Multi-Strategy	0.216	0.399	-0.095	0.008	0.234	0.213	0.299	0.152	0.201	0.019	1

Table 4.8 5-Year Average Correlation Coefficient Matrix of Industry Portfolios

This table provides the correlation among 12 industry portfolios with data obtained from Fama-French data library. The period between January 1994 and February 2006 is examined.

	Non-durable	Durable	Manufacture	Energy	Chemistry	Business Equipment	Tele-communication	Utilities	Shops	Health	Money	Other
Non-durable	1.000											
Durable	0.416	1.000										
Manufacture	0.568	0.766	1.000									
Energy	0.413	0.364	0.563	1.000								
Chemistry	0.668	0.538	0.740	0.422	1.000							
Business Equipment	0.178	0.518	0.603	0.251	0.256	1.000						
Tele-communication	0.386	0.551	0.517	0.217	0.325	0.640	1.000					
Utilities	0.454	0.242	0.276	0.534	0.286	-0.057	0.111	1.000				
Shops	0.555	0.673	0.679	0.365	0.539	0.572	0.642	0.144	1.000			
Health	0.530	0.297	0.364	0.262	0.411	0.373	0.436	0.335	0.359	1.000		
Money	0.707	0.671	0.683	0.503	0.631	0.425	0.571	0.430	0.707	0.521	1.000	
Other	0.467	0.676	0.725	0.453	0.547	0.715	0.715	0.249	0.779	0.481	0.746	1.000

Table 4.9 5-Year Average Correlation Coefficient Matrix of Hedge Fund Style Indexes

This table provides the correlation between hedge fund style indexes with data obtained from hedgefund.net. The period between January 1994 and February 2006 is examined.

	Credit Suisse/ Tremont	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long/ Short Equity	Managed Futures	Multi-Strategy
Credit Suisse/ Tremont	1.000										
Convertible Arbitrage	0.372	1.000									
Dedicated Short Bias	-0.539	-0.226	1.000								
Emerging Markets	0.724	0.266	-0.644	1.000							
Equity Market Neutral	0.267	0.259	-0.388	0.343	1.000						
Event Driven	0.683	0.556	-0.649	0.704	0.351	1.000					
Fixed Income Arbitrage	0.389	0.511	-0.047	0.232	0.068	0.332	1.000				
Global Macro	0.750	0.243	-0.109	0.436	0.112	0.323	0.426	1.000			
Long/ Short Equity	0.849	0.208	-0.721	0.677	0.302	0.647	0.154	0.410	1.000		
Managed Futures	0.076	-0.250	0.215	-0.150	0.074	-0.256	-0.038	0.285	-0.036	1.000	
Multi-Strategy	0.373	0.459	-0.165	0.182	0.101	0.256	0.349	0.247	0.270	-0.056	1.000

Table 4.10 Principal Component Analysis - Industry Portfolios

This table presents the total variance explained by the components using PCA extraction methods. The first two components contribute up to 67.39% of the total variance displayed by 12 industry portfolios.

Initial Eigenvalues

Component	Total	% of Variance	Cumulative %
1	6.61	55.06	55.06
2	1.48	12.33	67.39
3	0.92	7.66	75.05
4	0.79	6.61	81.66
5	0.53	4.42	86.08
6	0.4	3.3	89.38
7	0.3	2.48	91.86
8	0.28	2.34	94.2
9	0.25	2.08	96.27
10	0.22	1.86	98.13
11	0.12	1.01	99.14
12	0.1	0.86	100

Table 4.11 Principal Component Analysis - Hedge Fund Style Indexes

This table presents the total variance explained by the components using PCA extraction methods. The first four components contribute up to 76.68% of the total variance displayed by 10 hedge funds styles.

Initial Eigenvalues

Component	*Total*	*% of Variance*	*Cumulative %*
1	3.9	39.04	39.04
2	1.48	14.84	53.88
3	1.24	12.44	66.33
4	1.03	10.35	76.68
5	0.67	6.75	83.43
6	0.48	4.8	88.22
7	0.4	3.98	92.2
8	0.35	3.51	95.71
9	0.22	2.25	97.95
10	0.2	2.05	100

Table 4.12 Diversification Benefit among Industry Portfolios

This table provides the summary statistics of an equal weighted hedge fund style portfolios index. The formulas for each statistics are provided in part 4 of the methodology section. The industry data are from Fama-French data library website.The results are reported in units of 0.01.

		2 Industries	3 Industries	4 Industries	5 Industries	6 Industries
	Average	0.97	0.97	0.97	0.97	0.97
Mean	Min	0.56	0.66	0.71	0.75	0.77
	Max	1.32	1.32	1.27	1.21	1.17
	Average	4.49	4.23	4.09	4.00	3.95
Standard deviation	Min	3.48	3.26	3.22	3.22	3.23
	Max	6.54	5.80	5.46	5.14	4.91
	Average	-0.40	-0.48	-0.53	-0.56	-0.59
Skewness	Min	-0.74	-0.83	-0.84	-0.81	-0.77
	Max	-0.03	-0.19	-0.30	-0.38	-0.43
	Average	3.74	3.72	3.72	3.73	3.75
Kurtosis	Min	2.99	2.78	2.81	2.82	3.01
	Max	5.24	5.21	5.01	4.99	4.88
	Average	-39.27	-38.27	-37.59	-37.13	-36.80
Third Moment	Min	-129.43	-100.54	-87.71	-77.87	-68.52
	Max	-2.15	-11.56	-14.43	-16.94	-19.25
	Average	1779.70	1319.30	1122.90	1014.80	946.60
Fourth Moment	Min	465.59	347.87	331.75	352.78	354.75
	Max	6798.40	4090.20	3067.80	2574.70	2215.90
	Average	12.35	11.03	10.28	9.75	9.34
Max	Min	7.79	6.99	6.61	6.59	6.50
	Max	20.30	16.05	14.04	13.39	12.49
	Average	-14.41	-13.94	-13.66	-13.55	-13.53
Min	Min	-20.79	-19.73	-18.98	-18.36	-17.59
	Max	-9.27	-8.16	-7.99	-8.74	-9.47
	Average	0.22	0.23	0.24	0.24	0.25
Sharpe Ratio	Min	0.11	0.14	0.15	0.16	0.18
	Max	0.32	0.33	0.32	0.32	0.32
	Average	1.76	1.80	1.83	1.84	1.85
Omega	Min	1.33	1.43	1.47	1.52	1.57
	Max	2.24	2.28	2.24	2.21	2.18
	Average	0.33	0.34	0.35	0.36	0.36
Sortino	Min	0.16	0.20	0.22	0.24	0.25
	Max	0.54	0.51	0.51	0.50	0.49
	Average	1.62	1.68	1.70	1.71	1.72
Up/Down Ratio	Min	1.18	1.25	1.25	1.28	1.32
	Max	2.24	2.17	2.24	2.15	2.11

Table 4.13 Diversification Benefit among Hedge Fund Style Indexes

This table provides the summary statistics of equal weighted hedge fund style portfolios index. The formulas for the statistics are provided in the methodology section. The industry data are from Fama-French data library website and hedge fund style indexes data are from www.hedgefund.net. The results are reported in unit of 0.01.

		2 Styles	3 Styles	4 Styles	5 Styles	6 Styles
Mean	Average	0.72	0.72	0.72	0.72	0.72
	Min	0.23	0.34	0.44	0.50	0.55
	Max	1.06	1.02	0.97	0.94	0.91
Standard deviation	Average	2.00	1.70	1.51	1.37	1.28
	Min	0.72	0.74	0.82	0.78	0.73
	Max	3.46	2.96	2.53	2.15	1.88
Skewness	Average	-0.45	-0.34	-0.33	-0.33	-0.31
	Min	-2.58	-2.23	-1.79	-1.65	-1.74
	Max	0.99	1.00	0.91	0.57	0.41
Kurtosis	Average	6.63	5.72	5.37	5.20	5.04
	Min	2.91	2.69	2.64	2.62	2.61
	Max	17.57	13.24	12.35	12.43	12.63
Third Moment	Average	-2.07	-1.76	-1.31	-0.95	-0.67
	Min	-38.71	-23.81	-14.34	-8.55	-6.01
	Max	33.07	10.15	3.77	2.04	1.45
Fourth Moment	Average	174.46	74.29	41.54	26.53	18.24
	Min	1.22	2.09	1.55	1.14	1.21
	Max	1200.70	625.40	362.50	199.80	111.30
Max	Average	6.9411	5.9317	5.2681	4.8258	4.5329
	Min	2.10	2.07	2.10	2.26	2.08
	Max	16.35	12.50	10.15	8.62	7.58
Min	Average	-7.28	-6.03	-5.27	-4.75	-4.35
	Min	-17.40	-15.40	-12.75	-11.12	-9.52
	Max	-2.10	-2.33	-1.78	-1.40	-1.72
Sharpe Ratio	Average	0.42	0.45	0.49	0.54	0.58
	Min	0.08	0.16	0.27	0.37	0.44
	Max	0.93	0.93	0.91	0.88	0.91
Omega	Average	3.50	3.56	3.86	4.27	4.65
	Min	1.24	1.56	2.08	2.54	3.03
	Max	9.82	9.13	8.44	8.67	9.44
Sortino	Average	0.56	0.66	0.76	0.82	0.89
	Min	0.14	0.28	0.43	0.48	0.54
	Max	1.24	1.23	1.55	1.72	1.65
Up/Down Ratio	Average	2.70	2.59	2.61	2.78	3.00
	Min	0.91	1.29	1.43	1.70	1.86
	Max	6.42	6.58	6.68	5.35	5.35

__Figure 4.1 Range of Historical Industry Portfolio Returns__

This figure provides the maximum and minimum returns of industry portfolios during January 1994 and February 2006 with data obtained from the Fama-French data library website.

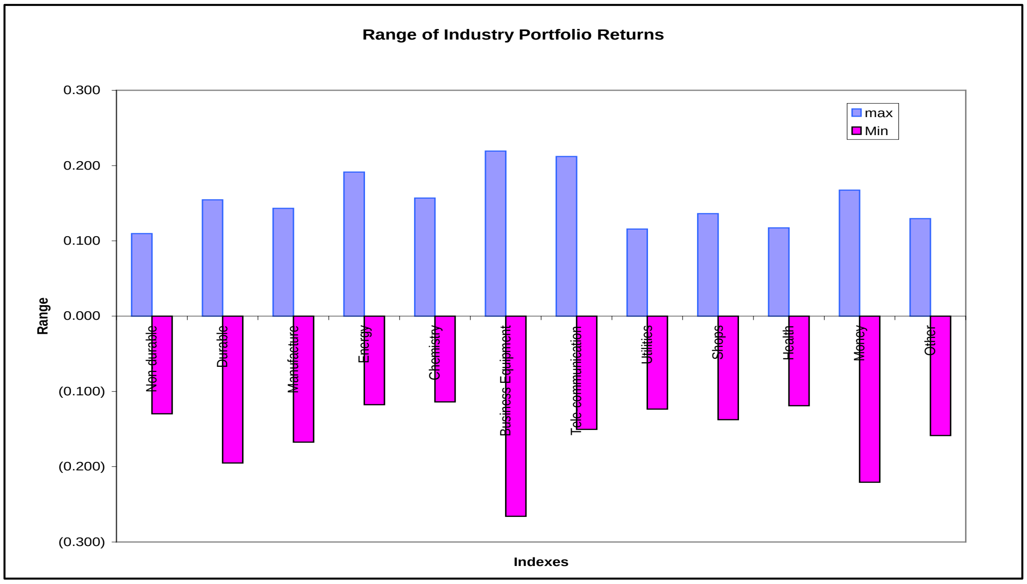


__Figure 4.2 Range of Historical Hedge Fund Returns__

This figure provides the maximum and minimum returns of hedge fund style indexes during January 1994 and February 2006. The data are obtained from www.hedgefund.net

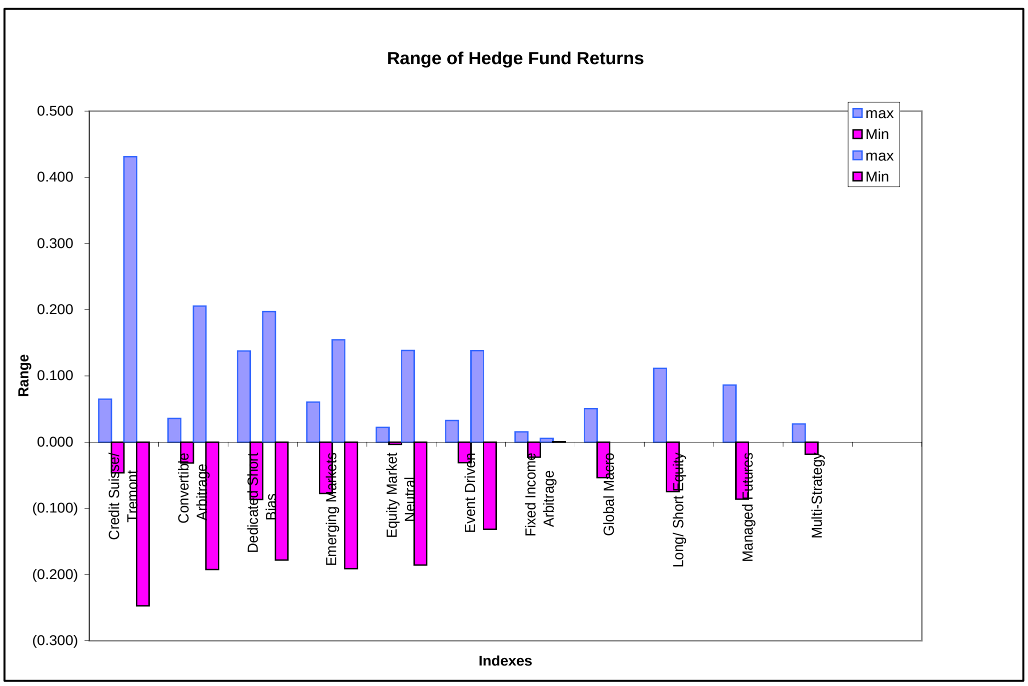


Figure 4.3 Mean-Standard Deviation Scatter Plot - Industry Portfolios

This figure provides the mean variance trade-off of industry portfolios during January 1994 and February 2006. The data are obtained from the Fama-French data library website.

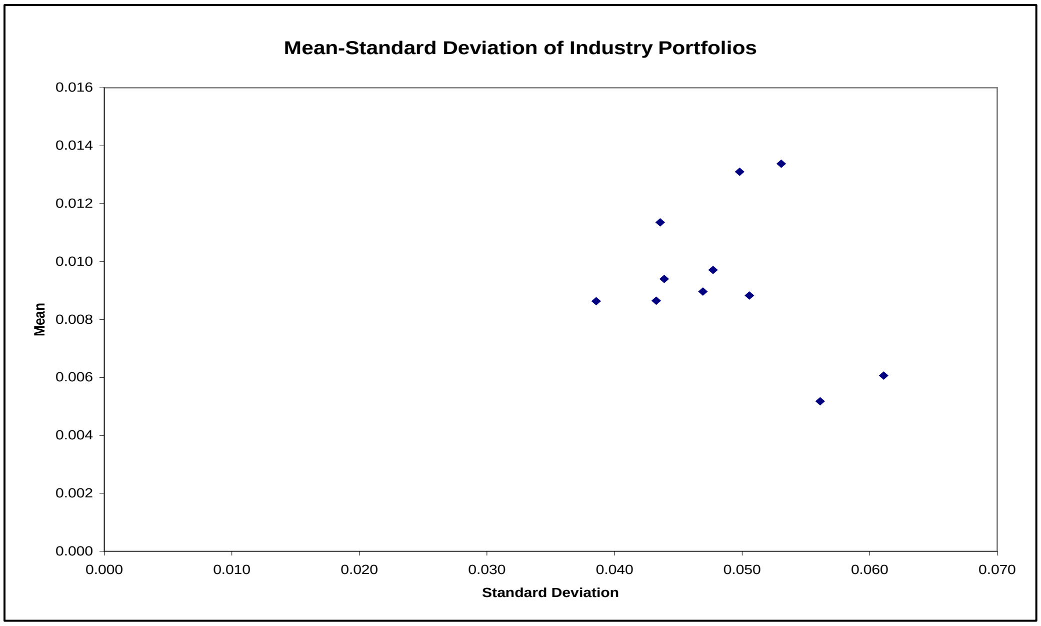


Figure 4.4 Mean-Standard Deviation Scatter Plot – Hedge Fund Style Indexes

This figure provides the mean variance trade-off of hedge fund style indexes during January 1994 and February 2006. The data are obtained from www.hedgefund.net

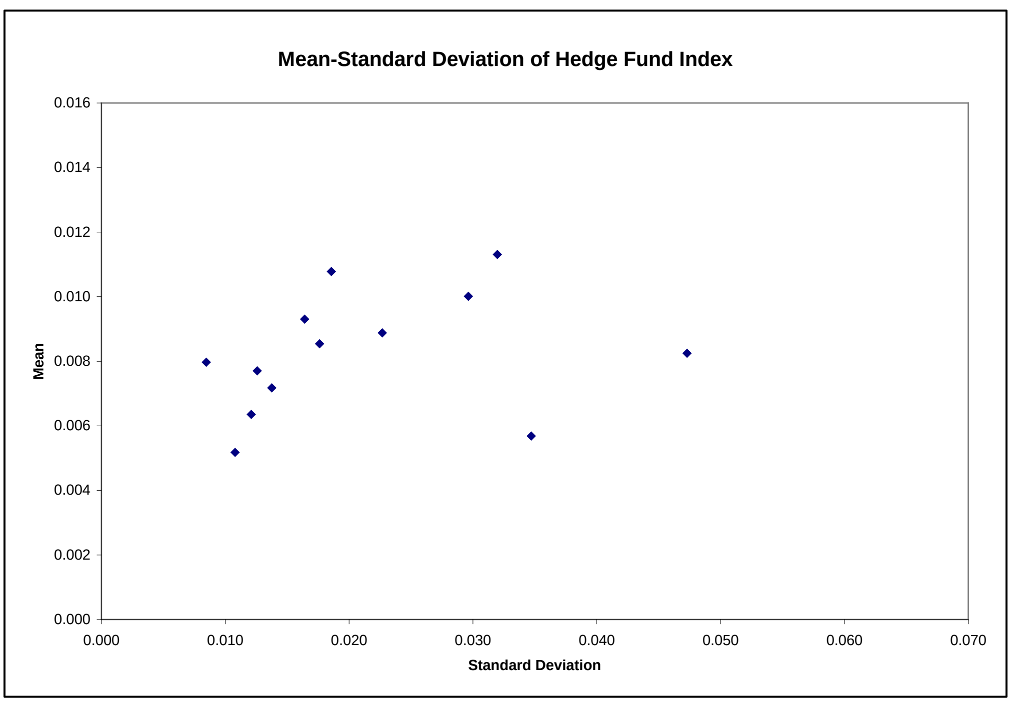


Figure 4.5 Distributions of Four Moments – Industry Portfolios

This figure provides the first four moments of industry portfolios during January 1994 and February 2006. The data are obtained from the Fama-French data library website.

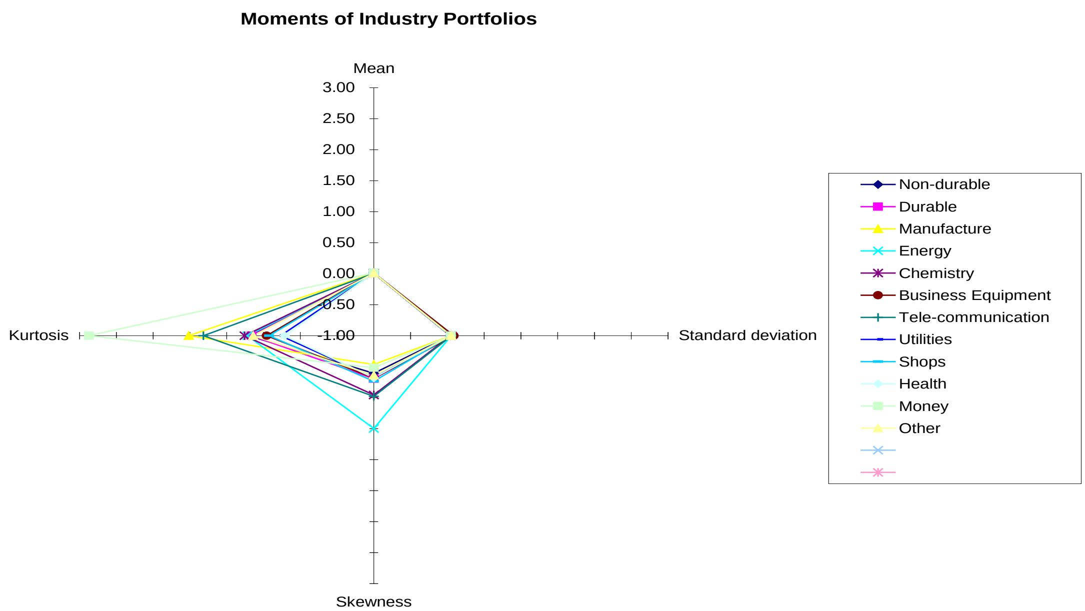


Figure 4.6 Distributions of Four Moments – Hedge Fund Style Indexes

This figure provides the first four moments of hedge fund style indexes during January 1994 and February 2006. The data are obtained from www.hedgefund.net.

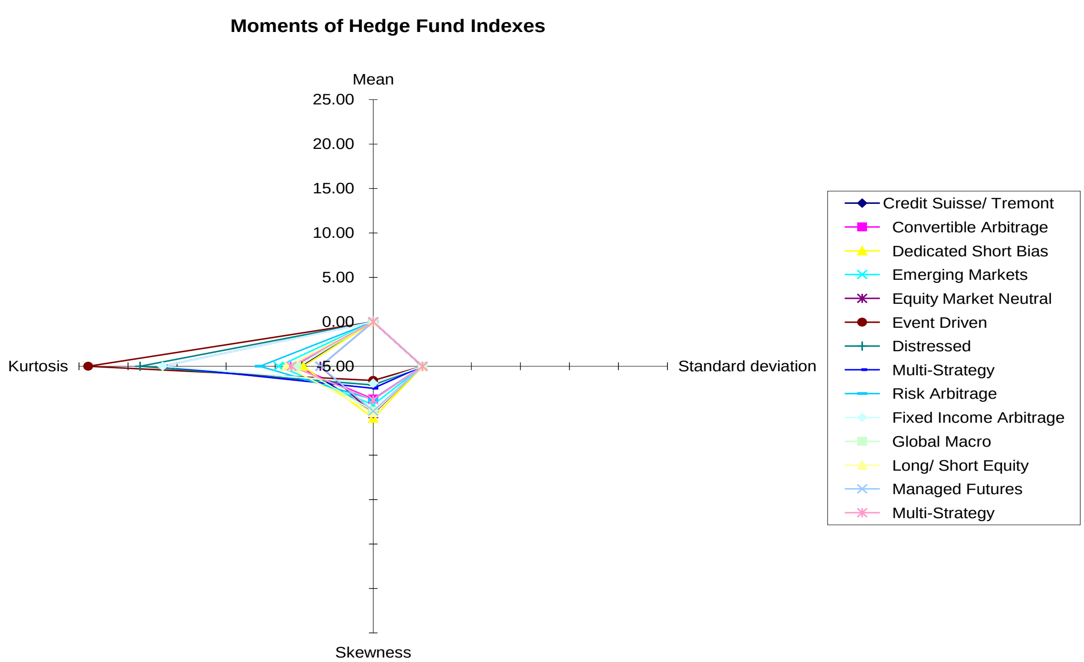
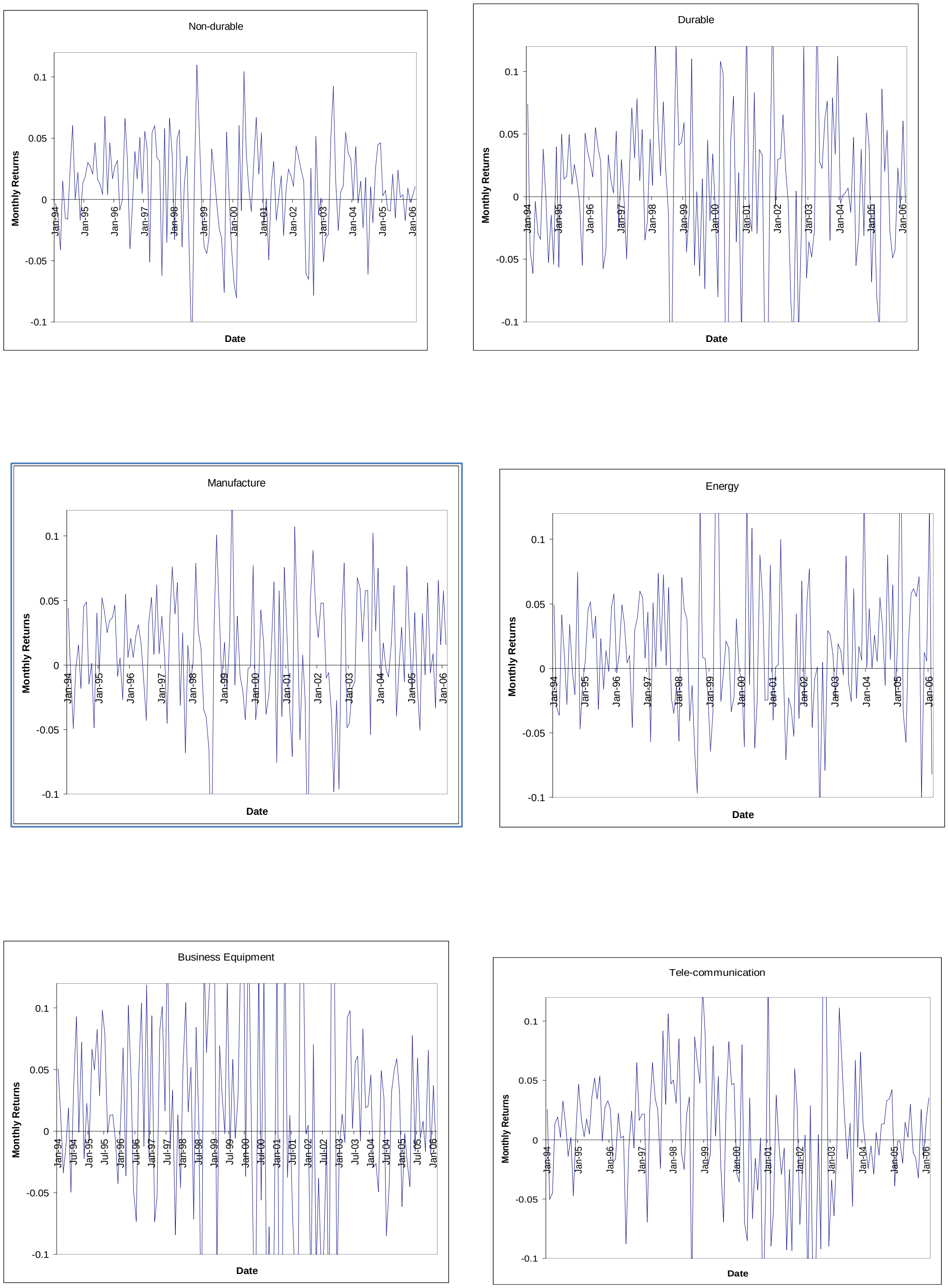
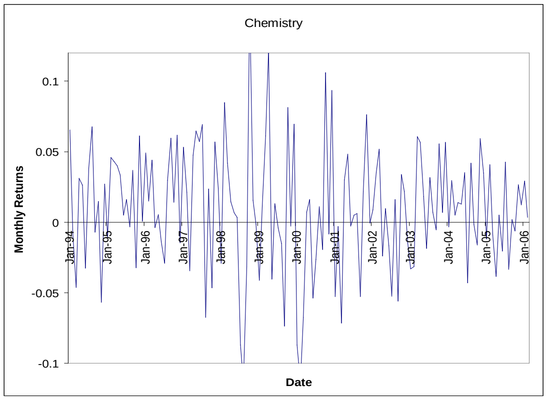


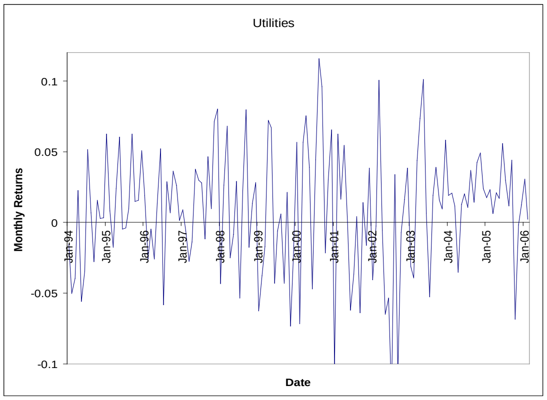
Figure 4.7 Historical Returns - Industry Portfolios

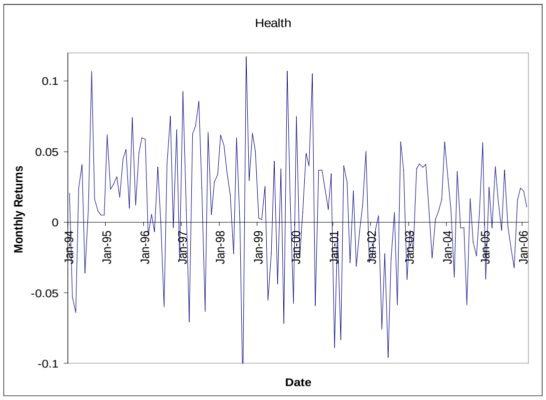
This figure provides the historical returns of industry portfolio during January 1994 and February 2006. The data are obtained from the Fama-French data library website.

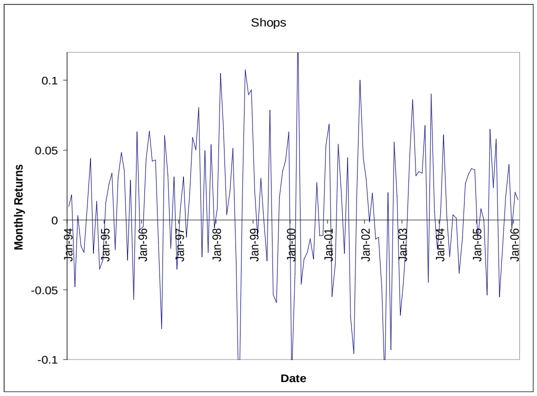


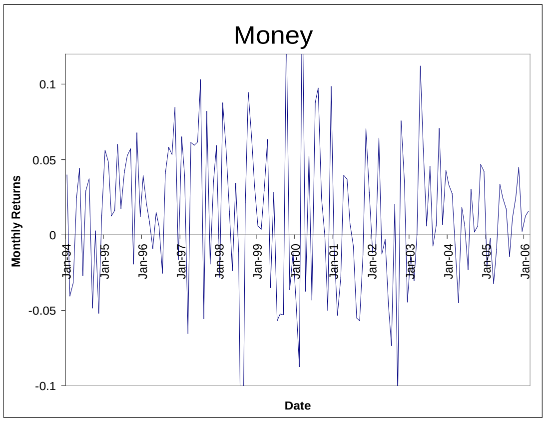
(Figure 4.7 continued)











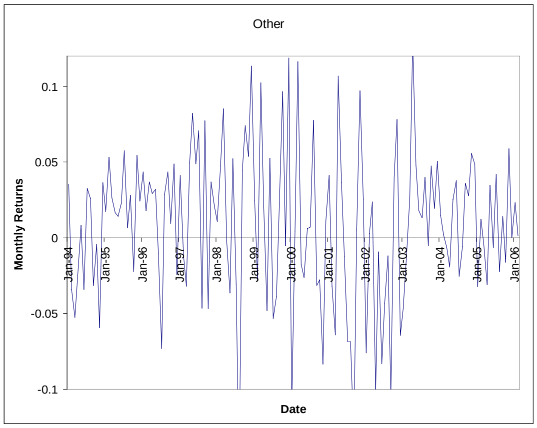
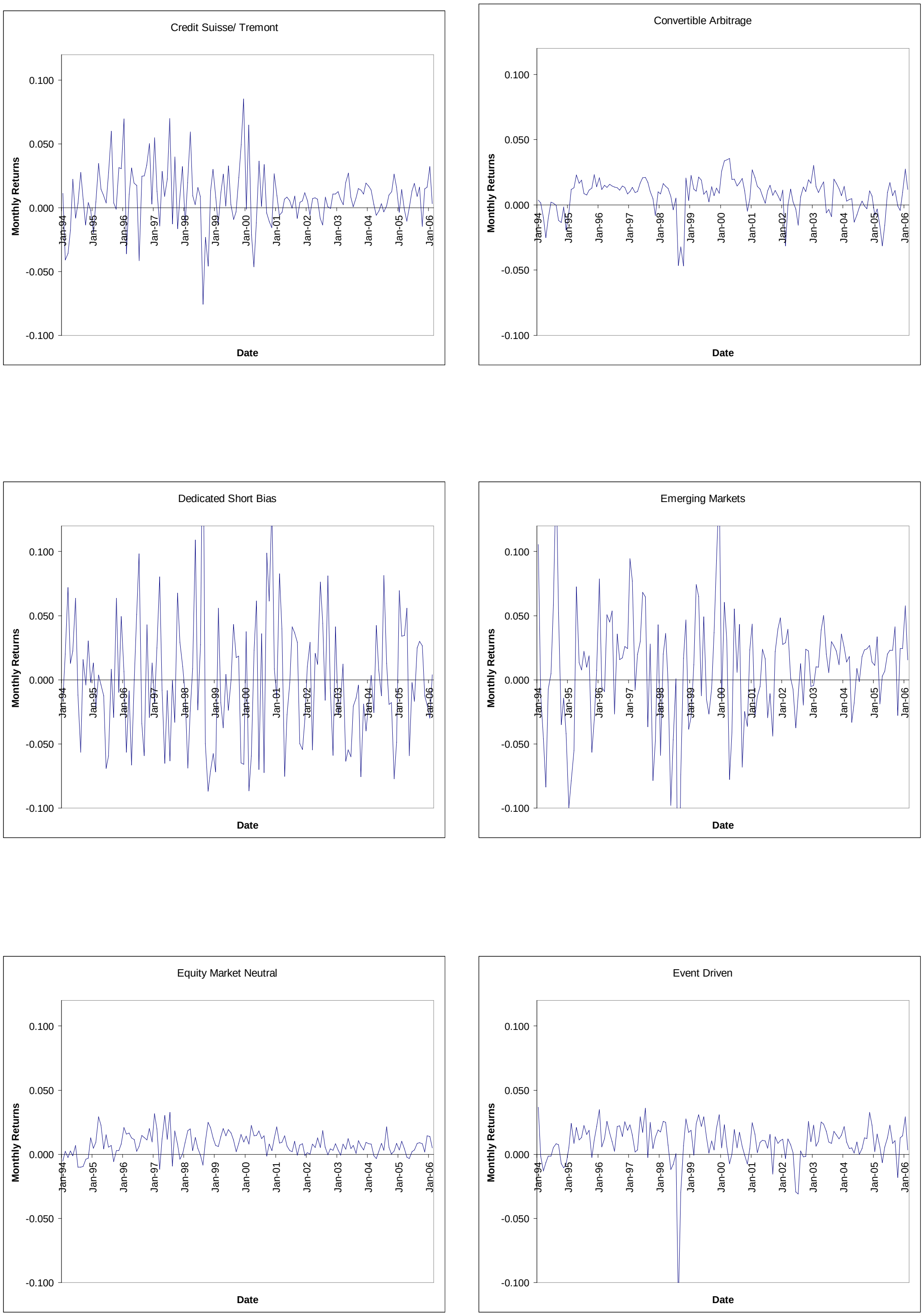
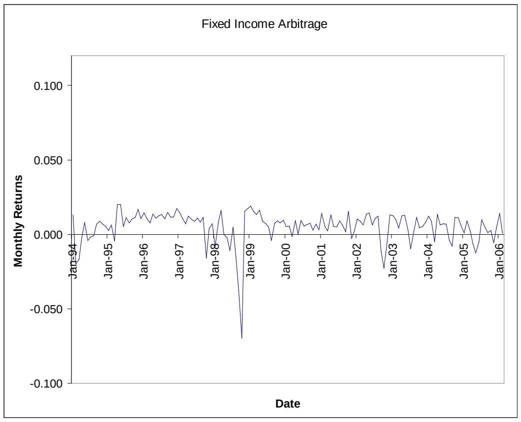


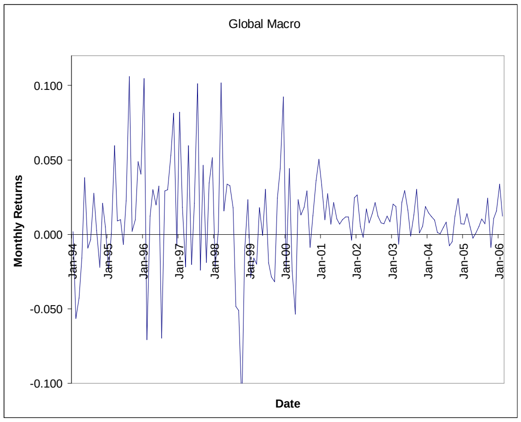
Figure 4.8 Historical Returns- Hedge Fund Style Indexes

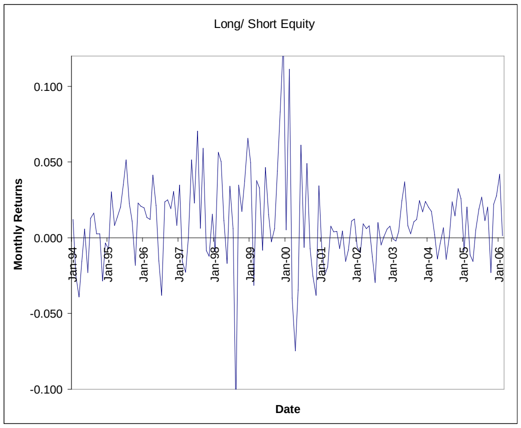
This figure provides the historical returns of hedge fund style indexes during January 1994 and February 2006. The data are obtained from www.hedgefund.net.

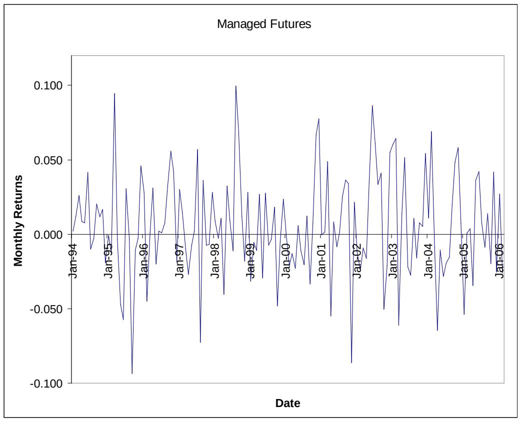


(Figure 4.8 continued)









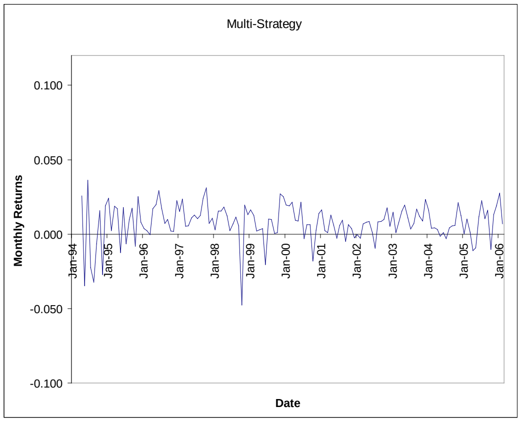


Figure 4.9 Risk Measures - Industry Portfolios

This figure provides the risk measure of industry portfolios during January 1994 and February 2006. The data are obtained from the Fama-French data library website. ND stands for Non-durables, DUR for Durables, MAU for Manufacture, ENE for Energy, CHE for Chemical goods, UTIL for Utilities and the rest as indicated.

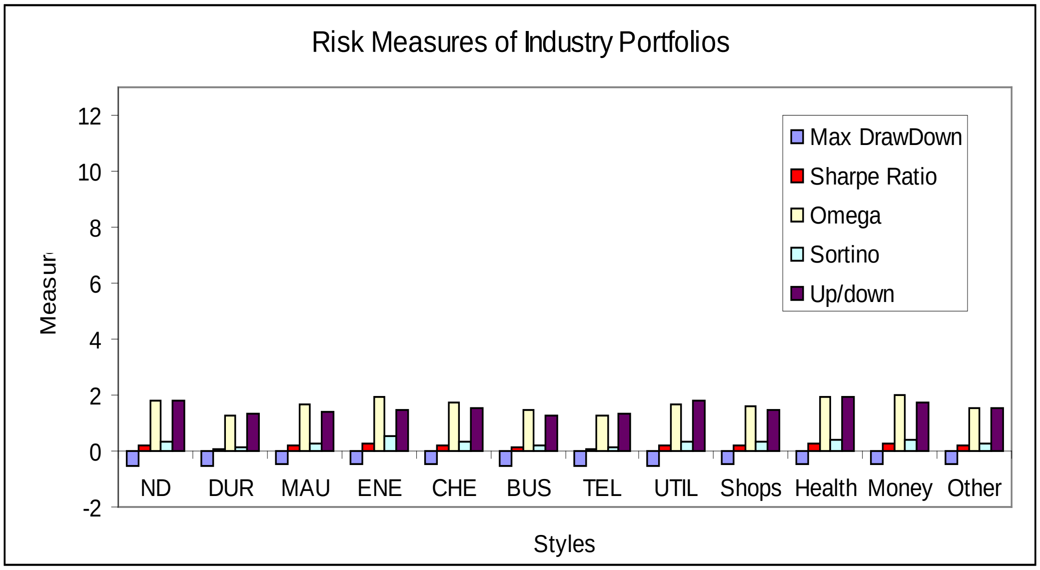


Figure 4.10   Risk Measures - Hedge Fund Style Indexes

This figure provides the risk measure of hedge fund style indexes between January 1994 and February 2006. The data are obtained from hedgeindex.net. CA refers to Convertible Arbitrage, DSB for Dedicated Short Bias, EM for Emerging Markets, EMN for Equity Market Neutral, ED for Event Driven, FIA for Fixed Income Arbitrage, GM for Global Management, LSE for Long/Short Equity, MF for Managed Futures and MS for Multiple Strategies.

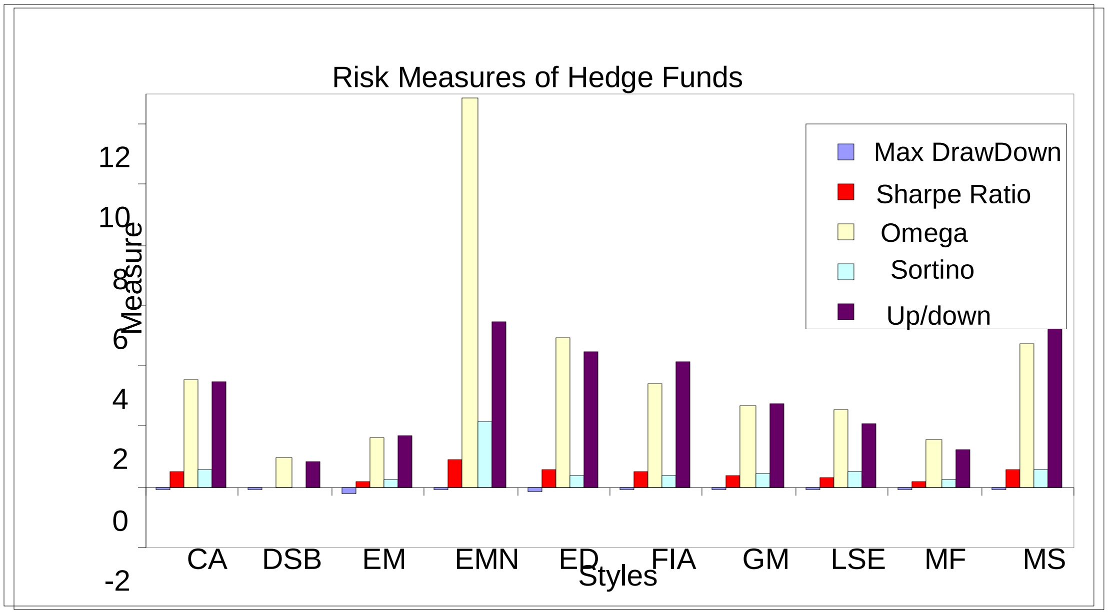


Figure 4.11 Eigen Value of Components Extracted by Principal Component Analysis – Industry Portfolios

This figure shows the eigen value of the components based on PCA data extraction on the historical return of 12 industry portfolios using the data from January 1994 to February 2006.

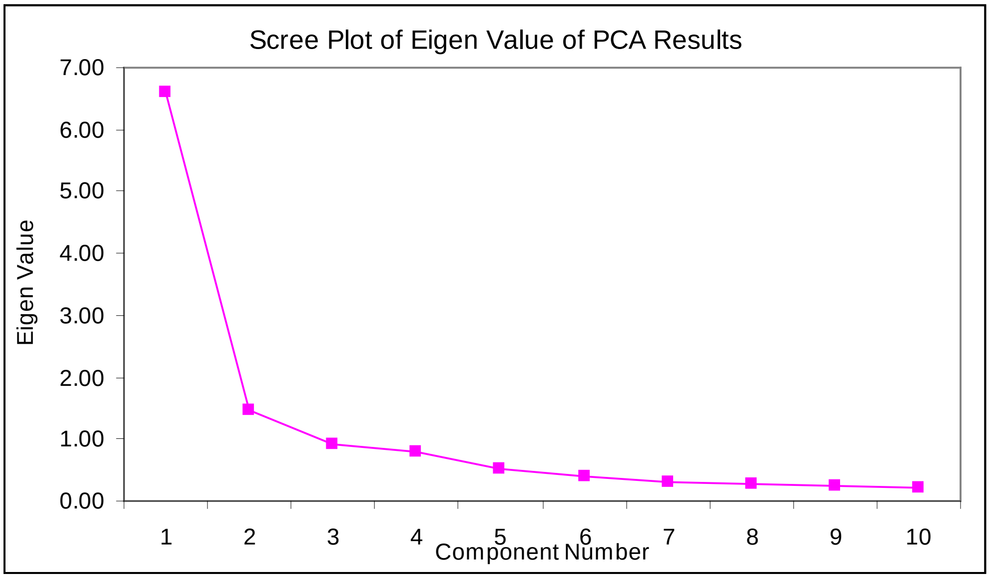


Figure 4.12 Eigen Value of the Components Extracted by Principal Component Analysis - Hedge Fund Style Indexes

This figure shows the eigen value of the components based on PCA data extraction on the historical return of 10 hedge funds style indexes using the data from January 1994 to February 2006.

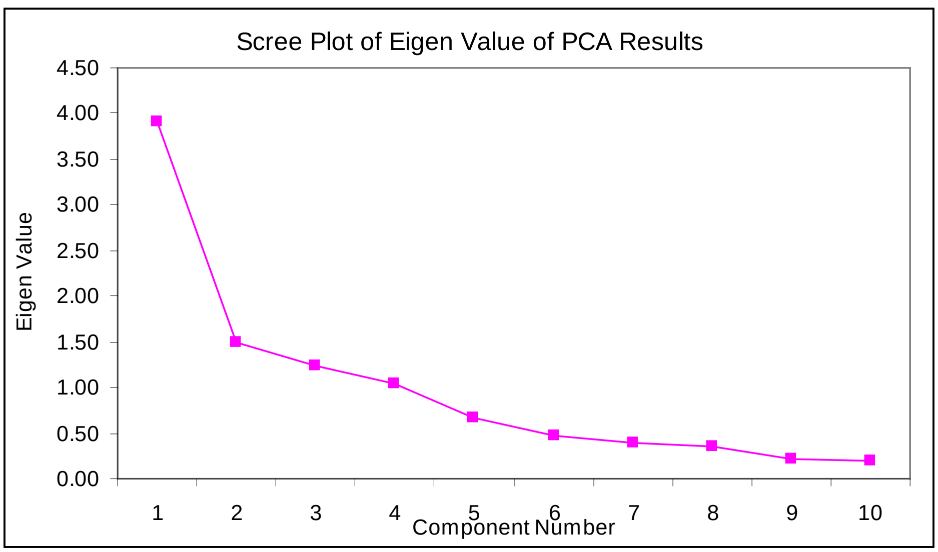
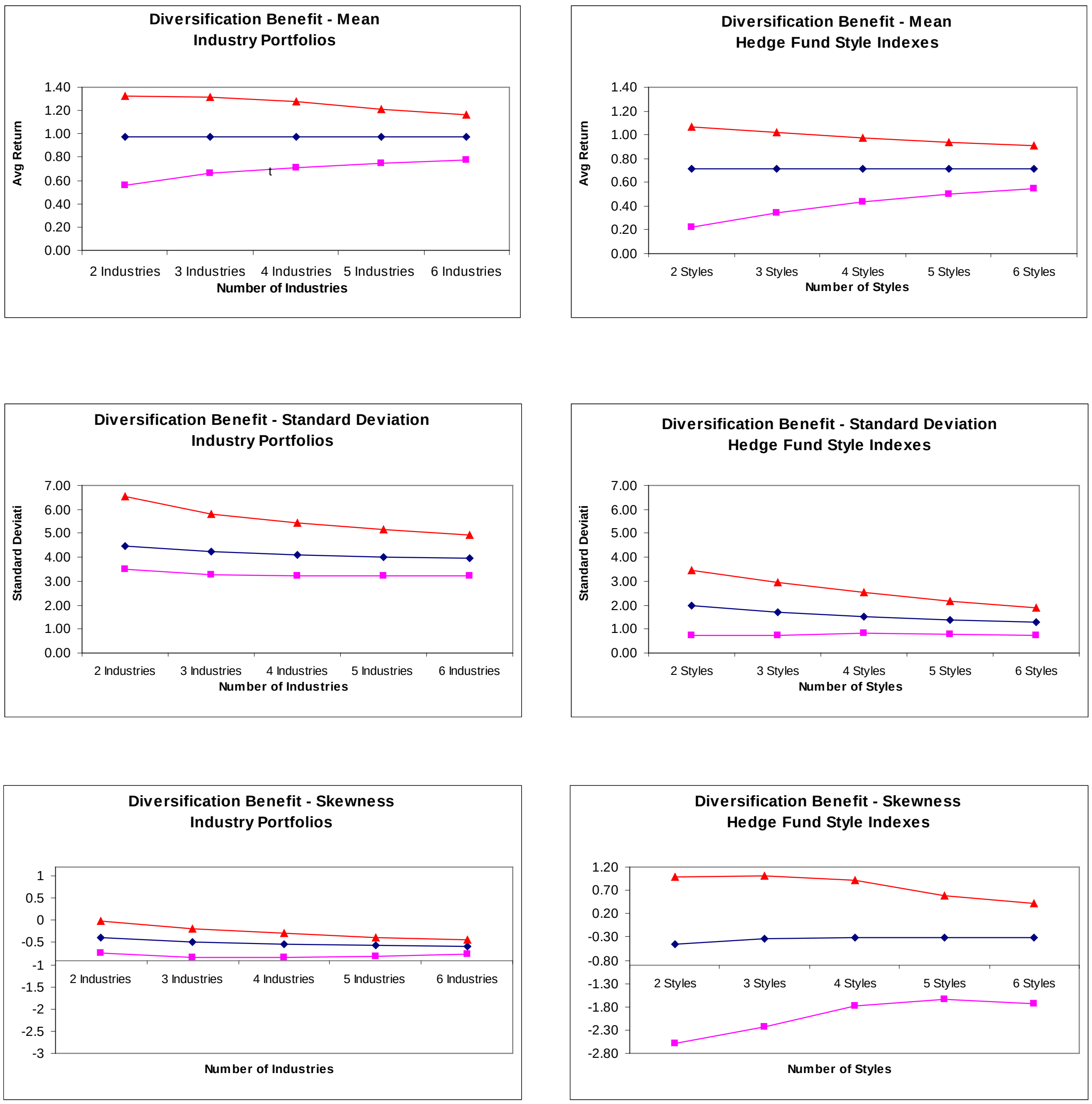
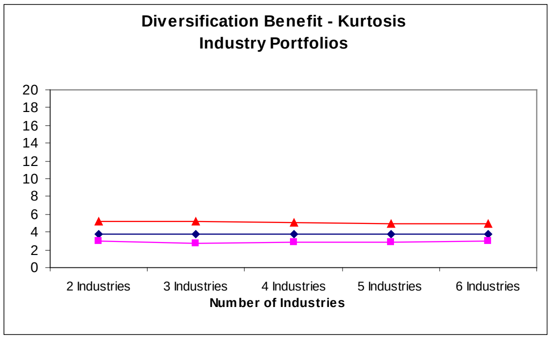


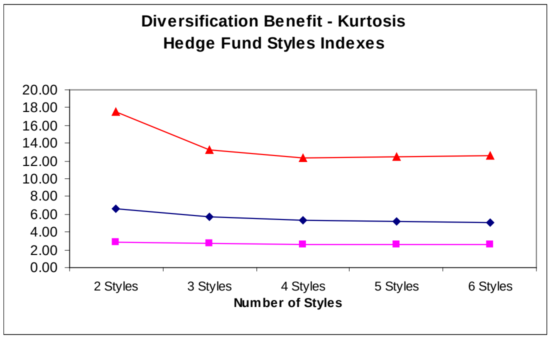
Figure 4.13 Potential Diversification Benefit

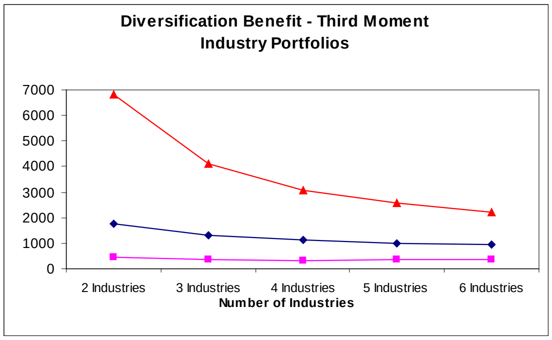
This figure provides the potential gains from diversification among industry portfolio during January 1994 and February 2006. The original return data for industry portfolio are obtained from the Fama-French data library website. The upper, middle and lower lines are the upper bound, average, and lower bound of each statistics

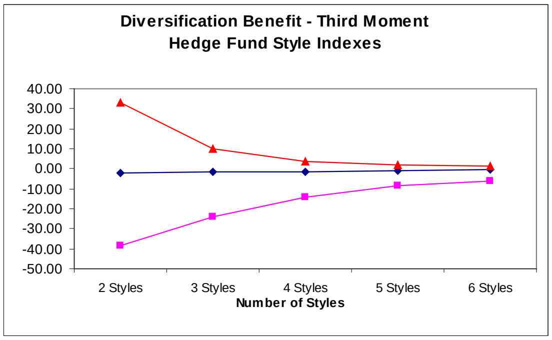


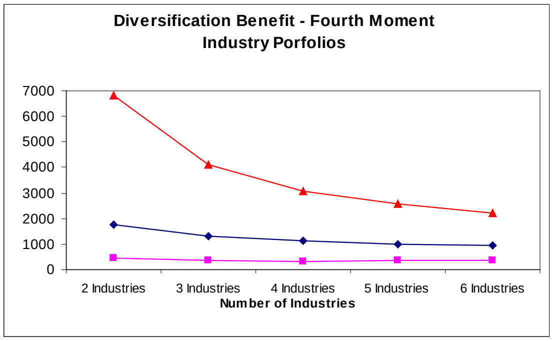
(Figure 4.13 continued)

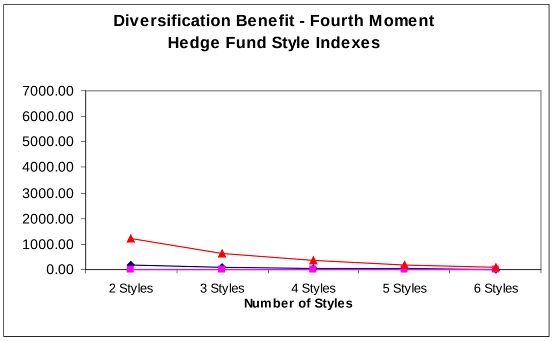




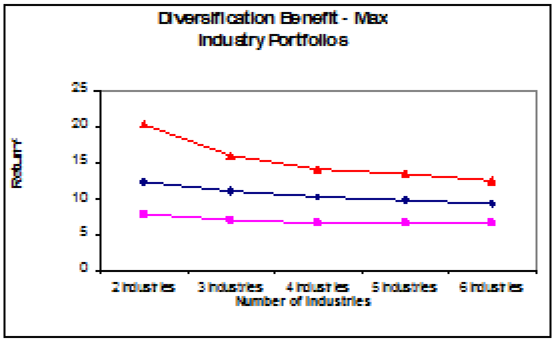


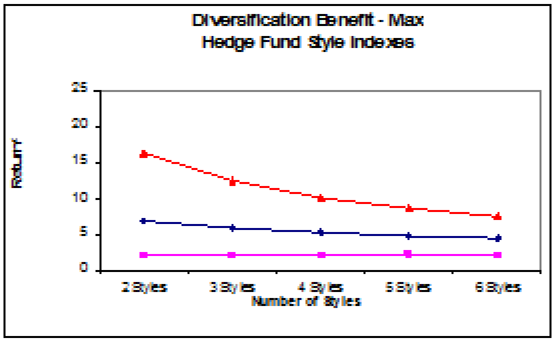


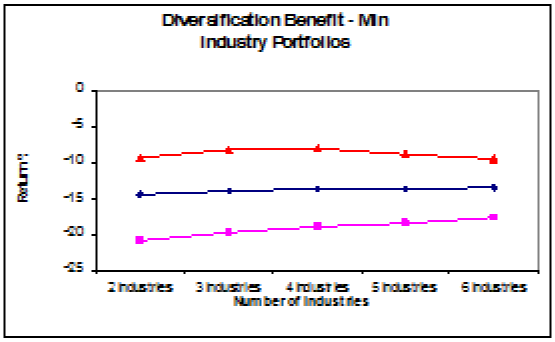


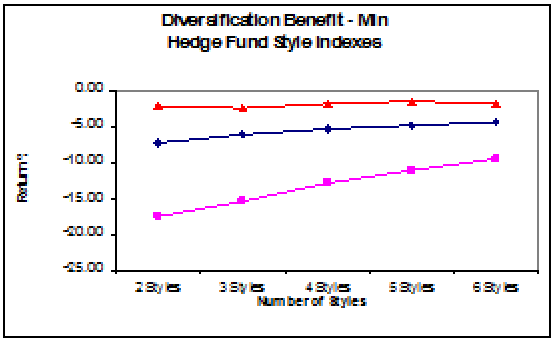


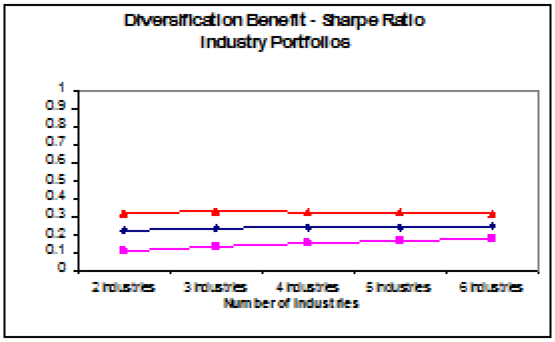
(Figure 4.13 continued)

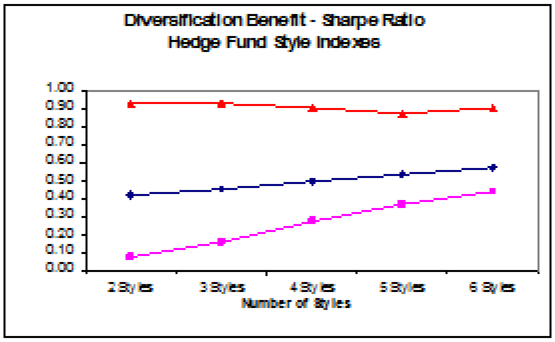




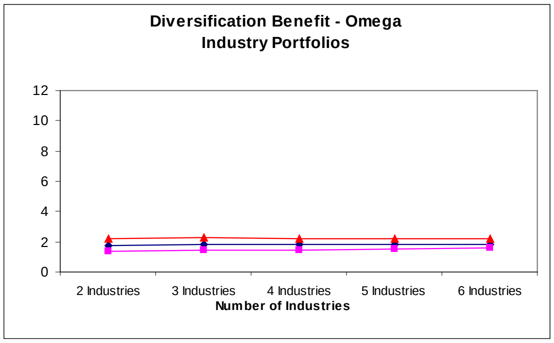


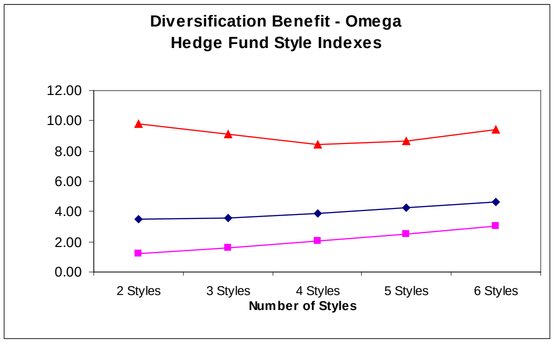


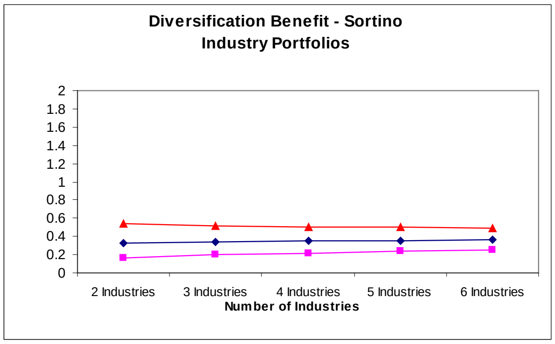


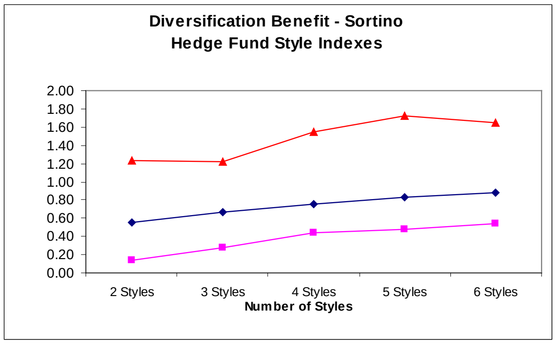


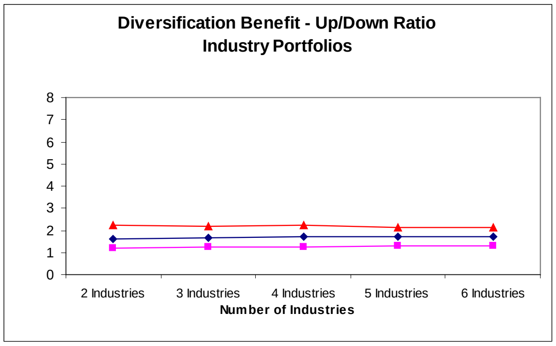
(Figure 4.13 continued)

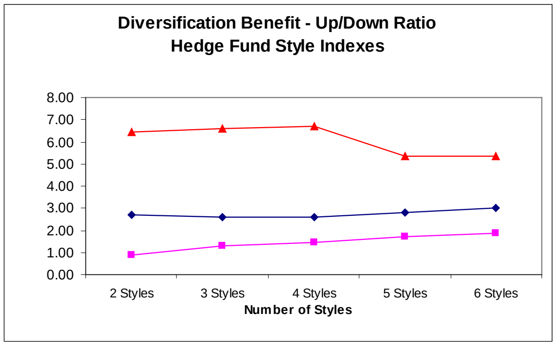












5. Conclusion

This paper investigates the rationale behind the existence of hedge fund performance fees. It studies the potential diversification benefit and tail risk of hedge funds. We compared the difference among different hedge fund styles and compare them with industry portfolios.

We find that the hedge fund performance fee serves the same basic purpose as the employee stock option through effective motivation. We empirically confirm that the performance fees are positively related to both hedge fund returns and risk adjusted returns.

The return distribution of different hedge fund styles varies widely as compared with industry portfolios and there is a credible benefit of diversifying among different hedge fund styles. Meanwhile, the tail risk of hedge funds is slightly larger than that of mutual funds based on the current month return distribution. Hedge fund tail risks are positively related to the VIX and the relationship strengthens during market downturns. Therefore, the diversification benefit of hedge funds is limited.