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ESSAYS ON HEDGE FUND RISK, RETURN AND INCENTIVES

By

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Acknowledgements

It is now 4 years since I walked out of the dealing room at Wachovia Bank in London for the last time. I had been a proprietary trader for over 13 years and many of my colleagues thought I was crazy to quit a well paid job in order to return to the school where I had been an undergraduate and study for a doctorate. With the benefit of hindsight perhaps they were the crazy ones for staying put, Wachovia Bank no longer exists, yet another victim of the recent credit crisis.

The journey from practitioner to academic has taken longer than I originally anticipated but that has been mainly because the more I learned, the more I realised I wanted to understand. I would like to thank my supervisors Prof. Dr. Andrew Clare and Prof. Chris Brooks for their support and feedback during the writing of this thesis. Andrew in particular has been there every day, and recognising how I tend to sometimes go “off-piste” he has always reminded me to focus on finishing my thesis.

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London, December 2009 Nick Motson

Declaration

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Abstract

There is no legal or regulatory definition of what constitutes a "Hedge Fund", though the generally accepted definition is that they are unregulated pools that invest in any asset class as well as derivative securities and use long and short positions, as well as leverage where the manager is compensated with a proportion of the returns. Hedge funds are not new, Alfred Winslow Jones in generally credited with the formation of the first hedge fund in 1949, however the industry remained small and relatively unnoticed for many years. In 1990 there were just 610 hedge funds managing approximately $39bn of capital, however by the end of 2007 the industry had grown to over 10,000 funds managing almost $2trn of capital. The credit crisis of 2008 which has caused hedge funds to suffer both investment losses and investor redemptions means that as of the end of 2008 the industry has contracted slightly with over 1,000 funds closing and the capital being reduced to $1.5trn.

This thesis contributes to a growing academic literature on hedge funds using both theoretical and empirical studies in several ways. In Chapter 2 I outline how the particular nature of hedge fund fee contracts affects the distribution of hedge fund returns and how using net of fee returns will lead to biased results when applying factor models. These facts have been completely ignored thus far in the literature as academics have generally applied the same techniques that have been previously used for mutual funds. I quantify the effect of ignoring the fee structure by replicating several empirical studies using both net and gross returns. In Chapter 3 I present an extensive empirical study of how the hedge fund managers adjust the risk of their funds in response to both their past returns relative to their high-water mark and their past returns relative to their peer group. I then attempt to reconcile these results with the various theoretical models that have been proposed. In Chapter 4 I examine the disparity between academic theory and practitioner behaviour with regard to the number of hedge funds required in a portfolio to adequately diversify risk. I identify a number of shortcomings in the original literature and demonstrate that due to the nature of the previous studies their conclusions were inevitable. I go on to present my own empirical study which suggests that practitioner behaviour of holding much more diverse portfolio is actually rational. In Chapter 5 I address the issues documented in the literature with factor models of hedge fund returns. As hedge funds follow dynamic trading strategies they tend to exhibit non-linear relationships to the standard asset classes. I attempt to overcome this problem by introducing time variation and non-linearity in two ways, firstly by using an asymmetric factor model where the factor exposures vary according to the state of economy and secondly by applying a two state Markov regime switching regression model. Adopting these approaches not only leads to an improvement the fit of the factor models, it also allows me to investigate if hedge funds alpha varies over time and to ascertain whether they deliver this alpha when investors need it most, namely in times of recession when the marginal utility of wealth is higher.

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CHAPTER 1

A REVIEW OF THE LITERATURE

1.1 INTRODUCTION

Academic research on the hedge fund industry is in its infancy when compared to the literature on mutual funds. Most of the key papers have been written during the last seven years, with the level of interest increasing rapidly in line with the growth of assets and the availability of reliable data. Research has followed the framework established for mutual funds as many of the same questions need to be answered. The key areas of research can be summarised under the following headings:

- What biases are present in the available hedge fund data?
- What drives hedge fund returns? – Are hedge funds truly absolute return vehicles or are there risk factors/exposures common to hedge funds that can be used to model the return generation process?
- Are these exposures stable over time? As hedge funds undertake dynamic trading strategies are static models capable of capturing the return generating process?
- How should we measure hedge fund performance, is their a reliable benchmark?
- What factors affect hedge fund survival rates?
- Is there evidence of superior performance and is it persistent over time?
- How to construct efficient portfolios of hedge funds?

1.2 BIASES IN HEDGE FUND DATABASES

A central issue in hedge fund research is the reliability of the available data, its incomplete nature and the existence of various biases. Unlike mutual funds, a database of the complete record of the entire hedge fund universe does not exist. There are two main reasons for the incomplete nature of the data. Firstly, reporting of hedge fund performance is voluntary, because hedge funds are structured as private investment vehicles they do not have to disclose their activities to the public. In order to avoid being regulated in the same way as mutual funds hedge funds cannot advertise their returns and promote themselves as investments for the general public, however most funds do report their returns to commercially available databases which allows them to effectively advertise their returns to accredited investors who subscribe to these databases. Secondly, the major commercially available hedge fund databases only came into existence in the mid 1990s with data prior to that point backfilled and prior to 1994 none of the databases retained records of funds that had ceased to report.

Fung and Hsieh (2002c) document that the constructions of hedge fund indices or portfolios face four potential sources of bias: survivorship, selection, instant history, and multi-sampling biases.

1.2.1 SURVIVORSHIP BIAS

Computing the returns of a portfolio (or index) using only those funds in existence at the end of the sample period will bias (most likely upwards) the results as it does not reflect the true return earned by an investor who would have invested in all funds available at the beginning of the period (alive and dead funds at the end of the period). The difference in return between a portfolio of only live funds and live plus dead funds is called the survivorship bias. Brown, Goetzmann and Ibbotson (1999) used data from the US Offshore Funds Directory for 1989-1995 and estimated survivorship bias at 3% per annum. Fung and Hsieh (2000c) used the TASS database for 1994-1998 and came to the same result of 3% per annum. Malkiel and Saha (2005) also used the TASS database and using a longer sample of 1994-2003 estimated the bias to be 3.75% per annum. Liang (2000) examined both the TASS and HFR databases for the period 1993-1997 and found the bias to be 2.24% for TASS but only 0.39% for HFR. It is clear that these numbers (except for Laing) are significantly higher than the 0.8-1.5% estimates for US mutual funds (see Malkiel (1995) and Brown and Goetzmann (1995)). Amin and Kat (2003b) estimate the survival bias in the TASS database for the period 1994-2001 leads to an overestimate in performance of approximately 2% per annum, but point out that for smaller funds the bias could be much larger (between 4% and 5%), they also point out that survivorship bias will introduce a downward bias in the standard deviation, an upward bias in the skewness, and a downward bias in the kurtosis.

It must be noted however, that in most cases the above estimates are calculated assuming that if a fund leaves the database this is due to liquidation, however a hedge fund might chose to stop reporting to a database because they are closed to new investment and no longer wish to attract capital.

1.2.2 SELECTION BIAS

As already mentioned not all hedge funds choose to report their performance to data vendors. Hedge fund managers are free to decide whether or not to report their performance and can choose the data vendor to whom they want to report. Therefore, the database population might not be representative of the whole population of hedge funds.

Selection bias could result in either an upward or downward bias. If one assumes that only funds with good performance want to be included in a database, then the resulting bias will clearly be upward. However, funds that have performed well in the past could have reached their critical size and have no need to attract new investors, hence they will have no more interest to report to databases, resulting in a downward bias. By its nature this effect is impossible to observe or quantify, although Fung and Hsieh (2000) estimate that these two offsetting effects should result in a negligible bias.

1.2.3 INSTANT HISTORY BIAS (OR BACK-FILLING BIAS)

When a new fund is added to a database it is generally accepted practice that the data provider back fills its database with the hedge fund historical returns. Before reporting to a data vendor, hedge fund managers usually undergo an incubation period during which they trade a smaller amount of capital. As it is unlikely that a fund with poor initial performance will begin reporting to a database, this back-filling will result in an upward instant history bias.

Estimation of the bias simply entails computing the difference between returns excluding and returns including the incubation period. Fung and Hsieh (2000) found that the median incubation period was 343 days, they went on to estimate the instant history bias by excluding the first 12 months of reported returns and came to the result of 1.4% per annum. Malkiel and Saha (2005) actually calculated the difference between backfilled and contemporaneously reported returns and came to a much higher result of 5.84%.

1.2.4 MULTI-PERIOD SAMPLING BIAS

This bias is not so much a function of the data but rather a function of the construction of the study. For most statistical work, the researcher will impose a minimum number of data points a fund must have to be included in the sample, in most cases this is 24 or 36 months. Although all researchers will consider this when constructing their study, Fung and Hseih (2000) are the only ones who have attempted to quantify it, for the period 1994-1998 they find that imposing a restriction of 36 months of data biased returns upwards by 0.6%.

1.2.5 BIASES IN THE DATA USED FOR THIS THESIS

The empirical studies in this thesis are conducted on data obtained from the TASS database. This database comprises of a “live database” which contains hedge funds that are currently reporting as well as a “graveyard database” which contains those funds that have previously reported but have now ceased reporting.

In all cases I only use data from 1994 onwards (this was when TASS began retaining data on graveyard funds) and use a combination of both the live and graveyard databases in order to minimise survivorship bias. I have however calculated what the impact of survivorship bias would have been had I not chosen to use the graveyard funds. The return of an equally weighted portfolio of all funds from January 1994 to December 2007 is 12.69% per annum, while the return of an equally weighted portfolio of only funds from the live database is 15.20%, thus the impact of survivorship bias is 2.51% which is in line with the findings of Brown, Goetzmann and Ibbotson (1999), Fung and Hsieh (2000c) and Amin and Kat (2003b) but somewhat lower than Malkiel and Saha (2005).

With regard to instant history bias, following the methodology of Malkiel and Saha (2005), I find that the return of an equally weighted portfolio of all funds from January 1994 to December 2007 with all back-filled information excluded is 9.50% per annum. Thus the effect of instant history bias is 3.19% which is between the 1.4% that Fung and Hsieh (2000) found and the 5.84% Malkiel and Saha (2005) found.

In chapter 2 I restrict my sample to those funds that have at least 36 reported monthly returns. I find that the return of an equally weighted portfolio of all funds from January 1994 to December 2007 with this restriction leads to a return of 13.43% per annum, i.e. an upward bias of 0.74% which is in line with the findings of Fung and Hseih (2000).

1.3 HEDGE FUND RETURN DRIVERS

1.3.1 MICRO-FACTORS

Much research has already been done on the effect on performance of fund specific factors such as the size and age of the fund and fee structures. Research in this area has been active because not only does it provide an insight into the possible agency and return generation issues for a fund it also forms the basis for a framework of selecting which one would expect to be the better performing funds.

Unfortunately, the results so far have in many cases been contradictory; this could be attributable to differences in data providers, sample periods and model specifications.

1.3.1.1 FUND SIZE

The effect of size on the performance of mutual funds has been extensively investigated. Perold and Salomon (1991) illustrate how the theoretical economies of scale for back office processing, marketing and research can be counteracted by diseconomies of scale stemming from the increased costs associated with larger transactions. As assets under management increase, position sizes will also increase, and the portfolio return as a percentage of assets will decline. This effect was tested empirically by Indro et al (1999).

For hedge funds the results have been somewhat contradictory with some studies finding that smaller funds outperform their larger counterparts, but others finding that regressing performance on size yields a positive coefficient.

The first paper to test the size versus performance relationship was Liang (1999). Using the HFR database with a sample period from 1994-96, the requirement of 36 consecutive monthly return observations meant his sample only contained 385 funds. Using a cross-sectional regression of average monthly returns against various fund characteristics he found that the coefficient on fund size was positive and significant illustrating a positive relationship between fund assets and performance. However, because the assets of the funds are taken only at the end of the period, the results could be interpreted as suggesting that successful funds attract more money over time and therefore have a positive correlation to past performance.
Using the MAR database with a sample period of 1990-1998, Edwards and Caglayan (2001), examine individual fund returns split by investment style. First they derive alphas from a six factor model (similar to Fama and French (1993, 1995, 1996), these six-factor alphas are then regressed on several fund specific factors including fund size and the reciprocal of size (in order to capture non-linearity in the size–performance relationship). For all hedge funds and for all investment styles except 'global macro' and 'global', both size variables are statistically significant. A positive coefficient on the size variable together with a negative coefficient on the size reciprocal variable indicates that hedge fund performance increases at a declining rate as fund sizes increase.

The opposite result was found by Brorsen and Harri (2002) using a dataset provided by LaPorte Asset Allocation and a sample period of 1977-1998. The authors included the fund size in regressions of returns and Sharpe ratios against past values as well as style analysis. In all cases they found the fund size coefficient to be negative and significant. They go on to hypothesise that this result is caused by the fact that hedge funds are created to exploit market inefficiencies and that the inefficiencies are finite.

Amenc and Martellini (2003) used the CISDM database, taking a sample of 581 funds that have returns from 1996-2003. They calculate the alpha based on a number of different models, such as the standard CAPM, a CAPM adjusted for the presence of stale prices and an implicit factor model extracted from a principal component analysis. They then go on to divide the sample into two equally sized groups by assets under management which they call large and small funds and calculate the average alpha for the two groups. For all models, the average alpha for large funds exceeds the average alpha for small funds and in most cases the difference is statistically significant. As with Liang (1999), because the assets of the funds are taken only at the end of the period, the results could be interpreted as suggesting that successful funds attract more money over time and therefore have a positive correlation to past performance, also the separation of the data into small and large funds is an extremely simplistic approach in their study.

A much larger sample was considered by Kazemi and Schneeweis (2003) by combining 5 different databases (HFR, CISDM, Altvest, Hedgefund.net and TASS) with a sample period of 1995-2001. Two size-based portfolios are constructed annually and alphas are calculated using both a linear explicit multi-factor model and a stochastic discount factor model. The authors find that large or small funds do not uniformly outperform the other group.

Herzberg and Mozes (2003) use also combined of 3 different databases (Altvest, Hedgefund.net and Spring Mountain Capital) with a sample period of 1995-2001. The authors find that smaller hedge funds outright performance is better than larger funds but barely significantly, while the difference is significantly positive regarding Sharpe ratios.

A proprietary database of 265 hedge funds was used by Hedges (2003) with a sample period of 1995-2002. Funds were sorted into 3 annually rebalanced size mimicking portfolios and the author found that smaller funds outperform larger funds and also that mid-sized funds performed the worst. The author hypothesises that this phenomenon is caused by the concept of mid-life crises for hedge funds managers.

Gregoriou and Rouah (2003) use the Zurich Hedge Fund Universe and LaPorte Asset Allocation System with a sample period of 1994-99. The authors analyse the correlation between the size of hedge funds and the geometric mean return, the Sharpe ratio and the

Treynor ratio and find no statistically significant correlation. It must be noted however that the sample is only composed of 204 hedge funds and 72 funds of hedge funds.
Using a the combined TASS, HFR and ZCM/MAR databases over the sample period 1994-2000, Agarwal, Daniel and Naik (2004) find that larger funds are associated with poorer future performance and suggest that hedge funds face decreasing returns to scale. In a thorough examination of the factors affecting the lifecycle of hedge funds Getmansky (2004) used the TASS database with a sample period of 1994-2003. A regression of current returns versus previous assets and a square of previous assets yields a positive and significant coefficient on the size of assets as well as a negative and significant coefficient on the square, thus implying a positive and concave relationship between current performance and past asset size. This result implies that there is an optimal size for a hedge fund. The author goes on to analyse individual strategies and finds that those that involve illiquid assets display a more concave relationship than those which involve liquid assets.

The same TASS database with the same sample period of 1994-2003 was used by Ammann and Moerth (2008). The authors rank funds according to their size and 100 asset percentiles are built for each month. The authors find that the bottom percentiles (from the 1st to the 20th) display the lowest returns, while the funds from the 21st to the 50th percentile display the highest returns. A linear regression reveals a significant positive relationship between size and average returns, at the 1% level. A subsequent quadratic regression finds a significant concave relationship similar to Getmansky (2004).

1.3.1.2 FUND AGE

In the mutual fund literature the effect of the age of the manager (which could be seen as a proxy for the age of a hedge fund) was considered by Chevalier and Ellison (1999). They found that older managers have worse performance than younger managers and offered two possible explanations, either younger managers work harder because they have a longer career ahead of them and are more likely to be fired for poor performance or that better managers tend to leave the industry before they get old. The results for hedge funds are inconclusive with some studies finding that younger funds perform better while other find that age is either insignificant or that older funds outperform.

Using a cross-sectional regression of average monthly returns against various fund characteristics Liang (1999) found that the coefficient on fund age (in months) was negative and significant. The author follows Chevalier and Ellison by hypothesising that the managers of younger funds work harder to build their reputations and attract assets. Using a combination of the HFR and MAR databases with a sample period 1988-95 Ackermann, McEnally and Ravenscraft (1999) test the effect of fund age on the Sharpe ratio. When regressing the Sharpe ratio on several fund characteristics including the age of the fund, they find that the resulting coefficient was insignificantly different from zero.

Edwards and Caglayan (2001) found when regressing their six-factor alphas on several fund specific factors, the coefficient for age was positive for all fund categories, but only statistically significant for global macro and market neutral.

A slightly different approach was applied by Howell (2001) using the TASS database with a sample period of 1994-2000. The author sorts the funds into deciles according to their maturity and finds that the youngest decile exhibits a return of 23.2%, while the whole sample median exhibits a return of 13.4%, a spread of 980 basis points in favour of young funds. However, it is clear that this simplistic methodology overestimates the spread because a potentially higher failure rate is not taken into account. The authors find that the proportion of failure by age is 7.4% for funds of one year or less, 20.3% for two-year-old funds, 18.6% for funds of three years or less, 15.8% for four-year-old funds, and 12.9% for five-year-old funds and the regression line of these results shows that the failure rate reaches a maximum level at 28 months and then declines at a constant rate of 2%-3% points per annum. Once the raw returns are adjusted for this failure rate, the authors find that the youngest decile exhibits a return of 21.5%, while the whole sample median is 13.9%, a slightly smaller spread of 760 basis points compared to the unadjusted returns. Interestingly, the spread between the decile of youngest funds and the decile of oldest funds is 970 points. The authors conclude that hedge fund performance deteriorates over time, even when the risk of failure is taken into account and consequently, the youngest funds seem particularly attractive.

Boyson (2003) used the TASS database with a sample period of 1994-2000 to analyse the relationship between hedge fund manager tenure and fund returns. The author examines how both return and risk measures are related to manager tenure and age. The results are that when manager tenure increases, risk-taking decreases, and when risk-taking decreases, returns decrease. Regressions show that each additional year of experience is associated with a statistically significant decrease in the annual returns of approximately -0.8%. The author hypothesises that this is as a result of increasing career concerns over time.

1.3.1.3 LEVEL OF FEES

Performance fees are a unique characteristic of the hedge fund industry. As I will demonstrate in chapter 2, the incentive fee can be though of as a call option on a percentage of the performance of the fund. The manager of the fund is long this option which is given to him by the investors as a reward for managing the fund. The objective of this compensation structure is to provide the manager with an incentive to generate larger returns. The relationship between the size of the incentive fees and the fund returns could work in either direction; it could be that the incentive structure works as it is designed or alternatively that those funds who have historically generated strong performance can justify larger fees.

Using a cross-sectional regression of average monthly returns against various fund characteristics Liang (1999) found that the coefficient on incentive fee was positive and significant, with a 1% increase in incentive fee increasing the monthly return by 1.3%
The effect of incentive fees on the Sharpe ratio was considered by Ackermann, McEnally and Ravenscraft (1999). When regressing the Sharpe ratio on several fund characteristics including incentive fees, they find that the resulting coefficient was positive and significant for 2, 4, 6 and eight year time windows.

De Souza and Gokcan (2003) find that incentive fees and performance are positively correlated. The authors hypothesise that higher incentive fees generating higher performance can either be explained by the fact that incentive fees are increased when a manager improves his performance or by the fact that the best managers in terms of performance demand higher incentive fees.

The effect of incentive fees on alpha was considered by Amenc, Curtis and Martellini (2003), they found that for all the models used, funds with high incentive fees (greater than or equal to 20%) produced higher alpha than the funds with low incentive fees, however, in the case of the implicit factor model the result was not statistically significant.

Agarwal, Daniel and Naik (2004) model the incentive fee as a call option on the value of the fund (taking into account high water marks), they calculate the delta which is the dollar change in incentive fee for a 1% change in the fund return. When regressed against returns the authors find that the coefficient on the lagged delta is positive and significant implying that funds with greater managerial incentives are associated with better future performance.

1.3.1.4 LOCKUP AND REDEMPTION PERIOD

The majority of hedge funds only provide limited liquidity to investors, as they often specify lock-up periods and withdrawals are subject to notice and redemption periods. This allows hedge funds to invest in illiquid securities without worrying about having to liquidate investments in order to repay investors. Intuitively one would expect that funds who offer less liquidity to investors should generate higher returns and the empirical research appears to confirm this as the case.

Using a cross-sectional regression of average monthly returns against various fund characteristics Liang (1999) found that the coefficient on lockup period was positive and significant, hypothesising that the lockup period prevents early redemptions, reduces cash holdings and allows managers to concentrate on relatively long horizons.

Using the HFR database with a sample period of 1996-2000, Kazemi, Martin and Schneeweis (2002) find that the redemption period seems to positively affect the returns. For a similar strategy; funds with a quarterly lockup have higher returns than those with a monthly lockup

Agarwal, Daniel and Naik (2004) regressed returns against several factors including the lockup period and found the coefficient to be positive and significant implying that funds with impediments to capital withdrawals are associated with better performance.

1.3.2 MACRO FACTORS

1.3.2.1 IDENTIFICATION OF FACTORS

Most of the empirical work on the effect of macro factors upon hedge fund returns builds upon the work of Jensen (1968) and Sharpe (1992). Their framework for the analysis of mutual funds involved the development of an asset class factor model to determine risk exposures in the form of expression (1)

$$R_t = \alpha + \sum_k \beta_k F_{kt} + \varepsilon_t \qquad (1)$$

where R_t represents the return on the fund at time t, F_{kt} represents the return on factor F_k at time t, β_k represent the sensitivity of the fund to factor F_k and α is the value added by the manager.

Sharpe regressed mutual fund returns against twelve asset classes returns and interpreted the resulting betas as the mutual funds historical exposures to the asset classes. Sharpe results showed that only a limited number of major asset classes were required to successfully replicate the performance of the universe of U.S. mutual funds. Sharpe's model is the building block of most risk-return research in hedge funds.

This approach was first applied to hedge funds by Fung and Hsieh (1997). The hedge fund data-set was constructed from an amalgamation of the Paradigm LDC and TASS databases with a sample period of 1991-95, extracting those funds with at least $5m under management and a minimum of 3 years of monthly return produced a sample of 320 hedge funds and 89 CTAs. The authors applied Sharpe's asset class factor model to this sample as well as a large sample of mutual funds in order to compare their respective exposures. The model assumed that hedge funds returns are linearly related to eight asset classes (mimicking portfolios), these classes included 3 equity (MSCI U.S. equities, MSCI non-U.S. equities and IFC emerging market equities), 2 bond (JP

Morgan U.S government bonds and JP Morgan non-US government bonds), 1 commodity (gold price), 1 currency (Fed TW dollar index) and 1 cash (1-month Eurodollar deposit rate) classes. For each hedge fund and mutual fund they regressed monthly returns against the eight asset class factors.

The results were strikingly different for hedge funds (and CTAs) compared to mutual funds, 47% of the mutual funds had R-squared higher than 75% and 92% had R-squared higher 50% while for hedge funds 48% have R-squared below 25%. The authors suggest that these low R-squared are due to hedge funds trading strategies; they vary exposures over time and may take long and short positions in the same asset classes. In order to address this the authors go on to perform factor analysis and extract 5 principal components which explain 43% of the cross sectional return variance, they then construct five "style factors" using the hedge funds most correlated with these principal components. Applying Sharpe's style regression on these five style factors yields varied results, for Value and Distressed the buy and hold approach explains between 56% and 70% of the returns but for Global Macro and System trading the results are less satisfactory. Finally the authors divide the monthly returns of each asset class into quintiles and calculate the average return of each asset class as well as each style factor for each state. The results show that the relationship between the style factors and standard asset classes is non-linear. The authors conclude that mutual funds tend to follow buy-and-hold trading strategies whereas hedge funds follow dynamic trading strategies and that these dynamic trading creates option-like returns payoffs.

Subsequent work by Fung and Hsieh and other authors has attempted to improve upon the explanatory power of the models using different sets of explanatory variables, sample periods and hedge fund databases or concentrating on individual strategies to reflect the heterogeneous nature of hedge funds but still within the Sharpe framework. The majority of the research has concentrated on either the addition of non-linear factors such as options or the use of time varying betas by rolling window regressions or statistical techniques such as the Kalman filter.

Schneeweis and Spurgin (1998a) used the Laporte database and a sample period of 1990-95 as well as a number of hedge fund indices. The authors ran a multi-factor regression analysis using thirteen independent variables, including stock, bond, currency and commodity indices as well as the absolute values and intra-month volatilities. They add absolute returns as independent variables to take account of timing abilities and volatilities to take into account the use of options strategies. The results were similar to Fung and Hsieh with the new factors being rarely statistically significant and adding little explanatory power.

For a small sample of 385 hedge funds from the HFR database with at least 36 months of consecutive monthly returns Liang (1999) regressed hedge fund returns against eight asset class factors (slightly different form those used by Fung and Hsieh). The results were similar to Fung and Hsieh though with somewhat higher R-squareds ranging from 23%-77%.

The merger arbitrage strategy was considered in isolation by Mitchell and Pulvino (2000). The authors generate their own return series from 4,750 mergers between 1963 and 1998 as well as examining the HFR merger arbitrage index for 1990-98. They find that returns are strongly and positively correlated with market returns during market downturns, but only slightly correlated in flat or booming markets. The authors suggest that merger arbitrage fund returns are similar to those obtained from writing uncovered index put options on the market index.

Trend following Commodity Trading Advisors (CTAs) were examined by Fung and Hsieh (2001). The authors argue that the systematic risk of trend-followers can not be simply observed by a linear factor model because returns tend to be large and positive during best and worst performing months of markets. They construct portfolios of primitive trend-following strategies (PTFS) using lookback straddles on currencies, commodities, interest rates, bonds and stock indices to model the performance of a perfect foresight trend-follower. When regressing the trend-following fund returns on a standard 8 factor model (similar to Fung and Hsieh 1997) the authors find little explanatory power with R-squared of less than 1%, but by using the five PTFS portfolios returns, they find an adjusted R-squared of 47.9%. The authors conclude that the systematic risk of trend-followers can not be simply observed by a linear factor model and this is illustrated by better explanatory power the PTFS have than simple buy-and-hold strategies.

Using the HFR database and a sample period of 1990-98, Agarwal and Naik (2000a) attempt to build upon Fung and Hsieh (1997) by capturing returns from trading strategy factors by returns on passive options strategies consisting in buying or writing put and call options on standard asset classes. The option strategies examined are buying or writing 1-month European puts or calls on the Russell 200 index, the MSCI Emerging Markets index, the Salomon Brothers World Government Bond index, the Lehman High Yield Composite index and the Federal Reserve Bank Trade-Weighted Dollar index, with at the money, half and one standard deviation out of the money strikes. The authors examine the returns of the ten hedge funds strategies reported in the HFR database individually using a stepwise regression procedure to identify the best independent variables. At an individual hedge fund level, they find that trading strategy factors are the most significant factors in 54% of cases, and the percentage of total R-squared attributable to trading strategy factors is approximately 51%. Thus the introduction of simple option positions in the factor model helps greatly in explaining the volatility of hedge fund returns with R-squares ranging from 37 to 75%.

The non-linearity of hedge fund returns to market factors are examined by Favre and Galeano (2002) using the HFR indices with a sample period 1990-99. Using the non-linear technique, Loess Fit regression they analyse the relationship between 10 hedge fund strategies and the LPP Index (a benchmark index for a Swiss institutional investor composed of equities and bonds). The authors find a significant degree of non-linearity with four of the ten strategies having concave payoffs (similar to selling options) and observe that the diversification benefits of hedge funds tend to disappear in cases of extremely negative market returns.

1.3.2.2 STABILITY OF HEDGE FUND EXPOSURES TO FACTORS

The stability (or non-stability) of exposures is certainly as important as finding exposures themselves, once hedge funds risk exposures to different factors have been defined, researchers would like to know whether they are stable over time, or not.
Brealey and Kaplanis (2001) use the TASS database and a sample period of 1994-99, they examine a sample of 128 funds which have a continuous record of monthly returns.

Initially the authors run a multiple regression using 31 independent variables (including equity, bond, currency and commodity variables), they regress each hedge fund strategy against what they consider the most relevant factor portfolios to identify average exposures. They then go on to test the stability of these exposures using recursive least squares, for each fund they use the firstr k+1 observations to obtain the first estimate of the slope coefficients and then, repeatedly, add one observation to the data set to revise the estimate. At each step, the last estimates of the regression coefficients are used to provide a one-step ahead forecast for the dependant variable and the recursive residual is calculated as the forecast error from this prediction scaled by its standard error. If the coefficients were stable then the recursive residuals will be independently and normally distributed with zero mean and constant variance. For the whole sample the null hypothesis of stability is rejected in 75% of cases. The authors conclude that although they have identified instability in the coefficients, monthly data is insufficient to pick up short-term variations due to the trade-off between increasing the number of datapoints and using more dated information. They find that 36 months of data minimises the out-of-sample forecasting error.

Gehin and Vaissie (2005) examine the EDHEC Alternative Indices with a sample period 1997-2004. The authors begin by determining a static model for the 9 indices identifying the significant factors from a sample of 18 risk factors including volatility, credit spread and term spread as well as more traditional factors. They go on to use the Kalman Smoother approach to analyse the relative importance of static and dynamic betas. They conclude that on average static betas account for 51.5% of the variability in returns with dynamic betas accounting for 23.6%. In terms of the level of returns, static betas account for almost 100% with the dynamic betas actually being negative. The authors give no indication of the statistical significance of the factors or measurement of the performance of the models so the results are hard to interpret.

1.4 HEDGE FUND PERFORMANCE AND ITS PERSISTENCE

1.4.1 DO HEDGE FUNDS GENERATE ABNORMAL RETURNS?

Following Sharpe (1992), one can interpret intercept term of asset class factor model (Jensen's alphas) as the unexplained performance or abnormal return of a fund. Therefore the fund is deemed to have generated an abnormal return if this intercept is significantly positive. Many authors have investigated the abnormal performance of hedge funds and the results are inconclusive, no doubt in part because this is a joint test of performance and of the model employed.

Using an eight factor model Liang (1999) finds abnormal positive returns for 7 out of 16 hedge fund strategies. Performance ranges from 0.64% to 1.26% per month (7.68% to 15.12% per year). For 2 strategies (growth and market neutral), he finds abnormal negative returns (-5.22% and -1.56% per month respectively). For the 7 others, he does not find any significant alpha. These figures are corrected for survivorship bias, but not for other biases.

Edwards and Caglayan (2001) employ a six factor model and find significant positive alphas for 25% of individual funds. The average alpha ranges from 1.08% to 2.38% per month (12.96% to 28.56% per year). These figures are corrected for survivorship and instant history biases, but the authors mention that a selection bias may exist in the performance measure.

Using the HFR database for the sample period 1990-98 (adjusting for survivorship bias of 0.3%pm), Agarwal and Naik (2000a) find significant positive alphas for 35% of hedge funds. Dividing the sample into 2 equal sub-periods they find that 38% had significant alpha in the first period while only 28% had in the second period.
Agarwal and Naik (2000b) examine the ten HFR hedge fund indices for the sample period 1994-98 using an eight factor model. The authors find that all of the indices (which are adjusted for survivorship bias) had significant positive alpha ranging from 0.53% to 1.25% per month.

An alternative approach to the performance problem is taken by Amin and Kat (2003a). The authors note that traditional measures such as Jensen's alpha and the Sharpe Ratio assume the normality of asset return distributions and the linearity of the relationship with respect to selected benchmarks which is not the case with hedge funds. Instead they propose a so-called efficiency test based on the payoff distribution pricing model of Dybvig (1988). The authors analyse the returns of 13 hedge fund indexes and 77 individual funds taken from the MAR database from May 1990 to April 2000 and find that the average hedge fund makes for quite an inefficient investment, but that a major part of the inefficiency costs of individual funds can be diversified away by investing in a portfolio of hedge funds or index.

Ibbotson and Chen (2005) use the TASS database with a sample period 1994-2004. The authors use a three factor model (factors used S&P 500 total return, U.S. Intermediate Government Bond returns, and U.S. Treasury Bills), with the constraint that all style weights sum to one but allowing individual weights to be negative or above one to account for shorting and leverage. They also include lagged betas as well as contemporaneous betas to control for the stale pricing impact on hedge fund returns. The results are that the pre-fee return from an equally weighted index of hedge funds is 12.8%, which consisted of fees (3.8%), alpha (3.7%) and returns from the betas (5.4%). The authors conclude that although the returns from the systematic betas exceeded the post-fee alpha, the alpha was approximately equal to the amount paid in fees giving what they consider to be a reasonable result that during the period the excess returns (gross alpha) were almost shared equally between the managers and the investors.

1.4.2 MARKET TIMING

Given the evidence above that hedge funds follow dynamic trading strategies it is logical to attempt to identify if this dynamic trading is profitable i.e. can hedge fund mangers time the market? Market timing is a performance-enhancing strategy that adjusts fund beta based on the manager's market return forecast and there is a large strand of academic literature that examines this for traditional mutual fund mangers which has could be extended to examine hedge funds. Two widely applied models of market timing are Treynor and Mazuy (1966) and Henriksson and Merton (1981).

Treynor and Mazuy (1966) argued that if a fund manager possesses the market timing skills, he will hold a greater proportion of the market portfolio whenever the return on the market is expected to be high and vice versa. Thus, the portfolio return will be a nonlinear function of the market return as described by expression (2)

$$R_{i,t} - R_f = \alpha_i + \beta_i\left(R_{m,t} - R_f\right) + \tau_{TM}\left(R_{m,t} - R_f\right)^2 + \varepsilon_{i,t} \tag{2}$$

If τ_{TM} is positive and significant then the fund manager possesses timing ability.

An alternative approach was proposed by Henriksson and Merton (1981). This model assumes the mutual fund manager has information about the direction of the market returns only, and not about the size of the return. Accordingly, the manager is assumed to receive a binary signal, which can take two distinct values depending on the true outcome of the market return, and based on those two signals, one of the two values of the portfolio β is chosen. In this case, the portfolio return can be expressed as a function of the market return by expression (3)

$$R_{i,t} - R_f = \alpha_i + \beta_i\left(R_{m,t} - R_f\right) + \tau_{HM} Max\left\lfloor -\left(R_{m,t} - R_f\right);0\right\rfloor + \varepsilon_{i,t} \tag{3}$$

where $Max\left\lfloor -\left(R_{m,t} - R_f\right);0\right\rfloor$ is an indicator function, which takes the value of one when the market return is above the risk-free rate and zero otherwise. Once again if τ_{TM} is positive and significant then the fund manager possesses timing ability

Chen and Liang (2007) test the market timing ability of a sample off 221 hedge funds who classify their strategy as market timing using both the Treynor and Mazuy (1966) and the Henriksson and Merton (1981) approaches. The authors find that the market timing coefficients are positive and significant at the 1% level for both specifications.

1.4.3 IS THERE EVIDENCE OF PERFORMANCE PERSISTENCE?

Testing for performance persistence is of major interest to both academics and practitioners. For academics measurement is a question of efficiency while for practitioners it is a question as to whether it is correct to base their allocation decisions on the track record of a fund. In the case of hedge funds it is extremely important to examine whether persistence is sensitive to the length of return measurement intervals because of the lockup and redemption periods demanded by the managers. Even if performance persistence is proven, if the persistence is shorter than the lock-up or redemption frequency then allocation based upon this will not be profitable.

Although some studies present conflicting results, there are some clear themes to the findings. There appears to be fairly strong evidence of short-term persistence, for horizons of up to six months, but this persistence weakens as one lengthens the measurement horizon.

Persistence can be tested by either a parametric or non-parametric methods. A parametric test for performance persistence involves regression of the return of the current period (explained variable) against the return for the previous period or periods (explanatory variable). When returns are regressed against lagged returns, if the result is a statistically significant positive coefficient then this is evidence of performance persistence. i.e. a hedge fund that performs well/badly over the previous period will also perform well/badly in the current period.

Non-parametric tests for performance persistence are based on the construction of a two-way winner-and loser contingency table. Winners are funds whose return is higher than the median return of all the funds following the same strategy over this period, and losers are funds whose return is lower. Persistence is defined as funds that are either winners over two consecutive periods (WW) or funds which are losers over two consecutive periods (LL) while non-persistence will be either WL or LW.

Once the contingency tables have been constructed there are a number of different methods to test the significance of the results.

Under the cross product ratio (CPR) test, the CPR is defined by expression (4)

$$CPR = \frac{(WW * LL)}{(WL * LW)} \tag{4}$$

Under the null hypothesis of no persistence, the ratio is equal to 1 because each of the four categories WW, LL, WL and LW represent 25% of all the funds. The statistical significance of CPR is tested via the calculation of the Z-statistic from expression (5)

$$Zstat = \frac{\ln(CPR)}{\sqrt{\frac{1}{WW} + \frac{1}{LL} + \frac{1}{WL} + \frac{1}{LW}}} \tag{5}$$

A Z-statistic greater than 1.96 indicates significant persistence at a 5% confidence level. An alternative to the CPR approach is to use a chi-squared test which compares the distribution of observed frequencies of the four categories with the expected frequencies of the distribution.

$$\chi^2 = \frac{\sum (O_i - E_i)^2}{E_i} \tag{6}$$

where O_i is the observed number of funds in each case of the contingency table, and E_i is the expected number of funds in each case, the degree of freedom is equal to 1 in the case of a table with 2 lines and 2 columns.

Using the TASS database with a sample period 1995-1998 Agarwal and Naik (2000b) investigate performance persistence by both a parametric (regression) and non-parametric (contingency table) methodology. Comparing abnormal returns and appraisal ratios for each e fund to the average return of funds following the same strategy, they find some degree of persistence. However it appears that this is mainly due to losers remaining losers rather than winners remaining winners.

Agarwal and Naik (2000c) use the HFR database with a sample period of 1982-98. Using a similar framework to Agarwal and Naik (2000b) the authors begin by analysing

hedge fund performance persistence for quarterly, half yearly and yearly intervals. They find evidence of persistence in short run (quarterly returns) but this reduces when one moves to yearly returns and persistence does not seem to be related to the hedge fund strategy. The authors then go on to analyse persistence in a multi-period framework using the Kolmogrov-Smirnov test, they find that the level of persistence is considerably smaller in a multi-period framework than in the two period framework.
Edwards and Caglayan (2001) also investigate performance persistence using both a parametric (regression) and non-parametric (contingency table) methodologies over a one and two year horizon. The authors find evidence of persistence at both one and two year horizons for both winners and losers.

A proprietary database provided by Financial Risk Management with a sample period of 1992-2000 was used by Bares, Gibson and Gyger (2003). Using a non-parametric test they analyse performance persistence over 1-month, 3-month, 6-month and 12-month time horizons by comparison to the median performance of funds following the same strategy. The authors find that as the time horizon lengthens the percentage of managers who show relative persistence decreases, at the one month horizon 25% of funds display persistence (13% positive and 12% negative) while at the 1 year horizon only 12% display persistence (6% positive and 6% negative). They also note that for most strategies the proportion of managers consistently performing above or below the median is generally equally distributed. The authors go on to test the performance persistence of hedge fund portfolios, using 1, 3, 5, 12, 18 and 36 month formation and holding period for hedge fund portfolios. The funds are ranked according to performance and then 10 portfolios of 20 funds are formed (5 best and 5 worst performing) , once again they find strong evidence of short term persistence comparable to the "hot hands" effect documented by Hendricks, Patel and Zeckhauser (1993) for mutual funds. Finally the authors test for persistence in alpha using a model based on PCA factors. Using a 36 month formation period they find little evidence of performance persistence.

By combining the MAR and HFR databases Capocci and Hubner, (2003) obtain a sample of 2,796 funds for the period of 1984-2000. They investigate persistence by ranking funds into deciles based on the estimated alpha from a multi-factor model and testing the significance of the spreads of returns between the deciles. The authors find no evidence of persistence in annual mean returns for best and worst performing funds they do however find evidence of persistence for middle decile funds. They hypothesize that this might be because although some hedge fund managers take large risks which cause them to have very high or low returns for short periods, the majority of hedge fund managers follow less risky strategies, which allow them to outperform the market for longer periods of time.

Kat and Menexe (2002) use the TASS database with a sample period 1994-2001. On the basis of the mean returns from the June 1994-November 1997 and December 1997-May 2001 periods, and according to the CPR test, they find no evidence of persistence for all the hedge funds considered as a group and for the strategies analysed one by one. Parametric tests indicate significant persistence for funds of funds and emerging market strategies.

The TASS database is also used by Baquero, G., Horst, J. and M. Verbeek, (2005) with a sample period 1994-2000. At a 3 month horizon they find evidence of positive persistence in raw fund returns, with the best performing 20% to 30% of the funds are expected to provide above average returns in the subsequent evaluation period. At a 12 month horizon the pattern is also consistent with positive persistence, though not statistically significant. After adjusting for risk by subtracting from the raw hedge fund returns the return of the corresponding style benchmark, at the quarterly and annual horizons, they find that on average the top deciles outperform their style benchmark

1.5 HEDGE FUND SURVIVAL RATES

Brown, Goetzmann and Ibbotson (1999) found the annual attrition rate to be 20% per year for the period 1989-95 using the US Offshore Funds Directory, but subsequent studies using other databases have found much lower rates. Liang (2000) finds that the annual hedge-fund attrition rate is 8.3% for the 1994–1998 sample period using TASS data, and Baquero, Horst, and Verbeek (2005) find a slightly higher rate of 8.6% for the 1994–2000 sample period. Brown, Goetzmann and Park (2001b) find that half-life of the TASS hedge funds is exactly 30 months, while Brooks and Kat (2002) estimate that approximately 30% of new hedge funds do not make it past 36 months and Amin and

Kat (2003b) find that 40% of hedge funds do not make it to the fifth year. Howell (2001) observed that the probability of hedge funds failing in their first year was 7.4%, only to increase to 20.3% in their second year.

Liang (2000), Fung and Hsieh (2000, 2002b), Baquero, Horst, and Verbeek (2005) and Getmansky, Lo, and Mei (2004) all find that surviving funds outperform non-surviving funds. The authors also find that investment style, size, and past performance are significant factors in explaining survival rates. Getmansky (2004) finds that the liquidation probabilities of individual hedge funds depend on fund-specific characteristics such as past returns, asset flows, age, and assets under management. Goetzmann, Ingersoll and Ross (2003), De Souza and Gokcan (2003), Agarwal, Daniel, and Naik (2004) and Getmansky (2004), all find that funds with higher returns tend to receive higher net inflows and funds with poor performance suffer withdrawals and, eventually, liquidation.

1.6 STATISTICAL PROPERTIES OF HEDGE FUND RETURNS

Brooks and Kat (2002) carried out a comprehensive study of 48 hedge fund indices from various providers for a sample period of 1995-2001. The authors found that in a traditional mean-variance framework hedge fund indices appear superior to traditional asset classes. However they also find that most hedge fund index returns are not normally distributed and exhibit negative skewness and excess kurtosis, the implication being that the Sharpe ratio overestimates the benefits of hedge funds. The authors also find that most of the indices exhibit significant positive autocorrelation coefficients (possibly as a result of marking to market of illiquid securities), which will result in the volatility of hedge fund returns being biased downwards. The authors implement a methodology commonly used in the real estate finance literature to unsmooth the hedge fund’s data series in order to assess the impact of autocorrelation, the result being significantly higher standard deviation estimates and consequently lower Sharpe ratios. The authors also illustrate that hedge funds do not appear to be perfectly un-correlated with traditional asset class returns, hedge fund returns are generally low and negatively correlated with bond indexes, but they present relatively high and positive correlation coefficients with equity indexes (especially the Russell 2000), the implication being that part of the hedge funds' systematic risk is market risk.

Getmansky, Lo and Makarov (2004) further investigate the issue of serial correlation using a sample of 908 funds from the TASS database with at least five years of returns history during the period 1977-2001. The authors find that 3 possible sources of serial correlation in hedge fund returns: time-varying expected returns, time-varying leverage and incentive fees with high-water marks cannot fully explain the high levels of serial correlation and so focus on the combination of illiquidity and smoothed returns. The authors propose methods for estimating the smoothing, a moving-average process and a simpler model based on linear regression under the assumption that true returns are generated by the linear single-factor model.

Agarwal , Daniel and Naik (2006) merge the CISDM, HFR, MSCI and TASS databases for the sample period 1994-2002 and find that average hedge fund return in December is two and a half times the average for the rest of the year. The authors investigate whether this December spike can be explained by an increase in the funds' risk exposures, by higher factor risk premiums or by funds' free-riding on end-of-year gaming by mutual funds but find that instead the spike arises due to funds managing their returns upwards in December. This is achieved by adding back in December the under-reported returns during earlier months of the year and by borrowing from future returns. The authors also find that the spike is more pronounced among funds whose incentive fee contracts are near-the-money and whose performance lags their peers, indicating that incentives may be driving the return management behaviour.

1.7 PERFORMANCE MEASUREMENT

As already mentioned the findings of Brooks and Kat (2002) and Getmansky, Lo and Makarov (2004) imply that the Sharpe ratio overestimates the benefits of hedge funds. Goetzmann, Ingersoll, Spiegel and Welch (2002) focus on methods to manipulate portfolio returns to achieve high Sharpe ratios and related measures. They derive the optimal strategy and show that the payoff structure resembles a portfolio that is short different fractions of out-of-the-money puts and calls, such that the fund distribution is left skewed because high Sharpe ratio strategies are, by definition, strategies that generate regular, modest profits punctuated by occasional crashes.

Bacmann and Scholz (2003) use various hedge fund indices and a sample period of 1994-2003 to compare the efficiency of the various performance indicators. The authors examine the ranking of the performance of 44 indices by the Sharpe ratio, the Sortino ratio, the Omega and the Stutzer index. The authors find that when compared to the Sharpe ratio rankings, using Sortino ratio 28 have the same ranking, 8 are upgraded and 8 are downgraded. Using Omega 36 have the same ranking, 3 are upgraded and 5 are downgraded and using Stutzer 37 have the same ranking, 3 are upgraded and 4 are downgraded. These results imply that despite its drawbacks, generally the Sharpe ratio does an adequate job of ranking funds.

1.8 CAPACITY

The question of capacity at individual fund level has been addressed by many authors who have considered whether fund size affects performance. Agarwal, Daniel and Naik (2004), Getmansky (2004) and Ammann and Moerth (2008) all find decreasing returns to scale for individual funds. More specifically the latter 2 papers find that the relationship is concave implying that there is an optimal fund size.

Gehin and Vaissie (2005) examine the EDHEC Alternative Indices with a sample period 1997-2004. After identifying significant factors from a sample of 18 risk factors including volatility, credit spread and term spread as well as more traditional factors, the authors calculate alpha from both a static model and a dynamic model using the Kalman Smoother approach. The authors term the alpha from the static model “total alpha” and from the dynamic model “pure alpha”. They hypothesise that the level of pure alpha depends on the quantity of market opportunities that are available to hedge fund managers (market capacity), while the level of value added through dynamic betas depends on the ability of hedge fund managers to time factors (fund capacity). When examining time series of total alpha and pure alpha the authors come to two major conclusions; firstly there is no clear evidence of a declining trend for alpha which indicates that the recent lower returns are not as a result of a capacity effect, secondly because in most cases the trend of dynamic betas is much more pronounced than that of pure alpha, hedge fund strategies' alpha is more limited by manager capacity than by market capacity.

Belratti and Morana (2005) use the TASS database with a sample period of 1984-2004 to and examine the linkage between flows and returns for nine categories of hedge fund strategies in order to determine whether hedge funds contribute to market efficiency through a negative correlation between flows and returns and specifically whether we are "in a phase of exhaustion of arbitrage opportunities" (capacity constrained). The authors use a construct a VAR model which incorporates time variability of the intercept and allows measurement of the interaction between flows and both returns and excess returns. They find, flows tend to depend positively on lagged returns, while returns tend to depend negatively on lagged flows only in 60% of the cases and conclude that the results are not consistent with the view that an excess supply of arbitrage capital has exhausted the set of available opportunities (capacity constraint).

1.9 FUNDS-OF-FUNDS AND DIVERSIFICATION

A fund-of-funds (FOF) is a hedge fund that invests in other hedge funds. Data from HFR shows that between 1994 and 2008 the number of FOFs has grown from 291 to 2,368 and as of the end of 2008 assets managed by funds-of-funds represents approximately 40% of the total assets managed by the hedge fund industry. A similar structure called a manager-of-managers exists in the mutual fund world but has been much less popular; there are several possible explanations for this

i. FOFs can allow investors to obtain exposure to hedge fund investments that are otherwise closed to individual investors.
ii. Funds-of-funds generally have much lower required investment minimums than those required by individual hedge funds
iii. Funds-of-funds provide investors access to a diversified portfolio of hedge funds which would otherwise require a prohibitively large amount of capital to replicate.
iv. Funds-of-funds provide access to information and professional due diligence that would otherwise be difficult and expensive to obtain.

However, despite all of the advantages listed above, investors in funds-of-funds pay a significant price. Not only does a FOFs pass on all of the fees charged by the underlying hedge funds in the FOFs' portfolio, they also charge their own management and performance fees. In the TASS database, the average management fee charged by funds-of-funds is 1.56% and the average FOFs' incentive fee is 7.89%. These fees are on top of an average management fee of 1.48% and an average incentive fee of 18.45% for individual hedge funds, so a FOFs investor is paying a total management fee of over 3% as well as foregoing over one quarter of the upside performance.

Brown, Goetzmann and Liang, (2003) use the TASS database with a sample period 1989-2000 to investigate the performance of FOFs compared to individual hedge funds and the impact of double layer of fees. The authors find that FOFs do indeed provide significant diversification benefits, the standard deviation of monthly FOF returns are one third lower than for individual hedge funds (2.86% versus 4.75%). However they also find that the average monthly after-fee return for FOFs is 0.86%, compared to the 1.38% return for hedge funds over the same period (the authors note that some of this discrepancy may be due to some extreme outliers as the median monthly after-fee return for FOFs is 0.79% versus 1.05% for hedge funds. Thus the Sharpe ratio is lower for FOFs than for individual hedge funds. They go on to analyse the impact of fees both at the individual fund and FOF level and conclude that the major reason for the underperformance of FOFs is the fee structure, mainly because the ultimate investor, not the FOF manager, bears the cost of incentive fees incurred whether or not the FOF makes money. They propose an alternative fee structure where the FOF would absorb the incentive fees generated by the individual managers in return for an enhanced incentive fee at the FOF level which would better incentivize the FOF manager.

Ineichen (2002) undertakes a largely qualitative assessment of the FOF industry as well as quantitave examples of FOF portfolio construction. The author concludes that FOFs add value because the hedge fund market is "informationally inefficient", however he goes on to point out that over time the fees are correlated with the set of exploitable opportunities.

A number of authors have replicated the methodology pioneered by Evans and Archer (1968) for portfolios of stocks and applied it to portfolios of hedge funds. Both Amin and Kat (2002) and L'Habitant and Learned (2002) examine the time series standard deviation of returns of randomly selected equally weighted portfolios of hedge funds of increasing size. The authors find that that the mean standard deviation of the portfolios falls at a decreasing rate as the number of hedge funds in the portfolio increases and conclude that portfolios of between 10 and 15 funds are adequately diversified. In chapter 4 I demonstrate that due to the nature of these studies, it is inevitable that their conclusions about the number of hedge funds coincide with the findings of Evans and Archer (1968) for portfolios of stocks.

Kat (2004) investigates whether it is possible for a FOF to offer investors access to a diversified basket of hedge fund whilst at the same time offering protection against negative skewness. The author proposes two possible solutions, either buying stock index puts plus leveraging or buying puts on the fund itself. The author concludes that though neither strategy is perfect they can both achieve the desired outcome.

Alexander and Dimitriu (2005) use the HFR database with a sample period 1990-2003 and attempt to develop a fund selection and optimal allocation process for FOFs. The authors apply 4 different factor models to identify alpha; a "base case" model that only has two factors (U.S. equities and Bonds), a "broad fundamental" model (using 17 factors covering equities, bonds, currencies, commodities and volatility), an "HFR" model (using the HFR indices as factors) and a "PCA" model (using investable portfolios replicating the first four orthogonal components from principal components analysis). Although the authors find substantial differences in the alphas estimated from the four different factors models, they find significant agreement on the sign of alpha and on the rank of a funds' alpha. They go on to test the performance of minimum variance portfolios based on selecting those funds with alpha significant at the 10% level versus both an equally weighted portfolio of all funds and to that of a randomly selected minimum variance portfolio. Using the period 1990-97 to calibrate and 1998-2003 as the out of sample test with six monthly rebalancing, the authors find that the performance of the portfolio based on alpha is superior to that of an equally weighted portfolio of all funds and to that of randomly selected minimum variance optimal portfolio.

1.10 THE CONTRIBUTION OF THIS THESIS TO THE LITERATURE

This thesis contributes to a growing academic literature on hedge funds using both theoretical and empirical studies in several ways.

In Chapter 2 I outline how the particular nature of hedge fund fee contracts affects the distribution of hedge fund returns and how using net of fee returns will lead to biased results when applying factor models. These facts have been completely ignored thus far in the literature as academics have generally applied the same techniques that have been previously used for mutual funds. I quantify the effect of ignoring the fee structure by replicating several empirical studies using both net and gross returns.

In Chapter 3 I present an extensive empirical study of how the hedge fund managers adjust the risk of their funds in response to both their past returns relative to their high-water mark and their past returns relative to their peer group. I then attempt to reconcile these results with the various theoretical models that have been proposed.

In Chapter 4 I examine the disparity between academic theory and practitioner behaviour with regard to the number of hedge funds required in a portfolio to adequately diversify risk. I identify a number of shortcomings in the original literature and demonstrate that due to the nature of the previous studies their conclusions were inevitable. I go on to present my own empirical study which suggests that practitioner behaviour of holding much more diverse portfolio is actually rational.

In Chapter 5 I address the issues documented in the literature with factor models of hedge fund returns. As hedge funds follow dynamic trading strategies they tend to exhibit non-linear relationships to the standard asset classes. I attempt to overcome this problem by introducing time variation and non-linearity in two ways, firstly by using an asymmetric factor model where the factor exposures vary according to the state of economy and secondly by applying a two state Markov regime switching regression model. Adopting these approaches not only leads to an improvement the fit of the factor models, it also allows me to investigate if hedge funds alpha varies over time and to ascertain whether they deliver this alpha when investors need it most, namely in times of recession when the marginal utility of wealth is higher.

CHAPTER 2

THE GROSS TRUTH ABOUT HEDGE FUND PERFORMANCE AND RISK: THE IMPACT OF INCENTIVE FEES

Abstract

Factor models are frequently applied to hedge fund returns in an attempt to separate the return from identified risk factors (beta) and from manager skill (alpha). More recently, these same techniques have been used to replicate the returns from hedge fund strategies with varying degrees of success. In this chapter I show that due to the particular nature of hedge fund incentive contracts, the use of net of fee returns can lead to considerably biased estimates of factor exposures which can distort the picture of fund manager performance. The solution I propose is to model the gross returns of hedge funds and the incentive fees independently, which gives a truer representation of the underlying return generating process. Using a large sample of hedge funds, I quantify the effect of this bias on both performance attribution and replication. I find that using net of fee returns understates the return attributable to beta by up to 58 basis points per annum. Following from this I find that some of the additional beta exposure can be captured by basing replication on gross rather than net returns. I also investigate the distribution of returns conditional upon the delta of the incentive option and find that the standard deviation is considerably higher for those managers who find themselves significantly above or below their high water mark, which could be interpreted as evidence of increased risk taking.

2.1 INTRODUCTION

One of the key differences between hedge funds and traditional investments is the fee structure. While mutual funds charge only a management fee that is a flat percentage of the assets under management, hedge funds generally also charge an incentive fee that is a proportion of any positive returns.

In this chapter I will demonstrate that this incentive fee is effectively a call option on a proportion of the performance of the fund which is given to the hedge fund manager by the investors. I will also demonstrate that the fact that incentive fees are usually accompanied by a high-water mark provision means that hedge fund fees are both time-varying and path-dependent, and hence the relationship between gross and net of fee returns is non-linear.

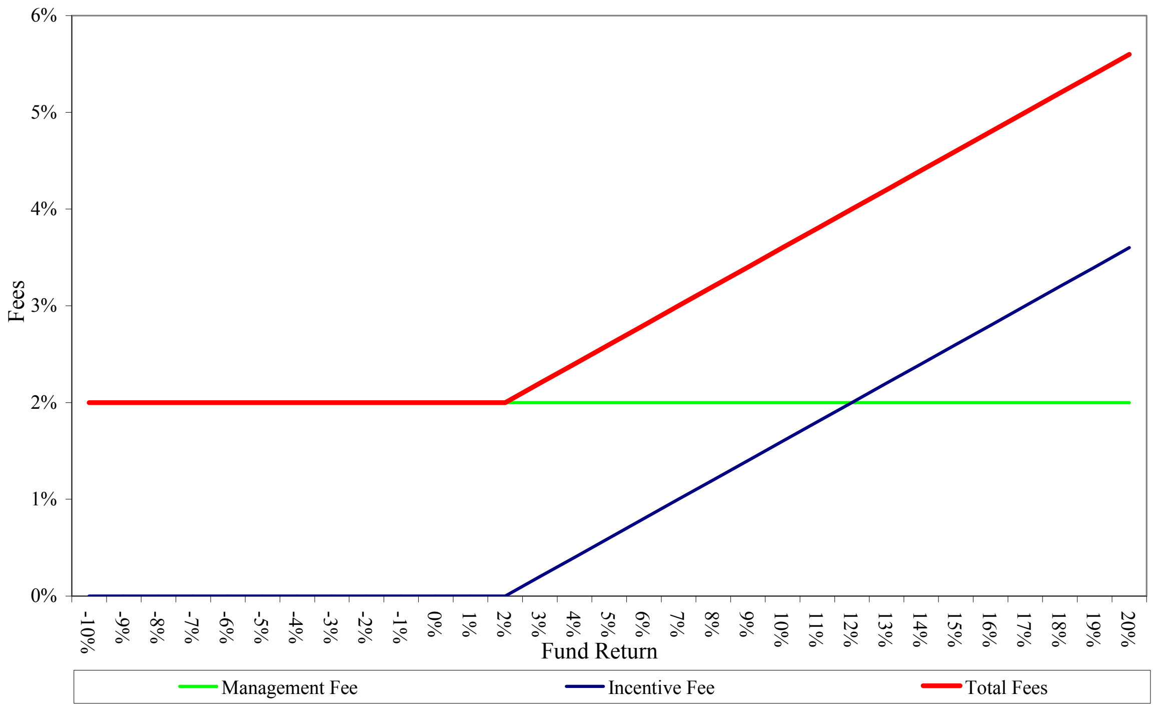
These facts have extremely important implications for the analysis of hedge fund performance as all of the reported returns are net of fees. Firstly, a flat management fee structure will simply cause the mean net return to be lower than the gross return leaving all other moments of the distribution unchanged, whereas the introduction of an incentive fee will affect all moments of the distribution. Secondly, since incentive fees are a function of the gross return, using net of fee returns can lead to considerably biased estimates of factor exposures which can distort the picture of fund manager performance. I illustrate these facts both by the use of stylised examples and empirical hedge fund data.

The solution I propose is to model the gross returns of hedge funds and the incentive fees independently, which gives a truer representation of the underlying return generating process. In order to do this I present an algorithm that can be used to calculate gross returns from the information contained in the TASS hedge fund database.

2.2 HEDGE FUND FEE CONTRACTS

Investors in hedge funds are generally charged an annual management fee that can range anywhere from 1% to 3% of assets under management, and also an incentive fee which is typically between 10% and 30% of annual profits, based upon the fund's overall performance. It is argued that the annual management fee is designed to cover the fund's operating costs while the incentive fee "incentivizes" the manager to produce absolute returns. This incentive fee is typically subject to two constraints: a "hurdle rate" and a "high-water mark". The hurdle rate is a benchmark return that must be exceeded before the performance incentive fees are payable. In practice, this hurdle rate is often set at zero, although benchmarks such as LIBOR are also common. The high-water mark means that each investor only pays performance fees when the value of their investment is greater than its previous highest value, which ensures that an investor only pays an incentive fee for positive performance once any previous underperformance has been recouped.

Figure 2.1: Management and Incentive Fees Payable Relative to Gross Fund Performance

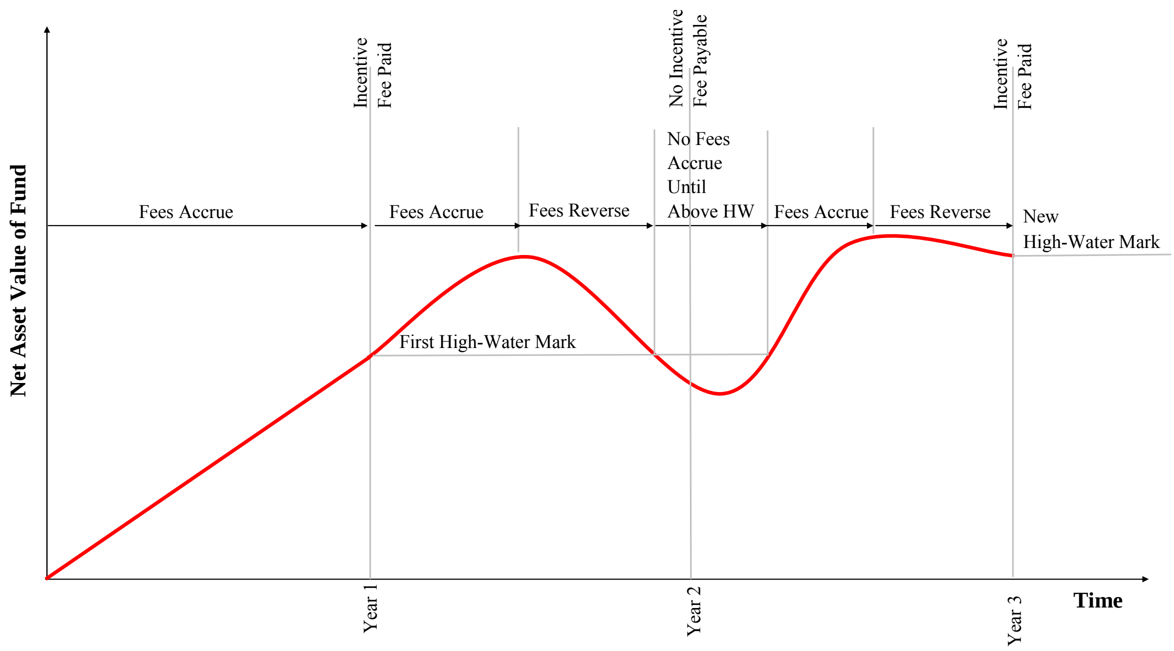


This figure depict fees payable to a hedge fund manager who charges a 2% management fee and a 20% incentive fee for various levels of gross return.

Figure 2.1 illustrates how the total fees payable for a fund that charges a 2% management fee and 20% incentive fee (with no high-water mark) vary according to performance. Until the fund generates a return of 2% to cover the management fee, no incentive fee is payable; thereafter, the incentive fees are 20% of the total performance above the 2% threshold. The payoff profile of this fee contract is identical to a call option on 20% of the fund performance with a strike of 2%.

Figure 2.2 illustrates how a high-water mark provision means that the incentive fees not only depend upon the total return of the fund, but also on how these returns evolve over time. In the first year, the fund is profitable and incentive fees that accrue throughout the year are paid at the end of year one; at this point, a high-water mark is set. During the first part of the second year, fees continue to accrue, but these fees reverse when the performance turns negative, with the result that no fees are payable at the end of the year. Only when the high-water mark set at the end of year one is passed do fees begin to accrue once more. The effect of the high-water mark is that the strike price of the incentive fee option is no longer simply the return required to cover the management fee, but instead is the return required to reach the high-water mark where incentive fees will begin to accrue.

Figure 2.2: The Effect of a High-Water Mark Provision on Incentive Fees



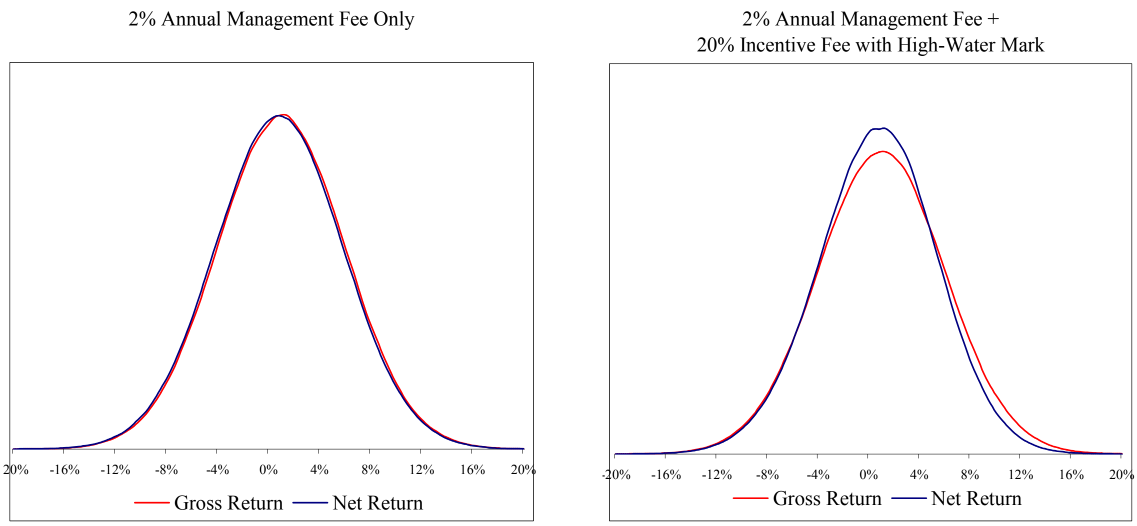
This figure illustrates the effect of a high-watermark provision on the incentive fees that are payable over a three year period for a hypothetical hedge fund.

The existence of such incentive fees and high-watermark provisions means that hedge fund fees are both time-varying and path-dependent, and therefore that the relationship between gross and net of fee returns is non-linear.

2.3 THE EFFECT OF INCENTIVE FEES ON THE DISTRIBUTION OF RETURNS

In order to investigate the effect of incentive fees on the distribution of returns I use Monte Carlo simulation. I simulate the gross return of 5,000 funds over a 100 year history, assuming that the underlying gross returns are 1% per month with a 5% standard deviation (comparable to historical equity market returns), and then compare the effect on net returns of only charging a 2% annual management fee with the effect of charging both a 2% management fee and a 20% incentive fee (with a high-water mark). The results of this simulation are presented in figure 2.3.

Figure 2.3: Monte-Carlo Simulation of the Effect of Incentive Fees



Summary Statistics

	Gross Return	Net Return
Mean	1.00%	0.83%
Standard Deviation	5.00%	5.00%
Skew	0.00	0.00
Kurtosis	3.00	3.00

Summary Statistics

	Gross Return	Net Return
Mean	1.00%	0.70%
Standard Deviation	5.00%	4.67%
Skew	0.00	-0.07
Kurtosis	3.00	3.08

This figure presents the results of a Monte Carlo simulation of 5,000 funds over a 100 year period where the gross returns have a monthly mean return of 1% with a standard deviation of 5%. The left panel assumes a 2% annual management fee (paid monthly) while the right hand panel assumes both a 2% management fee and a 20% incentive fee with a high-water mark provision.

For funds that charge only an annual management fee (for example, mutual funds), the distribution is simply moved to the left by 0.17% per month with all other moments unchanged. However, introducing a 20% annual incentive fee that is accrued monthly and paid annually with a high-water mark provision, leads to a more significant change in the distribution. First, the mean net return is 0.70%, implying that the mean incentive fee payable is 0.13% per month, which is clearly less than 20% of the 0.83% return net of management fees because fees are only payable on positive returns above the high-water mark. Second, the standard deviation of net returns is 4.67%, which is lower than the 5% for gross returns. This is because the fees act to smooth returns over time. So if, for example, the returns net of management fees but before incentive fees for two consecutive months are +1% and -1%, the net returns will be +0.8% and -0.8%. Third, the net returns exhibit negative skew because incentive fees will be charged on positive but not on negative returns. Finally, net returns exhibit excess kurtosis since the incentive fees have the impact of pushing the distribution away from the shoulders into the centre, and the standard deviation is lower.

In chapter 1 I highlighted that authors such as Brooks and Kat (2002) have found that hedge fund returns are not normally distributed and exhibit negative skewness and excess kurtosis. From the above it would appear that even if the gross returns themselves were normally distributed, the fee structure would lead to exactly these statistical properties, namely negative skewness and excess kurtosis.

2.4 PERFORMANCE ATTRIBUTION AND THE EFFECT OF INCENTIVE FEES ON THE RISK EXPOSURES OF AN INVESTOR

Most of the empirical work on the effect of market or risk factors on hedge fund returns builds upon the work of Sharpe (1992). His framework for the analysis of mutual funds involved the development of an asset class factor model to determine risk exposures of the form:

$$R_t = \alpha + \sum_{i=1}^{n} \beta_{i,t} F_{i,t} + \varepsilon_t \qquad (1)$$

where Rt represents the return on the fund at time t, Fi,t represents the return on factor Fi at time t, βi,t represents the sensitivity of the fund to factor Fi at time t and α is the value added by the manager.

Sharpe regressed mutual fund returns against twelve asset class returns and interpreted the resulting betas as representing the mutual funds' historic exposures to the asset classes. Sharpe's results showed that only a limited number of major asset classes were required to successfully replicate the performance of the universe of U.S. mutual funds. Sharpe's model is the building block of most risk-return research in hedge funds. This approach was first used in the hedge fund arena by Fung and Hsieh (1997), who applied Sharpe's asset class factor model to a sample of hedge funds and mutual funds using eight asset classes. The results were strikingly different for hedge funds compared to mutual funds: 47% of the mutual fund regressions had R-squared values higher than 75%, and 92% had R-squared figures higher than 50%. For the hedge fund regressions, 48% had R-squared values below 25%.

Subsequent work by Fung and Hsieh and other authors has attempted to improve upon the explanatory power of the models using different sets of independent variables, sample periods and hedge fund databases. Most of this work has been conducted within Sharpe's general framework. Some have concentrated on the addition of non-linear factors such as options (Agarwal and Naik (2000)) while others have estimated time-varying betas using either rolling window regressions (Fung and Hsieh (2004)), or by using statistical techniques such as the Kalman filter (Gehin and Vaissie (2006)). However, all of this work has been undertaken using net of fee returns and linear regression techniques, where the resulting betas are interpreted as representing the exposure of the investor to a specific source of systematic risk.

For mutual funds, the only difference between net and gross returns is the management fees that are a fixed percentage of the assets under management. As equation (2) illustrates, in this case the beta is the same for both the investor and the fund because the fees are independent of the fund return, and so the fees affect only the fund's alpha.

$$R_{GROSS,t} - FEES_t = \alpha + \sum_{i=1}^{n} \beta_{i,t} F_{i,t} + \varepsilon_t \qquad (2)$$

However, because hedge funds also charge incentive fees which are a fixed percentage of the profits above a certain threshold, the fees are not independent of the fund's return. For this reason, the beta of the fund and the beta of the investor can be different depending upon the performance of the fund, as represented by equation (3).

$$\beta_{Investor} = \beta_{Fund} - \beta_{IncentiveFee} \tag{3}$$

As I have already demonstrated, the incentive fee can be thought of as a call option on a percentage of the performance of the fund. The investor is short this option while the fund manager has the corresponding long position. Armed with this information, it is relatively simple to calculate $\beta_{IncentiveFee}$ from equation (4), where $\delta_{IncentiveOption}$ is the delta of the incentive option, $IncentiveFee\%$ is the percentage fee charged by the fund and β_{Fund} is the beta of the fund calculated by regressing the gross returns against the risk factor/factors.

$$\beta_{IncentiveFee} = \delta_{IncentiveOption} * IncentiveFee\% * \beta_{Fund} \tag{4}$$

If, for example, the fund charges a 20% incentive fee, then the boundary conditions are as follows:

i) *when the fund is a long way below the high-water mark* - all gains and losses from the fund will accrue to the investor with no incentive fees payable. $\delta_{IncentiveOption}$ will be close to zero and the exposures of the investor are the same as the exposures of the fund;

ii) *when the fund is a long way above the high-water mark* - all gains will result in further incentive fees being payable and losses will result in a reduction in the fees. $\delta_{IncentiveOption}$ will be close to 1, and hence the exposure of the investor will be 20% smaller than the exposure of the fund.

It is clear, then, that using net of fee returns to calculate betas will lead to biased estimates. The correct approach would be to model the gross returns of the fund and incentive fees separately. The possible consequences of modelling net rather than gross returns is best illustrated with a stylised example.

2.4.1 A STYLISED EXAMPLE OF THE PROBLEM: BETA PARTNERS

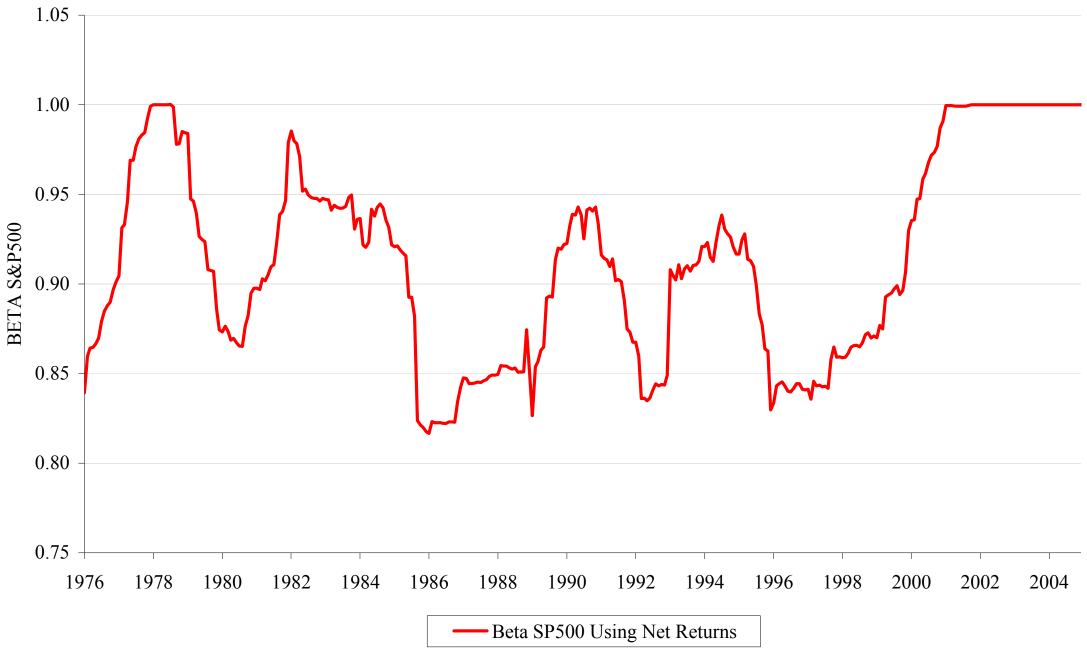
Suppose that a hypothetical hedge fund called "Beta Partners" was established in January 1975, and unbeknown to its investors, the fund simply invested 100% of its assets on a passive basis in the S&P 500 index. Beta Partners charges the standard 2% management fee, a 20% performance fee with a hurdle rate of 0% and a high-water mark provision.

Applying the approach suggested by Ibbotson and Chen (2006) to separate the sources of return into alpha, beta and costs (or fees) by a static linear regression of the net returns from Beta Partners against the S&P500 index yields a slope coefficient of 0.91 and an alpha estimate of -0.23% per month. This implies that over the 31 year period, the returns of Beta Partners comprise an alpha of -2.67% p.a., beta of 11.95% p.a. and fees of 4.32% p.a. However, in this stylized example we know that all of Beta Partners' returns are driven by beta and it is the fees that are distorting the picture. From equation (2) we know that the management fees will only affect the alpha estimate, however the introduction of incentive fee will mean that the beta estimate is also affected.

The correct approach would be to use the gross returns to calculate the alpha and beta estimates before subtracting the fees. This approach, as one would expect, yields an alpha estimate of zero and a slope coefficient of 1. Thus the compound annual returns are comprised of alpha of 0%, beta of 13.45% and fees of 4.03%.

The above illustrates that using returns net of fees understates both the alpha and beta components of the return of the fund. While it is clear that the investor does not receive all of these returns due to the fee structure, separating out the effect of fees from the fund returns gives the investor a far truer representation of the underlying return generating process of the fund and of the performance of the fund manager. If an investor were to follow the methodology of Fung and Hsieh (2004) in an attempt to analyse the exposure of Beta Partners to the S&P 500 using a 24-month rolling window regression on the net of fee returns, the results would be as shown in Figure 2.4.

Figure 2.4: Beta Partners – Rolling Window Regression



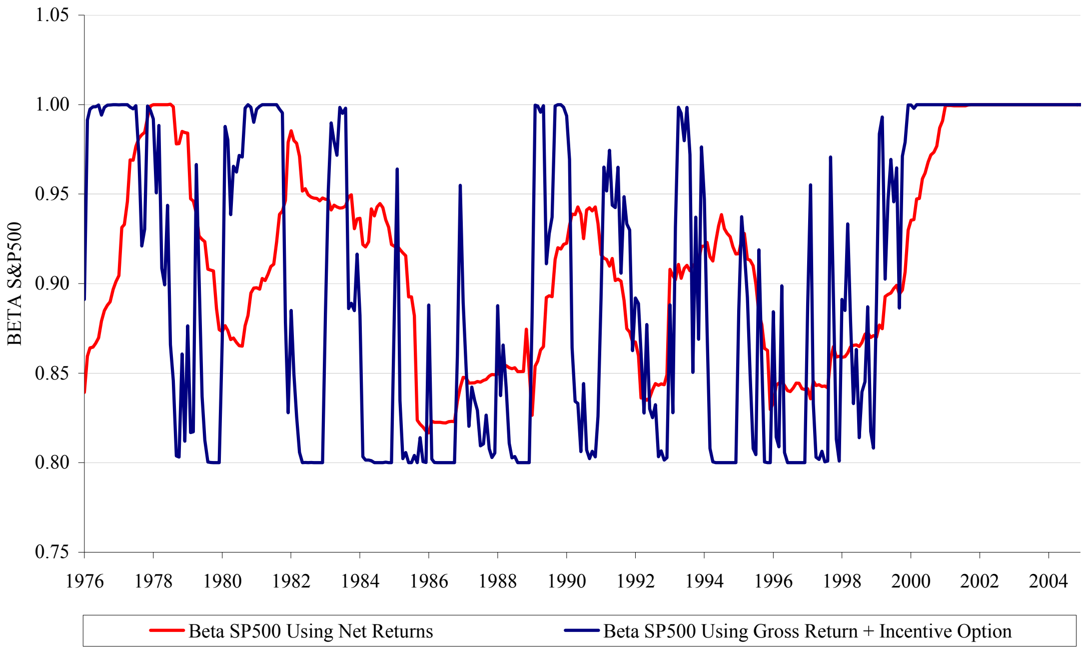
This figure presents slope coefficient of a rolling 24 month window regression of the net returns generated by the hypothetical fund Beta Partners on the S&P 500 index.

The rolling regression results show how the beta varies between a maximum of 1 and a minimum of 0.82 over the sample period. On the basis of this information an investor might conclude that Beta Partners is varying its exposure to the market over time but by construction, the actual beta of the fund is 1.0 at all times. All of the variation in exposure is actually coming from the change in the delta of the incentive fee option.

The true beta of the investor can easily be calculated from equations (3) and (4) once I have identified the delta of the incentive option. In this example, the incentive option is simply a 1-month call option on the S&P 500 with a strike set at the current high-water mark, and thus the delta can easily be calculated using the Black-Scholes equation. Figure 2.5 shows how the beta of the investor evolves over time.

As one would expect, from the boundary conditions outlined above, the investor's beta is always between 0.8 and 1. When the incentive option has zero delta, the investor and fund betas are the same. When the incentive option has a 100% delta, then the investor beta is 20% lower than that of the fund. The evolution of the investor's exposure is far less smooth using this procedure compared to using net returns; part of the reason for this is the re-setting of the high-water mark each January after incentive fees are paid. In fact, using net returns simply results in a moving average of the true investor beta.

Figure 2.5: Beta Partners – Investor Beta



This figure presents difference between the investor's true beta and the result obtained from using net returns. The red line is the slope coefficient of a rolling 24 month window regression of net returns on the S&P 500 index. The blue line is the investor beta calculated from slope coefficient of a rolling 24 month window regression of gross returns on the S&P 500 index and then applying equations (3) and (4)

2.5 EMPIRICAL ANALYSIS OF NET AND GROSS HEDGE FUND RETURNS

I now propose a technique for recovering gross of fee hedge fund returns and apply this to individual hedge fund performance data. The hedge fund return data are extracted from the TASS live and graveyard databases from January 1994 through to December 2006. More specifically, I extract monthly Net Asset Values (NAV) and fee structure details for all hedge funds that are denominated in US Dollars, that report monthly and that have at least 37 data points. These criteria result in a total sample of 2,837 funds of which 1,433 are currently reporting and 1,404 are no longer reporting. I recognise that this data will be subject to the various biases described by Fung and Hsieh (2002) and others, namely survivorship, instant history and selection bias. I minimise survivorship bias by using both the live and graveyard databases and by using data only from January 1994 when TASS began collecting data on graveyard funds. Instant history bias has been estimated by Fung and Hsieh to be approximately 1.4% pa. I estimate the size of the selection bias by comparing the return on the equally weighted return of my sample to the equally weighted return on all funds in the database. I estimate this to be 0.83% p.a.

Using these NAVs it is relatively straightforward to calculate monthly net and gross returns by making a number of realistic assumptions. To do this, the following assumptions are required:

i) Management fees are calculated and paid on a monthly basis

ii) Incentive fees are accrued on a monthly basis, but are only paid at the end of the calendar year

iii) Unless specified otherwise, the fund applies a high-water mark provision

iv) The fund implements an 'Equalisation Credit /Contingent Redemption' approach to calculating the NAV such that it is the same for all investors (for a more thorough explanation see McDonnell (2003)).

The net hedge fund return for period t is calculated using expression (5):

$$R_{NET_t} = \frac{\left(NAV_t - NAV_{t-1}\right)}{NAV_{t-1}} \tag{5}$$

The gross return calculation is calculated as follows:

$$R_{GROSS_t} = \frac{\left(NAV_t - NAV_{t-1}\right) + MgtFee_t + \left(AccruedIncentFee_t - AccruedIncentFee_{t-1}\right)}{\left(NAV_{t-1} + AccruedIncentFee_{t-1}\right)} \tag{6}$$

where

$$MgtFee_t = NAV_{t-1} \times \left(\frac{1}{1 - \frac{MgmtFee\%}{12}} - 1 \right) \tag{7}$$

and

$$AccruedIncentFee_t = \max\{0, NAV_t - HighWaterMark\} \times \left(\frac{1}{1 - IncentiveFee\%} - 1 \right) \tag{8}$$

at the end of each year, the accrued incentive fee is reset to zero and if necessary, the high-water mark moved upwards to reflect this.

Equation (6) is simply the change in the gross value of the fund calculated by adding back the management fees calculated from equation (7) and the incentive fees calculated from equation (8). In equation (8), because the incentive fees are only paid annually they are accrued every month until December when, if any fees are accrued they are paid and the high-water mark is adjusted upwards to reflect this payment.

By applying this technique to the NAV data extracted from the TASS database, I construct equally weighted indices for the ten strategies reported in the database as well as a broad index of all hedge funds in my sample.

2.5.1 THE STATISTICAL PROPERTIES OF NET AND GROSS RETURNS

Table 2.1 contains the summary statistics for the net and gross returns in the sample. Clearly, by construction, the compound annual, gross returns are higher than the net returns with the difference between the two being the fees. For my sample, the average fee charged has been 5.15% p.a., ranging from 2.57% for dedicated short bias to 6.07% for managed futures.

Table 2.1 The Statistical Properties of Net and Gross Returns

Panel A

	Sample Size		
	Live	Graveyard	Total
Convertible Arbitrage	72	69	141
Dedicated Short Bias	15	14	29
Emerging Markets	118	114	232
Equity Market Neutral	94	92	186
Event Driven	203	150	353
Fixed Income Arbitrage	78	73	151
Global Macro	66	93	159
Long Short Equity	591	575	1,166
Managed Futures	115	176	291
Multi Strategy	81	48	129
All Hedge Funds	1,433	1,404	2,837

Panel B

	Net					
	Compound Annual Ret	Annualised Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
Convertible Arbitrage	10.38%	4.23%	-0.80	5.15	46.69	0.00%
Dedicated Short Bias	-0.79%	18.06%	0.70	4.65	30.59	0.00%
Emerging Markets	14.41%	15.50%	-1.06	8.07	196.46	2.61%
Equity Market Neutral	11.01%	2.51%	0.50	2.67	7.29	0.00%
Event Driven	12.91%	4.41%	-1.61	10.40	422.76	0.00%
Fixed Income Arbitrage	9.16%	3.51%	-2.97	20.46	2210.69	0.00%
Global Macro	9.18%	5.99%	0.90	4.31	43.54	0.00%
Long Short Equity	16.29%	9.18%	0.03	4.54	15.41	0.05%
Managed Futures	9.83%	11.04%	0.30	2.81	2.57	27.68%
Multi Strategy	13.42%	4.70%	-0.39	5.45	43.11	0.00%
All Hedge Funds	13.17%	5.93%	0.05	4.07	7.54	2.31%

Panel C

	Gross					
	Compound Annual Ret	Annualised Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
Convertible Arbitrage	14.32%	4.81%	-0.65	4.88	33.99	0.00%
Dedicated Short Bias	1.77%	19.50%	0.84	5.31	52.87	0.00%
Emerging Markets	19.86%	16.75%	-0.85	6.90	117.89	0.00%
Equity Market Neutral	15.42%	2.96%	0.54	2.76	7.90	1.92%
Event Driven	17.43%	5.07%	-1.44	9.37	317.91	0.00%
Fixed Income Arbitrage	13.43%	3.83%	-2.64	17.79	1602.94	0.00%
Global Macro	13.62%	6.92%	1.01	4.62	32.35	0.00%
Long Short Equity	21.76%	10.47%	0.18	4.56	16.60	0.02%
Managed Futures	15.89%	12.59%	0.37	2.96	3.55	16.94%
Multi Strategy	18.45%	5.34%	-0.26	4.95	26.47	0.00%
All Hedge Funds	18.31%	6.72%	0.19	3.86	5.71	5.75%

The table presents summary statistics for equally weighted strategy indices constructed from a sample of funds from the TASS live and graveyard databases that are denominated in US Dollars, report monthly and that have at least 37 data points. Panel A presents the number of funds in each strategy. Panel B presents descriptive statistics for the net returns calculated from equation (5). Panel C presents descriptive statistics for the gross returns calculated from equations (6), (7) and (8).

When examining the standard deviation of returns, the empirical results are in line with the earlier Monte Carlo simulation, and in all cases the gross returns exhibit higher annualised standard deviation than net returns with the average difference being 0.78%. For skewness, the empirical results are also as expected with an average increase of 0.14. With regard to kurtosis the results are much less clear cut, with increases for some strategies and decreases for others. Overall, however, there is a reduction in kurtosis of 0.21. The combination of all of this means that gross hedge fund returns look far more "normal" than net returns and in fact, contrary to Brooks and Kat (2002), for my sample it would appear that on average hedge fund returns display positive skewness and do not exhibit significantly excess kurtosis.

2.6 PERFORMANCE ATTRIBUTION

In order to attribute hedge fund returns between alpha, beta and fees, Ibbotson and Chen (2006) carry out regressions on net of fee hedge fund returns, using S&P 500 total returns (including both concurrent and with a one-month lag), U.S. Intermediate-term Government Bond returns (including one-month lag), and cash (U.S. Treasury Bills) as benchmarks. They constrain all style weights to sum to one, but allow individual style weights to be negative or above one to account for shorting and leverage. Once they have calculated alphas, they deducted this from the net return to give the return from beta. Then, using the median management and incentive fee levels, they estimate what the fees on this total net return would have been to "gross it up".

I replicate Ibbotson and Chen's methodology using the net of fee returns for my sample of hedge funds and the following risk factors:

- the total return of the Wilshire 5000 composite index;
- the total return of Lehman US Aggregate Index; and
- one month USD LIBOR.

I then compare this to the results I obtain by calculating the gross return before performing the regressions. The results are presented in Tables 2.2 and 2.3 which are directly comparable to Tables 5 and 6 in Ibbotson and Chen (2006).

Table 2.2 Analysis of Sources of Return for Equally Weighted Hedge Fund Indices

Regression Results: 1994-2006							
		Compound Annual Return	Annual Alpha	Betas (Sum of Betas = 1)			
				Stocks	Bonds	Cash	RSQ
Convertible Arbitrage	Using Net Returns	10.38%	3.87% **	0.20	0.27	0.53	31.1%
	Using Gross Returns	14.32%	7.38% **	0.22	0.31	0.47	29.6%
Dedicated Short Bias	Using Net Returns	-0.79%	4.10%	-1.12	0.21	1.91	76.1%
	Using Gross Returns	1.77%	7.89% **	-1.22	0.17	2.05	77.0%
Emerging Markets	Using Net Returns	14.41%	4.27%	0.87	-0.17	0.30	41.7%
	Using Gross Returns	19.86%	8.86% **	0.94	-0.16	0.22	41.5%
Equity Market Neutral	Using Net Returns	11.01%	5.75% **	0.07	0.08	0.85	24.3%
	Using Gross Returns	15.42%	9.89% **	0.08	0.08	0.84	22.6%
Event Driven	Using Net Returns	12.91%	5.76% **	0.31	0.05	0.64	59.8%
	Using Gross Returns	17.43%	9.64% **	0.36	0.07	0.57	59.1%
Fixed Income Arbitrage	Using Net Returns	9.16%	3.84% **	0.07	0.11	0.82	9.6%
	Using Gross Returns	13.43%	7.79% **	0.08	0.13	0.79	10.7%
Global Macro	Using Net Returns	9.18%	2.81% *	0.18	0.37	0.45	16.2%
	Using Gross Returns	13.62%	6.78% **	0.20	0.43	0.36	15.8%
Long/Short Equity	Using Net Returns	16.29%	7.51% **	0.59	-0.07	0.48	69.3%
	Using Gross Returns	21.76%	12.21% **	0.66	-0.09	0.43	66.6%
Managed Futures	Using Net Returns	9.83%	5.05%	-0.10	0.94	0.17	11.5%
	Using Gross Returns	15.89%	10.88% **	-0.12	1.10	0.03	12.2%
Multi-Strategy	Using Net Returns	13.42%	6.91% **	0.25	0.01	0.74	49.5%
	Using Gross Returns	18.45%	11.46% **	0.28	0.01	0.71	48.1%
All HF	Using Net Returns	13.17%	5.69% **	0.37	0.09	0.54	58.6%
	Using Gross Returns	18.31%	10.20% **	0.41	0.11	0.48	56.5%

*This table presents the results of regressions of both net and gross hedge fund index returns on three risk factors. Stocks is defined as the total return of the Wilshire 5000 composite index, Bonds is the total return of Lehman US Aggregate Index and Cash is one month US Dollar LIBOR. The Betas are the slope respective slope coefficients and the alphas are the intercepts of the regression. Alpha values significant at the 5% level are denoted with * and those significant at 1% by **.*

Table 2.3 Analysis of Sources of Return for Equally Weighted Hedge Fund Indices

Sources of Return: Alpha, Beta, and Cost 1994-2006						
		Pre-Fee Return	Fees	Post-Fee Return	Alpha	Systematic Betas
Convertible Arbitrage	Using Net Returns	14.98%	4.60%	10.38%	3.87%	6.51%
	Using Gross Returns	14.32%	3.94%	10.38%	7.38%	6.94%
Dedicated Short Bias	Using Net Returns	1.01%	1.80%	-0.79%	4.10%	-4.89%
	Using Gross Returns	1.77%	2.57%	-0.79%	7.89%	-6.12%
Emerging Markets	Using Net Returns	20.01%	5.60%	14.41%	4.27%	10.13%
	Using Gross Returns	19.86%	5.46%	14.41%	8.86%	11.00%
Equity Market Neutral	Using Net Returns	15.76%	4.75%	11.01%	5.75%	5.26%
	Using Gross Returns	15.42%	4.41%	11.01%	9.89%	5.53%
Event Driven	Using Net Returns	18.14%	5.23%	12.91%	5.76%	7.16%
	Using Gross Returns	17.43%	4.52%	12.91%	9.64%	7.79%
Fixed Income Arbitrage	Using Net Returns	13.46%	4.29%	9.16%	3.84%	5.33%
	Using Gross Returns	13.43%	4.26%	9.16%	7.79%	5.64%
Global Macro	Using Net Returns	13.47%	4.29%	9.18%	2.81%	6.37%
	Using Gross Returns	13.62%	4.45%	9.18%	6.78%	6.84%
Long/Short Equity	Using Net Returns	22.37%	6.07%	16.29%	7.51%	8.78%
	Using Gross Returns	21.76%	5.47%	16.29%	12.21%	9.56%
Managed Futures	Using Net Returns	14.28%	4.46%	9.83%	5.05%	4.78%
	Using Gross Returns	15.89%	6.07%	9.83%	10.88%	5.01%
Multi-Strategy	Using Net Returns	18.77%	5.35%	13.42%	6.91%	6.50%
	Using Gross Returns	18.45%	5.03%	13.42%	11.46%	6.99%
All HF	Using Net Returns	18.46%	5.29%	13.17%	5.69%	7.48%
	Using Gross Returns	18.31%	5.15%	13.17%	10.20%	8.12%

This table presents the results of separating the total return of the hedge fund indices into that which is attributable to alpha, beta and fees with the alphas taken from table 2.2.

By construction, the alpha estimate for gross returns will be larger by at least the management fees, although in all cases, the increase is much larger than this (the average increase being 4.51% p.a.). For my sample using gross returns, alpha is significant at the 5% level for all 10 strategies, whereas when using net returns it is only significant for 6 of them. For all strategies, the magnitude of beta for the risky assets (stocks and bonds) is greater and consequently the return attributable to beta is also larger (the average increase being 0.64% p.a.). This implies that although the major impact of fees is indeed on alpha, the effect on beta is not insignificant.

2.7 FACTOR MODEL SPECIFICATION AND REPLICATION

Using gross rather than net of fee returns when attempting to duplicate hedge fund performance via factor replication should produce better results for two main reasons. First, as I have already demonstrated, the use of net of fee returns for performance attribution leads to an underestimation of the return that is attributable to beta, and hence it follows that using gross returns in attempting to replicate hedge fund returns should produce better results by capturing this additional beta return. Second, the option-like nature of incentive fees creates a non-linear payoff to the factors which should be eliminated by using gross returns.

In order to assess the difference between replicated net and gross hedge fund returns, I employ a methodology similar to that of Hasanhodzica and Lo (2007). However, whereas Hasanhodzica and Lo and others have used the same small number of factors for every strategy, I start with a large set of 11 candidate factors and undertake a procedure to identify the significant factors for each strategy individually. This is because of the heterogeneous nature of hedge fund strategies and the advantage is that it avoids the use of superfluous factors in the regressions. Table 2.4 shows the set of 11 candidate factors. These factors were chosen because they provide a broad cross section of risk exposures which have all been identified in previous studies as significant.

Table 2.4 Candidate Factors for Replication

Factors Requiring Investment

Name	Description	Datastream Mnemonic
MKT	Dow Jones Wilshire 5000 Composite Total Return	WILEQTY
CMDTY	GSCI Commodity Total Return	GSCITOT
BOND	Lehman US Agggregate Total Return	LHAGGBD
EMERGING	MSCI Emerging Markets Index Total Return	MSEMKFL
GLOBAL_STOCKS	JP Morgan Global Broad Excluding U.S. Total Return	JPMBXUS
GLOBAL_BONDS	MSCI World Excluding U.S. Total Return	MSWFXU
DVIX	Change In CBOE VIX Index	CBOEVIX

Cash Neutral Factors

Name	Description	Datastream Mnemonic
SMB	Dow Jones Wilshire Small Cap Minus Dow Jones Wilshire Large Cap (Both Total Return)	WILDJSC & WILDJLC
USD	Finex-US Dollar Index Return	NDXCS00
CREDIT	Lehman US Credit Intermediate Bond Index Minus Lehman Government Intermediate (Both Total Return)	LHCRPIN & LHGOVIN
SLOPE	Lehman US Treasury: 20+ Year Index Minus Lehman Short Treasury Index (Both Total Return)	LHTR20Y & LHSHORT

This table presents the set of candidate factors to be used for the hedge fund replication with their DataStream mnemonic. The factors are categorised as either requiring a cash investment or being cash neutral.

Importantly, all of the factors are investable via traditional funds, exchange traded funds or futures which is essential if they are to be used for replication. I classify the factors into two groups: those that require investment and those that are cash neutral. To ensure that when I construct clones and restrict the sum of betas to be equal to one, this restriction only applies to factors that require investment.

In order to identify the significant factors for each strategy, I first extract monthly returns for live and graveyard funds from the TASS database for January 1990 to December 1994 and construct equally weighted strategy indices. Although this sample will be severely affected by survivorship bias, because I am only looking to identify the factors that drive returns rather than making any judgements about performance, I feel that this is an acceptable approach. Next I run regressions for all possible combinations of one to eleven factors, a total of 2^{11} = 2,048 regressions, in order to identify the most parsimonious model, which I define as the one with the lowest Akaike Information Criterion (AIC). The results are shown in table 2.5.

Table 2.5 Results of Factor Selection

	AIC	R^2	MKT	SMB	USD	CMDTY	BOND	CREDIT	SLOPE	EMERGING	GLOBAL STOCKS	GLOBAL BONDS	DVIX
Convertible Arbitrage	-4.23	28.00%				-0.1676 (0.0761)		4.7782 (1.1339)					0.3358 (0.1400)
Dedicated Short Bias	-3.43	12.82%	-0.4704 (0.1512)										
Emerging Markets	-4.86	49.04%	0.1741 (0.0895)					1.7949 (0.8859)		0.1918 (0.0465)			
Equity Market Neutral	-6.00	18.97%	0.0976 (0.0559)	0.2139 (0.0688)		0.0903 (0.0336)							0.0219 (0.0643)
Event Driven	-6.09	57.78%	0.1432 (0.0659)		0.0979 (0.0568)		0.2597 (0.1718)	1.3747 (0.5388)		0.0589 (0.0275)			0.0373 (0.0616)
Fixed Income Arbitrage	-5.44	38.55%			0.3530 (0.1421)	-0.1130 (0.0409)		1.5706 (0.6105)				0.5375 (0.1492)	-0.0704 (0.0733)
Global Macro	-5.08	21.59%		-0.2030 (0.1227)				2.4284 (0.7591)		0.0731 (0.0443)	-0.1027 (0.0625)	0.3253 (0.1232)	
Long/Short Equity	-6.60	76.17%	0.2698 (0.0457)	0.1895 (0.0582)	0.1387 (0.0895)	0.0800 (0.0248)			0.0890 (0.0719)	0.0771 (0.0219)	-0.0388 (0.0297)	0.1854 (0.1116)	
Managed Futures	-4.46	5.02%			0.4379 (0.2274)					0.0000	-0.1298 (0.0737)	0.6477 (0.2698)	
Multi-Strategy	-5.01	31.16%			0.3873 (0.0940)	0.1032 (0.0542)	0.7322 (0.2531)	-3.6661 (0.9248)		0.1485 (0.0431)			

The table presents the results of the factor selection process. In each case the model with the lowest Akaike Information Criterion (AIC) was chosen. The figures in the body of the table are the resulting coefficients and the figures in parentheses are standard errors.

The findings are in line with what one would expect. Equity based factors are identified as significant for those strategies that involve equities such as long/short equity, dedicated short bias and event driven. Bond or credit factors are identified as significant for fixed income strategies such as convertible arbitrage and fixed income arbitrage. The R-squared of the regressions ranges from 5.2% for managed futures to 76.17% for long/short equity, showing that factor models appear to perform much more satisfactorily for some strategies than for others.

Having identified the factors that drive hedge fund returns for each individual strategy, I now attempt to construct linear clones using rolling window regressions. In addition to the factors identified above, I also introduce another factor, 1 month U.S. Dollar LIBOR, to allow for leverage. Using the factors identified above plus the LIBOR factor, for each individual hedge fund strategy I run a rolling window regression using a 24 month window from January 1995 to December 2006 as shown in equation (9)

$$R_t = \alpha + \sum_{i=1}^{n} \beta_{i,t} F_{i,t} + \varepsilon_t \qquad (9)$$

subject to $\sum_{i=1}^{n} \beta_{i,t} = 1$ for those factors classified as requiring investment plus LIBOR.

The estimated regression coefficients β^*_{it} are then used as portfolio weights to construct simple clone returns R^*_{it} using equation (10)

$$R^*_{it} = \sum_{i=1}^{n} \beta^*{}_{i,t} \qquad (10)$$

Since the volatility of these simple clones is unlikely to match the volatility of the hedge fund indices they are designed to replicate, using the simple clone returns from equation (10) I calculate a leverage factor γ from equation (11). This equation is the ratio of the historical volatility of the hedge fund indices to the volatility of the simple clones using a 24 month rolling window.

$$\gamma_{it} = \frac{\sqrt{\sum_{k=1}^{24} (R_{it-k} - \overline{R}_{it})^2 / 23}}{\sqrt{\sum_{k=1}^{24} (R^*_{it-k} - \overline{R}^*_{it})^2 / 23}} \tag{11}$$

This leverage factor is then used to calculate the clone returns $\hat{R}_{it}$ using equation (12)

$$\hat{R}_{it} = \left(\gamma_{it} R^*_{it}\right) - \left(1 - \gamma_{it}\right) LIBOR_t \tag{12}$$

This procedure was repeated for the indices and individual funds using both net and gross returns, which results in a clone series running for 10 years from January 1997 to December 2006, the results are presented in table 2.6.

In all cases, the return on the gross clones is greater in magnitude than for the net clones (more negative for dedicated short bias) although the standard deviation of the return is also slightly higher. The average improvement in return for the gross clones over the net clones is 0.24% for indices and 0.36% for individual funds. The improvement in performance of the gross clones would appear to be proportional to the goodness of fit of the model. The biggest improvement is seen in strategies such as long/short equity and event driven where the R-squared values of the regressions are high and the smallest improvement is for strategies such as equity market neutral and fixed income arbitrage where the R-squared is much lower. The correlation between the clone and fund returns is extremely high at over 85%, although there is no significant difference between the net and gross clones in either correlation or R-squared.

Table 2.6 Replication of Indicesand Individual Funds

Panel A - Replication of Indices 1997-2006

		Index		Clone			
		Compound Annual Return	Annual Standard Deviation	Compound Annual Return	Annual Standard Deviation	Mean R2 of Regression	Correlation Between Clone & Index
Convertible Arbitrage	Using Net Returns	10.10%	4.27%	5.65%	4.64%	20.97%	29.15%
	Using Gross Returns	14.03%	4.89%	5.95%	5.35%	20.01%	28.35%
Dedicated Short Bias	Using Net Returns	-1.74%	18.80%	-4.56%	20.88%	80.38%	87.91%
	Using Gross Returns	0.64%	20.23%	-5.71%	22.42%	81.19%	88.52%
Emerging Markets	Using Net Returns	15.02%	16.12%	6.53%	16.38%	73.48%	83.28%
	Using Gross Returns	20.66%	17.37%	6.47%	17.87%	72.91%	82.90%
Equity Market Neutral	Using Net Returns	9.48%	2.25%	4.47%	2.61%	23.65%	41.88%
	Using Gross Returns	13.46%	2.63%	4.61%	3.07%	23.28%	41.76%
Event Driven	Using Net Returns	12.12%	4.65%	7.16%	4.72%	66.02%	71.21%
	Using Gross Returns	16.55%	5.33%	7.78%	5.39%	64.67%	71.31%
Fixed Income Arbitrage	Using Net Returns	7.87%	3.34%	5.27%	3.71%	22.02%	50.36%
	Using Gross Returns	11.75%	3.63%	5.48%	3.99%	23.70%	50.74%
Global Macro	Using Net Returns	8.36%	5.28%	8.58%	6.89%	53.47%	61.82%
	Using Gross Returns	12.68%	6.07%	9.25%	8.01%	53.30%	62.18%
Long/Short Equity	Using Net Returns	15.22%	9.73%	8.03%	10.79%	91.90%	90.55%
	Using Gross Returns	20.51%	11.08%	8.64%	12.38%	90.70%	89.98%
Managed Futures	Using Net Returns	9.23%	10.70%	10.72%	12.39%	26.14%	32.30%
	Using Gross Returns	14.98%	12.30%	11.75%	14.19%	26.50%	32.77%
Multi-Strategy	Using Net Returns	13.54%	4.87%	6.04%	5.12%	65.39%	69.49%
	Using Gross Returns	18.54%	5.53%	6.34%	5.81%	63.67%	68.94%
All HF	Using Net Returns	12.54%	6.20%	7.44%	6.91%	65.58%	86.69%
	Using Gross Returns	17.51%	7.01%	7.68%	7.71%	64.85%	85.54%

Panel B - Replication of Individual Funds 1997-2006

		Index		Clone			
		Compound Annual Return	Annual Standard Deviation	Compound Annual Return	Annual Standard Deviation	Mean R2 of Regression	Correlation Between Clone & Index
Convertible Arbitrage	Using Net Returns	10.10%	4.27%	5.28%	4.75%	-99.50%	29.40%
	Using Gross Returns	14.03%	4.89%	5.59%	5.40%	-4.21%	29.06%
Dedicated Short Bias	Using Net Returns	-1.74%	18.80%	-4.92%	25.54%	55.52%	88.55%
	Using Gross Returns	0.64%	20.23%	-6.17%	27.19%	56.29%	89.12%
Emerging Markets	Using Net Returns	15.02%	16.12%	6.83%	21.07%	36.41%	83.43%
	Using Gross Returns	20.66%	17.37%	6.82%	22.98%	36.22%	83.17%
Equity Market Neutral	Using Net Returns	9.48%	2.25%	5.11%	3.10%	12.68%	40.15%
	Using Gross Returns	13.46%	2.63%	5.27%	3.57%	13.00%	39.78%
Event Driven	Using Net Returns	12.12%	4.65%	8.55%	5.50%	26.31%	65.45%
	Using Gross Returns	16.55%	5.33%	9.41%	6.31%	26.02%	65.55%
Fixed Income Arbitrage	Using Net Returns	7.87%	3.34%	5.02%	4.26%	12.71%	51.08%
	Using Gross Returns	11.75%	3.63%	5.20%	4.65%	13.18%	51.18%
Global Macro	Using Net Returns	8.36%	5.28%	8.47%	8.59%	21.67%	57.04%
	Using Gross Returns	12.68%	6.07%	9.04%	9.94%	21.75%	56.96%
Long/Short Equity	Using Net Returns	15.22%	9.73%	8.05%	13.07%	40.17%	90.14%
	Using Gross Returns	20.51%	11.08%	8.77%	14.95%	39.90%	89.71%
Managed Futures	Using Net Returns	9.23%	10.70%	12.40%	13.45%	17.36%	34.25%
	Using Gross Returns	14.98%	12.30%	13.36%	15.44%	17.66%	34.27%
Multi-Strategy	Using Net Returns	13.54%	4.87%	7.23%	6.56%	23.51%	69.29%
	Using Gross Returns	18.54%	5.53%	7.61%	7.44%	23.51%	68.59%
All HF	Using Net Returns	12.54%	6.20%	7.99%	8.46%	24.02%	86.53%
	Using Gross Returns	17.51%	7.01%	8.35%	9.45%	28.75%	85.45%

Panel A presents the results of the factor replication of the hedge fund indices while Panel B presents the results for individual funds. The replication is achieved by applying equations (9) to (12) to the factors identified in table 2.5.

2.8 THE EFFECT OF INCENTIVE FEES ON THE RISK TAKING BEHAVIOUR OF FUNDS

I have already demonstrated how the payoff profile of hedge fund performance fees is identical to a call option on a percentage of the fund's performance. The rationale for this fee arrangement is to "incentivize" the hedge fund manager to produce absolute returns. However, the reality is that the arrangement encourages managers to maximise the value of this fee option; their motivations could be different depending upon the delta of the option. When the delta is high, the bulk of the value in the option comes from its moneyness and little from its volatility. But when the delta is low, the reverse is true. Authors such as Scanlan and Siegel (2006) have suggested that managers who are significantly below their high water mark might have an incentive to increase risk.

This has been investigated for CTAs by Fung and Hsieh (1997a) and by Brown, Goetzmann, and Park (2001), who both find little evidence of increased risk taking by managers below their high water mark. They hypothesise that career and reputation concerns as well as the increased risk of redemptions offset the adverse risk-taking incentives created by the incentive fee contract.

In order to investigate whether this is the case for the hedge funds in my sample, I examine the distribution of returns conditional upon the delta of the incentive option. Calculation of the exact delta of the fee option is problematic because I do not have an appropriate model or a true estimate of the implied volatility, so instead I use the "moneyness" of the option as a proxy for delta. Moneyness is defined as

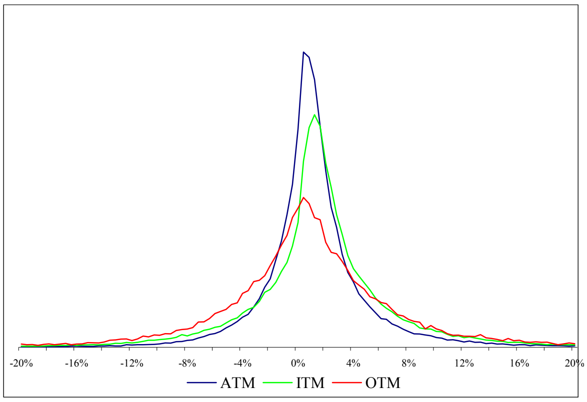
$$Moneyness_{t_t} = \frac{NAV_t}{HighWaterMark_t} \qquad (13)$$

For my sample of 2,837 funds, I calculate the moneyness at each data point giving us a total of 229,101 observations. In order to investigate the relationship between the delta of the incentive option and the distribution of returns I divided the moneyness into 3 sub-samples:

- “At The Money” (ATM) where moneyness is greater than 95% and less than 105%
- “In The Money” (ITM) where moneyness is greater or equal to 105%
- “Out Of The Money” (OTM) where moneyness is less than or equal to 95%

Using these sub-samples, I examine the properties of the distribution of gross returns at time *t*+1 conditional upon the moneyness at time *t*, the results are presented in Figure 2.6.

Figure 2.6: The Effect of Incentive Fees on the Risk Taking Behaviour of Funds



Summary Statistics

	ATM	ITM	OTM	Whole Sample
Mean	1.25%	1.71%	0.98%	1.38%
Standard Deviation	4.94%	6.41%	8.51%	6.16%
Skew	3.86	1.65	1.95	2.41
Kurtosis	110.53	35.42	57.01	68.64
Observations	109,813	84,608	34,680	229,101

Results of Kolmogorov-Smirnov Test

	OTM	ATM	ITM
OTM		0.1403 (0.000)	0.1398 (0.000)
ATM	0.1403 (0.000)		0.1033 (0.000)
ITM	0.1398 (0.000)	0.1033 (0.000)	

This figure presents the distribution of returns at time t+1 conditional upon the moneyness of the incentive option at time t for three sub samples of the data. These sub-samples are defined as “At The Money” (ATM) where moneyness is greater than 95% and less than 105%, “In The Money” (ITM) where moneyness is greater or equal to 105% and “Out Of The Money” (OTM) where moneyness is less than or equal to 95%. The tables present summary statistics for the three samples as well as pair-wise Kolmogorov-Smirnov tests of the null hypothesis that the samples are the same.

The three distributions appear to be very different. This is confirmed by the results of pairwise Kolmogorov-Smirnov tests, and in all cases I can reject the null hypothesis that the distributions are the same. The standard deviation of the OTM sample is statistically larger than for either the ATM or the ITM samples, which appears to support the hypothesis that hedge funds increase their risk when they are below their high water mark. However, it also appears that ITM funds also increase their risk, so it might be that funds who are ATM actually reduce their risk.

2.9 CONCLUSIONS

In this chapter I have demonstrated that estimating the factor exposures of hedge funds using net of fee returns will lead to biased results due to the non-linear impact of incentive fees. I have proposed an alternative procedure to estimate the exposures of the fund using gross returns and the effect of fees independently that is simple to implement. I have also illustrated, via a stylised example that the proposed procedure will lead to far more accurate estimates of investor exposures when the return generation process is known.

Using a large sample of hedge fund returns, I have shown that using net of fee returns understates the return attributable to beta by up to 58 basis points per annum. Following from this, I have demonstrated that some of this additional beta exposure can be captured by basing replication on gross rather than net returns.

I have also investigated the distribution of returns conditional upon the moneyness of the incentive option and found that the standard deviation is considerably higher for those managers who find themselves significantly above or below their high water mark. These results could be interpreted as evidence of increased risk taking and I will investigate this result further in the next chapter.

CHAPTER 3

LOCKING IN THE PROFITS OR PUTTING IT ALL ON BLACK? AN EMPIRICAL INVESTIGATION INTO THE RISK-TAKING BEHAVIOUR OF HEDGE FUND MANAGERS

Abstract

The ideal fee structure aligns the incentives of the investor with those of the fund manager. Mutual funds typically only charge a management fee which is a proportion of the funds under management. Hedge funds on the other hand generally change an incentive fee which is a fraction of the fund's return each year in excess of the high-water mark. The justification generally given for these incentive fees is that they provide the manager with the incentive to target absolute returns. As these incentive fees can be considered a call option on the performance of the fund (the fee structure gives the managers the positive fees with profits but no negative fees with losses), it is possible that the managers incentives might vary according to the delta of this option. A number of recent papers have examined the optimal investment strategies of money managers in the presence of incentive fees within a theoretical framework with seemingly conflicting results. In this chapter, using a large database of hedge fund returns, I examine the risk taking behaviour of hedge fund managers in response to both their past returns relative to their high-water mark and their past returns relative to their peer group. I then attempt to reconcile these results with the theoretical frameworks proposed.

3.1 INTRODUCTION

The ideal fee structure aligns the incentives of the investor with those of the fund manager. Investors will normally be looking to maximise their risk-adjusted return while fund managers will seek to maximise their fees. Mutual funds typically only charge a management fee which is a proportion of the funds under management. This traditional fee structure can only align fund manager and investor objectives to a limited degree: if the investor is unsatisfied with the performance of the manager they can usually withdraw their funds thus reducing the fee to zero. Hedge funds on the other hand generally charge both a management fee and an incentive fee which is a fraction of the fund's return each year in excess of a high-water mark. It is clear that this structure aligns the objectives of these two parties more closely since they both stand to benefit from incrementally better performance.

However hedge fund incentive fees are a contentious issue for two important reasons. First the fees can be very large as a proportion of the fund and can therefore be a drag on the performance of the fund[1]. Depending upon the variance of returns Goetzmann *et al* (2003) estimate that the performance fee effectively costs investors between 10 and 20 percent of the portfolio. Clearly investing in a hedge fund would only be rational if they provide a large, positive risk-adjusted return which compensates for these fees.

The second and perhaps more interesting issue is whether the incentive fees provide the manager with the right incentives anyway. On the one hand Anson (2001), who describes incentive fees as a “free option”, argues that the option-like nature of the incentive fee will lead the manager to increase the volatility of returns in order to maximise the value of this option. This is a view that is partially supported by Goetzmann *et al* (2003) who state that “*the manager has the incentive to increase risk provided other non modelled considerations are not overriding*”. An opposing view is presented by L’Habitant (2007) who considers the incentive fee as an option premium paid to the hedge fund manager by the investor. This premium ensures that the manager will optimise the size of the fund to keep returns high because the incentives for superior performance can be greater than for asset growth. He argues that the absence of incentive fees (for example in mutual funds) leads the manager to maximise funds under

[1] In the previous chapter for the period from 1994 to 2006 I found fees cost on average 5.15% pa.

management, which is not necessarily in the interests of the investor who is seeking to maximise risk-adjusted returns.

Several academic papers have examined the effect that incentive fees have upon the optimal dynamic investment strategies of fund managers within a theoretical framework. Typically these papers present a framework with one risky and one riskless asset and then examine the allocation the manager would make to each asset under various scenarios. The theoretical results provide a range of possible behaviour depending upon: the assumptions made about manager preferences'; the possibility of fund liquidation; and the assumed level of the management's stake in the fund. Thus the models illustrate the importance of what Goetzmann *et al* (2003) describe as *"non-modelled considerations"*, or what could also be described as implicit rather than explicit contract terms.

The explicit terms of the compensation contract are that investors agree to pay the manager a fixed percentage of positive returns while accepting all of the downside, if the contract was this simple then the manager would, as Anson (2001) describes, simply possess a call option on the future performance of the fund which would provide the manager with an incentive to increase risk. However, there are also many implicit terms to the contract that are more difficult to model, some of which will mitigate this problem and others that may exacerbate it. For example, investors will expect the hedge fund manger to invest a substantial percentage of their own net worth in the fund and penalise them for poor performance (or for excessive risk taking) by withdrawing their funds (just as a mutual fund client would). This will mitigate some of this risk taking. However, risk taking might be exacerbated if as has been illustrated using mutual fund flow data, fund flows are a convex function of past performance where good performance leads to significant fund inflows, but where poor performance leads to smaller net outflows. This results in manager compensation having a call option-like feature that can induce the manager to indulge in excessive risk-taking.

In this chapter I present empirical evidence of the influence of the hedge fund industry's typical fee structure on the risk taking behaviour of hedge fund managers. My analysis takes explicit account of the option-like features of the compensation structure. I also analyse the various hedge fund strategies separately rather than assuming that manager behaviour is effectively unaffected by their strategies, which is often the implicit assumption of other work in this area. Amongst other things, my results enable me to distinguish between and to say something about the competing theoretical models that seek to identify the relationship between incentives and hedge fund manager behaviour. To do this I use a large database of hedge fund returns and identify each fund's position relative to its peer group and to its high-water mark. After identifying the position of each fund in each of these two ways I can then examine whether hedge fund managers adjust the volatility of their fund in response to their performance relative to other hedge funds or the "moneyness" of the performance option.

I aim to answer questions of the following kind: do those funds that find that their incentive option is out of the money "*put it all on black*" and increase risk; do they maintain risk levels; or do they reduce them? I then attempt to reconcile these results with the theoretical frameworks proposed.

The rest of the chapter is organised as follows: Section 2 reviews the theoretical literature related to my analysis, Section 3 outlines the data and construction methodology, Section 4 presents the results and Section 5 concludes.

3.2 A REVIEW OF THE THEORETICAL MODELS OF BEHAVIOUR IN THE PRESENCE OF INCENTIVE FEES

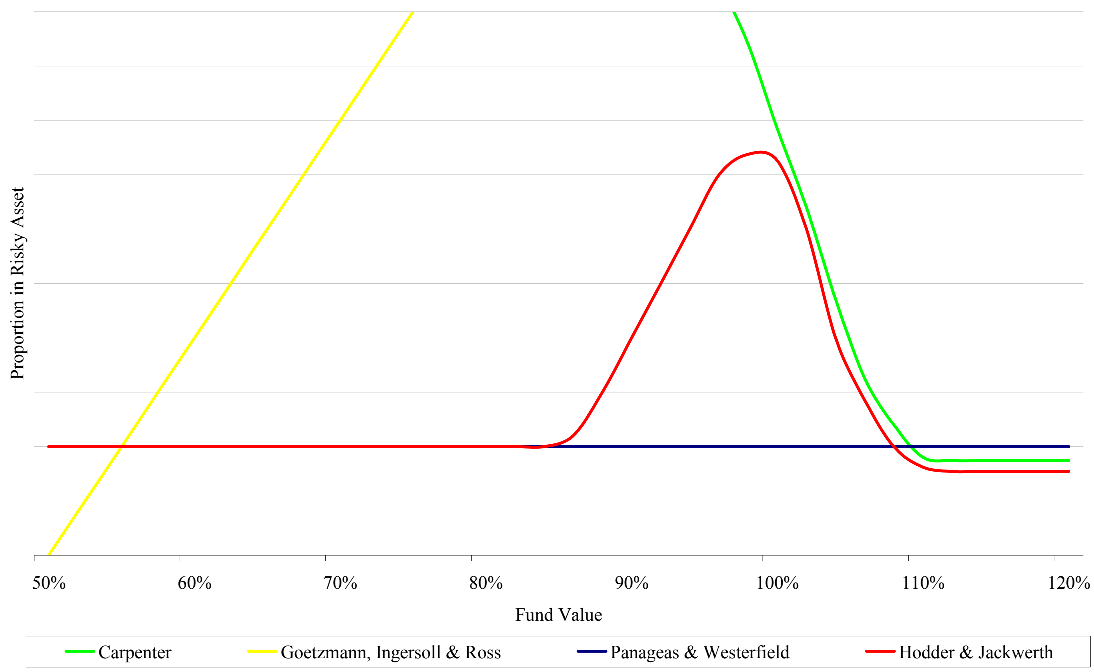
The conflicting results of theoretical models of fund manager behaviour in the presence of incentive fees and the importance of the implicit terms is clearly illustrated by contrasting the findings of Carpenter (2000), Goetzmann et al (2003), Hodder and Jackwerth (2007) and Panageas and Westerfield (2008). Carpenter (2000) examined the optimal risk taking behaviour of a risk-averse mutual fund manager who is paid with a call option on the assets they control (similar to hedge fund incentive fees). She found that a manager paid with an incentive fee increases the risk of the fund's investment strategy if the fund's return is below the hurdle rate and decreases the risk if the fund is above the hurdle rate. Carpenter's analysis is for a single evaluation period and does not consider the possibility of the fund being liquidated unless the value goes to zero. Goetzmann et al (2003) provide a closed-form solution to the cost of hedge fund fee contracts subject to a number of assumptions in a continuous time framework. They model incentive fees as an option and find that the cost of the contract rises as the portfolio's variance rises and hence conclude that the manager has the incentive to increase risk "provided other non modelled considerations are not overriding". The authors include the possibility that the fund can be liquidated if its value falls below a specified boundary and show that as the fund's value approaches this boundary the manager will reduce risk. So whereas Carpenter's theoretical manager would increase (decrease) risk as the fund value falls (rises) Goetzmann et al's would decrease (increase) risk as it falls (rises).

Hodder and Jackwerth (2007) consider the optimal risk-taking behaviour of an expected-utility maximising manager of a hedge fund who is compensated by both a management fee and an incentive fee. The authors also examine the effect of several implicit terms including the manager's own investment in the fund, a liquidation barrier where the fund is shut down due to poor performance and the ability of the manager to voluntarily shut down the fund as well as to enhance the fund's Sharpe Ratio through additional effort. Using a numerical approach they find that seemingly slight adjustments to the compensation structure can have dramatic effects on managerial risk taking behaviour. Specifically, they find that the existence of a liquidation barrier and an assumption that the managers own a percentage of the fund inhibits excessive risk taking as the fund value falls.

Panageas and Westerfield (2008) find that a manager compensated with an incentive fee and a high-water mark will place a constant fraction in the risky asset if they are operating in an infinite horizon setting. The intuition behind this is that the manager does not optimise just one option but an infinite time series of options, a manager who is below the high-water mark could increase the value of the current option by taking excessive risk today. However this will decrease the value of future options because it will also increase the probability of negative returns while the high-watermark is still fixed.

In Figure 3.1 I present a stylised summary of the differences between Carpenter's (2000), Goetzmann et al's (2003), Hodder and Jackwerth's (2007) and Panageas and Westerfield's (2008) models of fund manager behaviour in the presence of incentive fees.

Figure 3.1
Comparison of Risk Choices Under Various Theoretical Models of Behaviour



This figure shows how the optimal proportion of assets held in the risky asset varies with fund value under four different theoretical models of behaviour, Carpenter (2000), Goetzmann, Ingersoll and Ross (2003), Hodder and Jackwerth (2007) and Panageas and Westerfield (2008)

Figure 3.1 clearly illustrates the striking difference between Carpenter's and Goetzmann *et al*'s models of behaviour. Carpenter assumes that the fund will only be liquidated if the fund value goes to zero hence as the value of the fund falls the manager increases risk to increase the chance of collecting incentive fees without fearing liquidation. On the other hand, Goetzmann *et al* have a fixed liquidation boundary, thus as the fund value approaches this boundary the manager decreases risk in order to reduce the probability of liquidation. In the model of Panageas and Westerfield the manager holds a constant level of risk. Hodder and Jackwerth's model lies somewhere between the other three.

However, even in the absence of incentive fees there are implicit terms to the compensation contract that could encourage excessive risk taking. Chevalier and Ellison (1997) showed that if fund flows are a convex function of past performance, that is to say that more money flows into strong performers than out of weak performers, because the management fees are a fixed percentage of assets under management they will display call option like features. This in turn creates incentives for fund managers to increase or decrease the risk of the fund that are dependent on the fund's year-to-date return. Sirri and Tufano (1998) and others have confirmed that flows in and out of mutual funds do exhibit this convexity, superior relative performance leads to the growth of assets under management while there is no substantial outflow in response to poor relative performance. This flow/performance relationship was investigated for hedge funds by Agarwal, Daniel and Naik (2004) who find that funds in the top quintile of performers exhibit an inflow of 63%, while the bottom quintile exhibits an outflow of only 3%.

An empirical investigation of the risk taking behaviour of mutual funds for the 16 year period from 1976 to 1991 was undertaken by Brown, Harlow and Starks (1996). Using a contingency table approach they showed that mutual fund managers undertake what they termed as “tournament behaviour”, with funds whose mid-year returns were below the median (losers) increasing volatility in the latter part of the year by more than those funds whose mid-year returns were above the median (winners). The authors concluded that this behaviour was a direct consequence of the adverse incentives described above. Managers who have performed poorly by mid-year have incentives to increase their risk level to try and improve their ranking by the year-end; whereas managers with strong mid-year performance appeared to reduce risk in order to maintain their ranking.

The empirical relationship between risk taking and incentives in hedge funds has been examined by Ackermann, McEnally and Ravenscraft (1999) and Brown, Goetzmann and Park (2001) and many others. Using a regression approach Ackerman *et al* (1999) found a positive and significant relationship between the Sharpe ratio and the level of incentive fees but no statistically significant relationship between the level of risk (as measured by the standard deviation of returns) and the level of incentive fees. The authors concluded that this was evidence that the incentive structure was effective because it attracted top managers while not increasing their propensity to take on risk. Using a sample of hedge funds and commodity trading advisors (CTAs) from the TASS database Brown, Goetzmann, and Park (2001) showed that survival probability depends on absolute and relative performance, excess volatility, and on fund age. Perhaps not surprisingly the authors found that excess risk and poor relative performance substantially increased the probability of termination which they argue is a cost sufficient to offset the adverse incentive of excessive risk taking provided by the fee contract. Using a contingency table approach similar to Brown, Harlow and Starks

(1996) they found that funds tend to increase (decrease) their risk in response to poor (strong) relative performance but not in response to their absolute performance.

3.3 DATA AND METHODOLOGY

3.3.1 DATA

A major limitation of earlier studies is that they implicitly assume that hedge funds are a homogenous asset class. In practice however, the term "hedge fund" refers to the structure of the investment vehicle rather than the investment strategy being followed. Different strategies have varying levels of risk and historic return which makes a strategy level comparison essential if the results are to be meaningful. The data that I use in this study has been extracted from the TASS live and graveyard databases from January 1994 through to December 2007. More specifically, I extract monthly Net Asset Values (NAV), strategy details and inception dates for all hedge funds that are denominated in US Dollars, that report monthly and that have reported for at least one full calendar year over this sample period. These criteria result in a total sample of 4,990 funds of which 2,449 are currently reporting and 2,541 are no longer reporting. The data are summarised in Table 3.1.

Table 3.1
Summary Statistics for Hedge Fund Sample 1994-2007

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Convertible Arbitrage	26	38	40	47	51	64	75	81	104	120	122	105	97	66
Dedicated Short Bias	11	13	12	14	17	17	22	18	18	19	20	19	20	15
Emerging Markets	46	72	101	120	132	149	155	149	144	144	166	190	219	228
Equity Market Neutral	12	20	31	41	55	77	106	116	148	170	175	188	194	163
Event Driven	63	80	104	134	162	174	194	215	233	273	314	341	319	284
Fixed Income Arbitrage	19	30	41	55	55	67	69	77	91	115	144	166	159	132
Global Macro	48	55	61	68	83	87	76	77	89	112	135	139	147	131
Long/Short Equity Hedge	175	225	278	375	468	554	659	762	840	899	968	1,015	1,055	950
Managed Futures	156	175	169	179	186	176	178	172	160	172	188	210	217	214
Multi-Strategy	20	25	36	51	62	73	85	101	119	153	176	192	238	266
Total	576	733	873	1,084	1,271	1,438	1,619	1,768	1,946	2,177	2,408	2,565	2,665	2,449
Median Fund Size ($m)	6.6	5.5	6.1	8.0	11.0	11.3	15.6	18.9	20.0	20.7	27.0	28.9	31.2	60.0
Mean Fund Size ($m)	56.4	46.4	51.4	62.2	79.2	64.2	69.8	79.9	86.3	93.3	127.6	143.3	169.5	250.8
Median Age (months)	24	27	29	30	33	36	39	41	41	42	41	43	45	52
Mean Age (months)	37	38	40	41	44	47	49	51	52	54	56	58	61	68

This table presents summary information for the sample of hedge funds collected from the TASS database. Only funds that are denominated in US Dollars, report monthly performance and that have a return history spanning at least one full calendar year are included. The statistics for fund size are based on funds that report this information and thus do not represent every fund in the sample. Fund age is calculated based on the reported inception date of the fund.

The total number of funds has increased rapidly over time from just over 500 in 1994 to approximately 2,500 in 2007, of which the long/short equity category comprised 950. The mean and median fund sizes have also increased over time, the difference between these two statistics indicate that the sample is dominated by smaller funds. There is a similar but less pronounced pattern in the fund age.

Using the net asset values (NAVs) of each fund as reported in the TASS database I calculate the monthly gross returns of each hedge fund over time using the a the procedure outlined in Chapter 3. I use gross rather than net returns in order to isolate changes in risk that are a result of manager behaviour rather than being due to the mechanics of the incentive contract since as I demonstrated in the previous chapter incentive fees can have the effect of lowering the standard deviation of observed net returns when a fund is above its high-water mark which could clearly bias the results.

Calculation of the exact delta of the fee option is problematic because I do not have an appropriate model or a true estimate of the implied volatility, so instead I use the "moneyness" of the option as a proxy for delta. Moneyness is defined as:

$$Moneyness_{fMy} = \frac{NAV_{fMy}}{HighWaterMark_{fMy}} \tag{1}$$

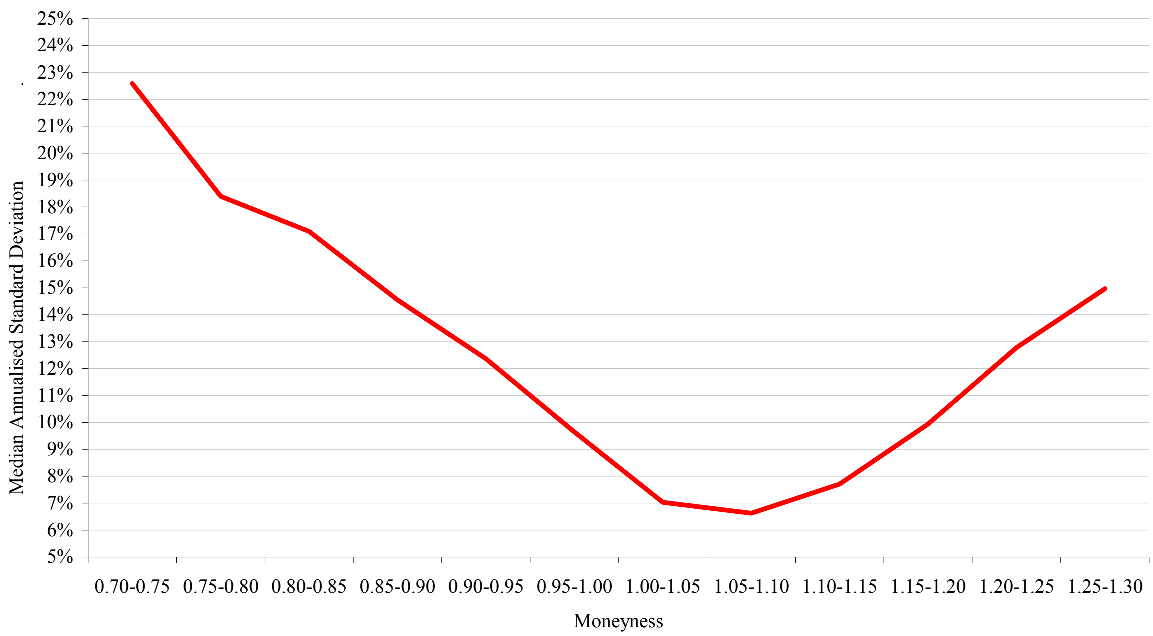
where $Moneyness_{fMy}$ defines fund f's value after M months of the year relative to its previous maximum value as represented by its high water mark at time, $HighWaterMark_{fMy}$

3.3.2 METHODOLOGY

One has to be extremely careful when interpreting the relationship between the risk choices of a fund manager in response to returns because the two are inherently linked. In the previous chapter, figure 6 showed the distribution of hedge fund returns conditional upon the moneyness of the incentive option for three sub-samples defined as "at the money" (ATM), "in the money" (ITM) and "out of the money" (OTM). The standard deviation of both the OTM and the ITM samples were statistically larger than for the ATM sample, which could support the hypothesis that hedge funds increase their risk when they are significantly below or above their high-water mark as defined in expression (1).

However there is an alternative explanation for the above result: funds that produce high return volatility are more likely to have extremely positive (or negative) performance and hence more likely to be classified as in (or out) of the money. Whereas funds with low return volatility are less likely to have had extreme return outcomes and hence are more likely to be classified as at the money. In order to investigate this I calculate the annualised standard deviation of gross returns for the funds in my sample for each calendar year as well as the moneyness of the incentive option at the end of the year. I then split the sample into 12 sub-samples based on levels of moneyness between 0.70 and 1.30 and calculate the median standard deviation for each sub sample. The results are presented in Figure 3.2.

Figure 3.2
Median Annualised Standard Deviation by Moneyness of Incentive Option



This figure shows the median historical annualised standard deviation of returns versus various levels of moneyness measured at the end of each calendar year.

The “V” shape of figure 3.2 illustrates that the alternative explanation of my earlier results is extremely possible. Those funds with historically lower standard deviation are more likely to be closer to “at the money” whereas those with higher standard deviation are more likely to be significantly in or out of the money.

In order to examine whether funds adjust the risk of their portfolios in response to their performance I need to examine the standard deviation of returns before and after a specific assessment point in time.

Using gross monthly hedge fund returns I calculate the annualised performance of fund f between January and month M. Specifically, for each fund *f* in a given year *y*, I calculate the M-month cumulative return as follows:

$$\text{Return}_{fMy} = \left[\left(1+r_{f1y}\right)+\left(1+r_{f2y}\right)+.....\left(1+r_{fMy}\right)\right]^{\frac{12}{M}} - 1 \qquad (2)$$

where r_f is the monthly gross return for hedge fund f. In my initial analysis I set M to 6 (June), but I also allow month M to vary between April and August so that the return is measured over periods ranging from four to eight months. I refer to this period as the "assessment period", that is, the period over which I assess the performance of each fund.

In order to analyse whether hedge funds adjust the risk of their portfolios in the post assessment period, that is from month M to December, I follow Brown *et al* (1996) and calculate the Risk Adjustment Ratio (RAR) using the following expression:

$$RAR_{fy} = \frac{\sqrt{\left(\frac{\sum_{m=M+1}^{12}\left(r_{fmy}-\bar{r}_{f(12-M)y}\right)^2}{(12-M)-1}\right)}}{\sqrt{\left(\frac{\sum_{M=1}^{M}\left(r_{fmy}-\bar{r}_{fMy}\right)^2}{M-1}\right)}} \qquad (3)$$

where RAR_{fy} represents the RAR of fund f in year y. Expression (3) is simply the ratio of the standard deviation of returns for the post assessment period to the standard deviation of returns over the assessment period. In my base case the assessment period is from January to June (M=6). This analysis is conducted using non-overlapping assessment and post assessment periods.

As well as assessing the performance of the fund from January to month M, I also calculate the moneyness of the incentive fee option at the end of month M. The performance of any fund over the assessment period might be above the median return for its strategy, but still may not be sufficient to lift the fund's performance above its high water mark and therefore may not be enough for the manger to be able to claim a performance fee. By using moneyness as a way of categorising the position of the fund and therefore the fund manager's attitude to risk, I can assess the influence not only of relative performance, but also the value of the incentive option on manager behaviour.

I analyse the post-assessment performance of fund f relative to the performance of the hedge fund strategy to which it belongs. I therefore ask whether the funds adjust their behaviour relative to their peer group. I normalise the post assessment return and the RAR by using the following expressions:

$$Normalised\,\mathrm{Re}turn_{fMy} = \mathrm{Re}turn_{fMy} - Median\left[\mathrm{Re}turn_{sMy}\right] \quad (5)$$

$$Normalised\ RAR_{fMy} = RAR_{fMy} - Median\left[RAR_{sMy}\right] \quad (6)$$

where *s* is one of the ten individual strategies being considered such that *Normalised Return* and *Normalised RAR* are measures of how fund f either performed or changed risk relative to other funds following the same strategy for a particular period. A value greater (less) than zero for each expressions (5) and (6) should therefore be taken to indicate that the fund in question has either outperformed (underperformed) its peer group, or increased (decreased) its risk by more (less) than its peer group for the particular period in question.

Using the variables calculated above I construct 2x2 contingency tables in order to test whether hedge funds adjust their risk in response to either their relative performance or the moneyness of their incentive option. Specifically I construct two 2x2 tables where I split the funds into those with high (Normalised RAR>0) or low (Normalised RAR<0) Risk Adjustment Ratios conditioned upon either past performance or moneyness. The null hypothesis in each case is that the percentage of the sample population falling into each of the high or low RAR categories is independent of either the return or the moneyness. The statistical significance of these frequencies is tested in 2 ways:

i) a chi-square test having one degree of freedom (though this might be mis-specified as it assumes the cell counts are independent); and

ii) the log odds ratio, which is robust to the misspecification of the chi-square test and also provides additional information regarding the direction and level of dependence.

Although the contingency table approach will identify whether there is any directional relationship between the Risk Adjustment Ratio and either past performance or the moneyness of the incentive option, this approach assumes that the relationship is linear. In order to examine further this relationship I construct tables where Normalised RAR is conditioned upon either:

i) 12 levels of moneyness between 0.70 and 1.30, and

ii) 10 Deciles of relative performance

For each of these sub-samples I then test whether the median Normalised RAR is significantly different from zero using the Wilcoxon Signed Rank test.

3.4 RESULTS

In panel A of Table 3.2 I present summary statistics of the median annualised return for each strategy and for all funds on an annual basis using a 6 month assessment period; in Panel B I present the median moneyness for the same break down of funds over the assessment period; while in Panel C I present the RAR for the assessment period for the same stratification.

These results clearly illustrate the heterogeneous nature of the ten hedge fund strategies being examined. For example consider a global macro hedge fund in 1994 that produced an annualised return of 1% in the first half of the year and had a RAR of 0.80. Treating hedge funds as one homogenous group would classify this as being below the 1.5% median return and below the 0.85 median RAR, yet it is considerably above the median return of -8.3% and above the median RAR of 0.74 for funds following the same strategy, namely global macro. Additionally market conditions at particular points in time can affect different strategies in different ways, for example the median RAR for fixed income arbitrage funds during the 1998 LTCM/Russian debt crisis was 2.93, but it was only 1.33 for global macro funds and 1.84 for all hedge funds.

Table 3.2
Summary Statistics Return, Moneyness and Risk Adjustment Ratio (RAR)
1994-2007

Panel A: Median (Annualised) Gross Return

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Convertible Arbitrage	-5.4%	18.6%	24.9%	19.3%	14.4%	19.9%	28.2%	22.4%	11.3%	16.5%	1.4%	-7.3%	17.4%	12.5%
Dedicated Short Bias	57.1%	-8.7%	-4.7%	2.7%	-2.6%	-14.5%	-16.1%	7.2%	39.9%	-18.5%	-4.3%	7.8%	-0.3%	-8.1%
Emerging Markets	-5.0%	-0.8%	38.5%	51.5%	-19.2%	47.2%	8.4%	15.5%	20.7%	42.3%	7.3%	12.0%	17.3%	29.8%
Equity Market Neutral	6.9%	17.4%	23.0%	20.6%	14.5%	12.7%	20.5%	12.8%	6.9%	7.6%	5.1%	7.8%	14.5%	13.3%
Event Driven	9.7%	23.8%	25.5%	20.1%	17.8%	23.6%	21.6%	11.5%	4.2%	23.5%	10.3%	8.1%	17.7%	18.2%
Fixed Income Arbitrage	9.5%	17.6%	20.3%	21.2%	11.7%	19.6%	12.1%	15.8%	15.7%	12.8%	9.1%	7.7%	12.9%	11.9%
Global Macro	-8.3%	19.9%	13.5%	14.1%	8.5%	4.7%	6.3%	11.3%	11.9%	18.5%	1.0%	6.2%	7.6%	15.2%
Long/Short Equity Hedge	-0.3%	32.6%	35.6%	27.7%	24.5%	42.0%	20.2%	8.2%	2.5%	18.1%	6.8%	6.1%	14.2%	24.1%
Managed Futures	2.7%	22.1%	4.7%	16.4%	4.9%	7.4%	-3.0%	5.1%	13.0%	22.3%	-8.3%	-0.5%	15.8%	12.4%
Multi-Strategy	-2.5%	18.6%	20.5%	21.1%	16.7%	23.0%	28.1%	14.9%	6.6%	14.8%	6.2%	4.1%	14.5%	18.9%
All Funds	1.5%	21.6%	23.7%	22.5%	15.2%	24.3%	15.8%	11.3%	7.3%	17.5%	5.9%	6.3%	14.5%	18.9%

Panel B: Median Moneyness

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Convertible Arbitrage	0.97	1.04	1.07	1.05	1.05	1.06	1.08	1.07	1.03	1.06	1.01	0.94	1.04	1.04
Dedicated Short Bias	1.11	1.00	0.83	0.96	0.96	0.93	0.91	0.89	0.98	0.89	0.71	0.65	0.61	0.53
Emerging Markets	0.97	0.96	1.06	1.09	0.90	0.83	0.92	0.97	1.04	1.07	1.02	1.02	1.06	1.08
Equity Market Neutral	1.01	1.04	1.06	1.05	1.04	1.03	1.07	1.03	1.02	1.01	1.01	1.02	1.04	1.04
Event Driven	1.02	1.06	1.07	1.05	1.06	1.06	1.05	1.04	1.02	1.06	1.02	1.01	1.06	1.07
Fixed Income Arbitrage	1.03	1.05	1.05	1.06	1.03	1.04	1.02	1.04	1.04	1.03	1.02	1.02	1.04	1.04
Global Macro	0.92	1.00	1.05	1.03	1.03	0.99	1.00	1.02	1.01	1.04	1.00	0.99	1.02	1.03
Long/Short Equity Hedge	1.00	1.06	1.13	1.07	1.07	1.08	1.03	1.01	1.01	1.01	1.01	1.00	1.05	1.08
Managed Futures	0.98	1.03	1.00	1.03	1.00	0.99	0.97	1.01	0.97	1.10	0.98	0.96	1.04	1.02
Multi-Strategy	1.00	1.02	1.06	1.06	1.05	1.05	1.07	1.04	1.02	1.04	1.01	1.00	1.05	1.06
All Funds	1.00	1.04	1.07	1.05	1.04	1.04	1.03	1.03	1.02	1.03	1.01	1.00	1.05	1.06

Panel C: Median RAR

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Convertible Arbitrage	1.00	0.78	1.14	1.27	2.09	1.03	0.90	0.67	1.84	0.89	0.59	0.72	0.54	2.18
Dedicated Short Bias	0.92	1.09	1.59	0.92	2.06	1.24	1.01	1.19	1.39	0.84	1.50	1.18	0.88	1.34
Emerging Markets	0.89	0.59	0.72	1.65	1.75	1.02	0.74	1.29	0.94	0.86	0.70	1.18	0.51	1.68
Equity Market Neutral	0.96	1.25	0.96	0.97	1.65	0.87	0.75	0.80	1.44	1.01	0.99	1.05	0.83	1.40
Event Driven	0.85	0.97	0.97	1.02	2.58	0.93	0.70	1.09	1.20	0.77	1.10	1.08	0.85	1.62
Fixed Income Arbitrage	0.88	0.86	1.00	1.14	2.93	1.09	0.84	1.24	1.14	1.20	0.81	0.87	0.92	1.93
Global Macro	0.74	0.97	0.98	0.99	1.33	1.14	0.89	0.87	0.99	0.98	0.93	1.09	0.72	1.87
Long/Short Equity Hedge	0.87	1.31	1.15	1.08	1.78	1.02	0.66	0.92	1.25	0.88	1.09	1.06	0.65	1.68
Managed Futures	0.80	0.85	1.01	1.36	1.81	0.96	1.50	1.10	1.17	0.68	0.74	1.02	0.83	1.33
Multi-Strategy	0.82	1.07	0.85	1.33	1.97	1.07	0.79	0.86	1.35	0.90	0.89	1.14	0.66	2.13
All Funds	0.85	0.97	1.00	1.17	1.84	1.01	0.76	0.97	1.24	0.86	0.95	1.05	0.71	1.68

This table presents median values for various statistics for both individual strategies and for all funds in the sample using a 6 month assessment and post assessment period. Panel A presents the median annualised return for M=6 calculated from equation (2) in the text. Panel B presents the median moneyness for M=6 calculated from equation (4). Panel C presents the median risk adjustment ratio calculated from equation (3) for M=6.

Although I do calculate the performance statistics described in Section 3 above treating all hedge funds as one group, I believe that the results are more meaningful when they are considered by strategy.

3.4.1 CONTINGENCY TABLES

Table 3.3 shows the contingency table results using the period from January to the end of June in each full year as the assessment period (M=6) categorised by their returns over the assessment period (Panel A) and by moneyness at the end of June (Panel B), and therefore the period from July to December as the post assessment period.

Panel A shows that over the full sample period I can reject the null hypothesis of independence between the relative return and RAR. More specifically, the Low Return/High RAR and High Return/Low RAR cells have statistically significantly larger frequencies than the other two outcomes. This result is in line with the findings of Brown *et al* (1996) for mutual funds: those funds that have generated returns that are below the median for their strategy over the first six months of the year are likely to increase risk more than the median fund possibly in order to try and improve their whole-of-year ranking; while those funds that have achieved above median returns for their strategy are more likely to decrease risk, possibly in order to protect their returns and relative performance rankings. Taking each year individually, the log odds ratio shows that the relationship is in the same direction for 12 out of the 14 years in the sample and is statistically significant for ten of these years.

Panel B shows that for the full 14 year sample period I can reject the null hypothesis of independence between moneyness and the subsequent RAR with the Below HW Mark/High RAR and Above HW Mark/Low RAR cells having statistically significant and larger frequencies than the other two outcomes implying that those funds that find themselves below their high-water marks after six months increase risk relative to the median risk during the post assessment period, and those funds above it decrease risk. When I look at individual years, the log odds ratio shows that the relationship is only in the same direction for 11 out of the 14 years in the sample and is only statistically significant for 5 of them. In fact in 2007 the relationship is statistically significant and in the opposite direction – implying that in this year funds that were below their high water mark after 6 months reduced their risk relative to the median risk during the post assessment period.

Table 3.3 -Contingency Tables of Relative Returns, Moneyness and Risk Adjustment Ratio

Panel A

	Observations	Below Median Return		Above Median Return		Log Odds Ratio	Std Error Log Odds	t-value	Chi-Square
		Lower RAR	Higher RAR	Lower RAR	Higher RAR				
1994	576	25.69%	23.96%	24.65%	25.69%	-0.1113	0.1667	-0.67	0.45
1995	733	21.96%	26.74%	28.38%	22.92%	0.4103	0.1486	2.76	7.65**
1996	873	20.39%	27.26%	29.90%	22.45%	0.5769	0.1369	4.21	17.87**
1997	1,084	21.86%	27.86%	28.41%	21.86%	0.5044	0.1225	4.12	17.06**
1998	1,271	23.92%	25.18%	26.28%	24.63%	0.1162	0.1123	1.04	1.07
1999	1,438	20.38%	27.96%	29.83%	21.84%	0.6283	0.1068	5.88	34.87**
2000	1,619	22.30%	26.25%	27.86%	23.59%	0.3293	0.0998	3.30	10.91**
2001	1,768	23.53%	25.57%	26.64%	24.26%	0.1764	0.0952	1.85	3.43
2002	1,946	22.51%	26.16%	27.60%	23.74%	0.3007	0.0910	3.31	10.95**
2003	2,177	20.26%	28.25%	29.86%	21.64%	0.6547	0.0869	7.53	57.24**
2004	2,408	22.84%	25.71%	27.20%	24.25%	0.2329	0.0817	2.85	8.14**
2005	2,565	25.03%	22.92%	25.07%	26.98%	-0.1613	0.0791	-2.04	4.16*
2006	2,665	22.78%	26.38%	27.35%	23.49%	0.2992	0.0777	3.85	14.85**
2007	2,449	23.23%	24.50%	26.87%	25.40%	0.1093	0.0809	1.35	1.82
1994-2007	23,572	22.68%	25.91%	27.47%	23.94%	0.2708	0.0261	10.37	107.61**

Panel B

		Below High-Water Mark		Above High-Water Mark		Log Odds Ratio	Std Error Log Odds	t-value	Chi-Square
		Lower RAR	Higher RAR	Lower RAR	Higher RAR				
1994	576	25.52%	25.17%	24.83%	24.48%	0.0004	0.1667	0.00	0.00
1995	733	15.14%	18.01%	35.20%	31.65%	0.2795	0.1574	1.78	3.16
1996	873	9.51%	11.68%	40.78%	38.03%	0.2759	0.1664	1.66	2.76
1997	1,084	8.39%	9.32%	41.88%	40.41%	0.1401	0.1593	0.88	0.77
1998	1,271	14.63%	14.24%	35.56%	35.56%	-0.0272	0.1238	-0.22	0.05
1999	1,438	11.89%	15.79%	38.32%	34.01%	0.4027	0.1188	3.39	11.55**
2000	1,619	16.12%	17.11%	34.03%	32.74%	0.0984	0.1056	0.93	0.87
2001	1,768	17.48%	18.55%	32.69%	31.28%	0.1039	0.0991	1.05	1.10
2002	1,946	20.40%	20.91%	29.70%	28.98%	0.0494	0.0921	0.54	0.29
2003	2,177	12.68%	15.34%	37.44%	34.54%	0.2712	0.0958	2.83	8.04*
2004	2,408	16.74%	19.27%	33.31%	30.69%	0.2228	0.0851	2.62	6.87*
2005	2,565	18.87%	15.36%	31.23%	34.54%	-0.3066	0.0836	-3.67	13.50**
2006	2,665	7.69%	10.81%	42.44%	39.06%	0.4229	0.1010	4.19	17.68**
2007	2,449	5.76%	4.29%	44.34%	45.61%	-0.3229	0.1358	-2.38	5.69
1994-2007	23,572	13.85%	14.78%	36.30%	35.07%	0.0997	0.0288	3.46	11.96**

*Proportions in the body of the table give the proportion of funds that fall into each classification. Each fund was required to have a complete return history for each calendar year. Above and below median measures are defined as Normalised Return or RAR greater or less than zero. The log odds ratio is the log of the ratio of the product of the second and third columns to the product of the first and fourth with standard error and the t-value measures the significance of this ratio. The chi-square number represent the statistics from the 2x2 contingency tables with 1 degree of freedom. Values significant at the 5% level are denoted with * and those significant at 1% by **.*

These results imply that although hedge fund managers adjust their risk in response to both their relative returns and according to the moneyness of the incentive option the effect is more pronounced in the former rather than the latter case. This is borne out by the fact that the log odds ratio of 0.2708 is greater overall when performance is benchmarked against the median performance (last row, column (7) of Table 3.3, Panel A) compared with a logs odds ratio of 0.0997 when performance is assessed as a function of the moneyness of the fund at the start of the post assessment period (last row, column (7) of Table 3.3, Panel B).

After considering the case of M=6 I now consider other assessment and post assessment periods. My original choice of M=6 was a relatively arbitrary one. It may be that funds change their risk exposures in response to their performance relative to their peers, or because of the moneyness of the incentive option earlier, or later in the year. In Table 4 I present results analogous to those in Table 3 but with M=4, 5, 6, 7 and 8. My assessment periods are therefore either from January to April (M=4) or from January to May (M=5) etc; and I calculate the moneyness of the fund at the end of April (M=4) or at the end of May (M=5) etc. The results are all for the full 14 year sample rather than for individual years[2].

Panel A in Table 3.4 shows that for all assessment periods the effect of relative return on normalised RAR is statistically significant but at a declining rate, as evidenced by the declining value of the log odds ratio that falls from 0.2401 to 0.1597. This result suggests that fund managers are more likely to change their risk taking behaviour earlier on in the year rather than later in the year – and most likely halfway through the year. The effect of moneyness (presented in panel B) appears to be only statistically significant for M=6 and M=8, with the log odds ratio increasing from -0.0024 to 0.0931 as we move from M=4 to M=8.

These results imply that hedge fund managers care more about relative return early in the year but more about the value of their incentive option (absolute return) later on in the year. One possible explanation for this is that as the year moves towards its end managers have less chance or opportunity to improve their ranking but can attempt to

[2]I repeat the results for M=6 here for completeness. Yearly results for each value of M are available on request.

Table 3.4 - Contingency Tables of Relative Returns, Moneyness and Risk Adjustment Ratio Varying the Assessment Period

Panel A

Assessment Period	Obs	Below Median Return		Above Median Return		Log Odds Ratio	Std Error Log Odds	t-value	Chi-Square
		Lower RAR	Higher RAR	Lower RAR	Higher RAR				
(4,8)	23,574	22.82%	25.68%	27.32%	24.18%	0.2401	0.0261	9.20	84.65**
(5,7)		22.64%	25.88%	27.50%	23.98%	0.2704	0.0261	10.35	107.34**
(6,6)		22.68%	25.91%	27.47%	23.94%	0.2708	0.0261	10.37	107.61**
(7,5)		23.31%	25.44%	26.83%	24.42%	0.1819	0.0261	6.97	48.63**
(8,4)		23.56%	25.41%	26.59%	24.44%	0.1597	0.0261	6.13	37.54**

Panel B

Assessment Period	Obs	Below High-Water Mark		Above High-Water Mark		Log Odds Ratio	Std Error Log Odds	t-value	Chi-Square
		Lower RAR	Higher RAR	Lower RAR	Higher RAR				
(4,8)	23,574	15.92%	15.81%	34.22%	34.05%	-0.0024	0.0280	-0.08	0.01
(5,7)		14.94%	15.52%	35.20%	34.34%	0.0633	0.0283	2.24	5.01
(6,6)		13.85%	14.78%	36.30%	35.07%	0.0997	0.0288	3.46	11.96**
(7,5)		14.40%	14.94%	35.74%	34.92%	0.0599	0.0286	2.09	4.38
(8,4)		14.33%	15.21%	35.82%	34.64%	0.0931	0.0286	3.26	10.62**

*Proportions in the body of the table give the proportion of funds falling into each classification. Each fund was required to have a complete return history for each calendar year. Above and below median measures are defined as Normalised Return or RAR greater or less than zero. The log odds ratio is the log of the ratio of the product of the second and third columns to the product of the first and fourth with standard error and the t-value measuring the significance of this. The chi-square number represents the statistics from the 2x2 contingency tables with 1 degree of freedom. Values significant at the 5% level are denoted with * and those significant at 1% by **.*

maximise the fees they will receive by increasing risk, though the data does not support this. The proportion of funds that are below their high-water mark that increase risk actually falls from 15.81% over the (4,8) assessment period to 15.21% over the (8,4) assessment period. Rather the result appears to be driven by the proportion of funds that are above their high-water mark who reduce risk which increases from 34.22% to 35.82%.

3.4.2 DISAGGREGATED ANALYSIS

Having ascertained that there appears to be a relationship between the risk taking decisions of hedge fund managers and both their relative performance and the value of their incentive option using 2x2 contingency tables I now examine the relationship across a broader cross-section of relative returns and moneyness.

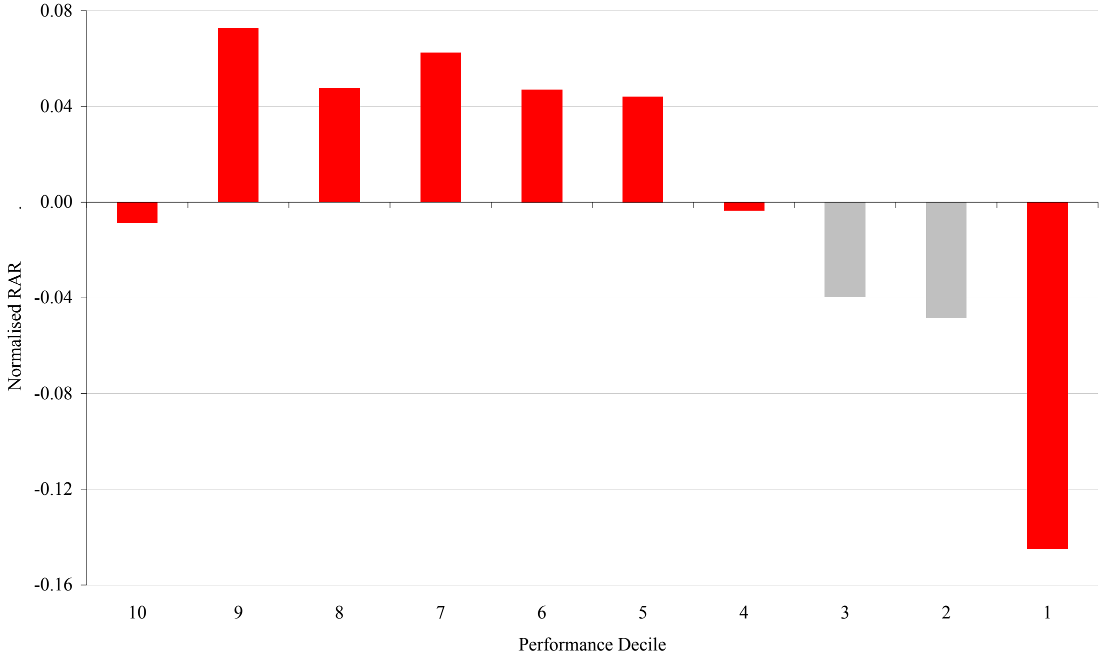
Table 3.5 presents the results for the effect of relative performance on Normalised RAR for M=6. These results are shown in Figure 3.3 too. Although the funds in the top four performance deciles reduce risk this reduction is only statistically significant for the first and fourth deciles. Meanwhile there is a statistically significant increase in risk for the fifth to the ninth performance deciles. This confirms my previous results and is consistent with the mutual fund literature that shows that fund managers react to their implicit incentives to increase (decrease) risk in order to improve (maintain) their ranking by year end.

Table 3.5 - Median Normalised Risk Adjustment Ratio by Performance Decile

Assessment Period	Performance Decile	10	9	8	7	6	5	4	3	2	1
(6,6)	Observations	2,132	2,275	2,304	2,378	2,363	2,427	2,397	2,438	2,432	2,426
	Median Normalised RAR	-0.0088**	0.0726**	0.0475**	0.0624**	0.0470**	0.0441**	-0.0036**	-0.0397	-0.0484	-0.1449**
	Wilcoxon Statistic	-2.9985	-10.3075	-9.2600	-10.6714	-9.5400	-8.6747	-5.2503	-0.6152	-0.3410	-8.1947
	p-Value	0.0027	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.5384	0.7331	0.0000

*The table presents the normalised risk adjustment ratio by performance decile as well as the test statistics for a Wilcoxon signed rank test of this median. Values significant at the 5% level are denoted with * and those significant at 1% by **.with * and those significant at 1% by **.*

Figure 3.3 - Median Normalised Risk Adjustment Ratio by Performance Decile



This figure shows the median normalised risk adjustment ratio by performance decile with statistically significant values in red and others in grey

Table 3.6 presents the results for the effect of the moneyness of the incentive option (absolute performance) on subsequent Normalised RAR for M=6. These results are shown in Figure 3.4 too.

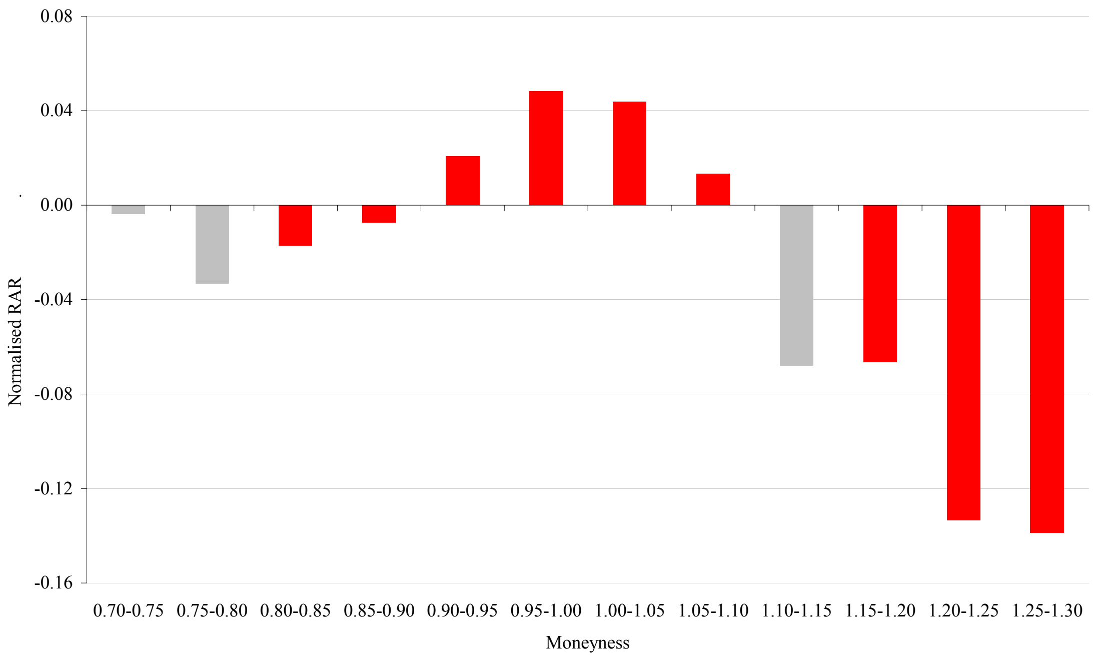
Here we see that there is evidence of a statistically significant change in risk behaviour across the moneyness categories. For moneyness above 1.15, that is for fund's that are 15% above the high-water mark half way through the year, there appears to be a statistically significant risk reduction, this is in line with the theoretical models presented by Carpenter (2000) and Hodder and Jackwerth (2007) who describe this as "locking in" behaviour. However for moneyness between 1.05 and 0.90 that is 5% above to 10% below the high - water mark after six months there is a statistically significant increase in risk. More interestingly we can see that for funds that are more than 10% below their high water mark after the first half of the year there is a reduction in risk taking behaviour and this reduction in risk is statistically significant for levels of moneyness down to 0.80. These results clearly do not support Carpenter's model but are much closer to the model proposed by Hodder and Jackwerth.

Table 3.6 - Median Normalised Risk Adjustment Ratio by Moneyness

Assessment Period	Moneyness	0.70-0.75	0.75-0.80	0.80-0.85	0.85-0.90	0.90-0.95	0.95-1.00	1.00-1.05	1.05-1.10	1.10-1.15	1.15-1.20	1.20-1.25	1.25-1.30
(6,6)	Observations	244	300	460	810	1,358	2,796	6,292	5,140	2,420	1,197	691	342
	Normalised RAR	-0.0037	-0.0332	-0.0171*	-0.0074*	0.0207**	0.0481**	0.0437**	0.0133**	-0.0678	-0.0665*	-0.1334**	-0.1387**
	Wilcoxon Statistic	-1.1305	-0.4416	-2.0408	-2.5126	-4.7442	-9.4457	-15.7107	-9.3987	-0.3358	-1.9776	-3.9762	-2.9477
	p-Value	0.2583	0.6588	0.0413	0.0120	0.0000	0.0000	0.0000	0.0000	0.7370	0.0480	0.0001	0.0032

*The table presents the normalised risk adjustment ratio by performance decile as well as the test statistics for a Wilcoxon signed rank test of this median. Values significant at the 5% level are denoted with * and those significant at 1% by **.*

Figure 3.4 - Median Normalised Risk Adjustment Ratio by Moneyness



This figure shows the median normalised risk adjustment ratio by performance level of moneyness with statistically significant values in red and others in grey

3.4.3 VARYING THE ASSESSMENT PERIOD

Table 3.7 presents the results for the effect of relative performance on Normalised RAR for a assessment periods ranging from (4,8) to (8,4). The results are broadly consistent across all assessment periods with a large negative and significant normalised RAR for the top performing decile and smaller positive normalised RAR for lower deciles.

Table 3.8 presents the results for the effect of moneyness on Normalised RAR for a assessment periods ranging from (4,8) to (8,4). In contrast to the results for the response to relative performance, here I find significant changes in response as I vary the assessment period. As the assessment period increases from M=4 to M=8, although the results for above 1.10 moneyness are broadly consistent, with a normalised RAR significantly below zero, managers that are below their high-water mark appear to change their behaviour. In the early part of the year normalised RAR is below zero for levels of moneyness below 0.85 (in some cases this is statistically significantly), however as we move towards August (8,4) there is a significant increase in risk, in fact for the (8,4) assessment period the median normalised RAR is significantly above zero for all levels of moneyness below 1.15.

Table 3.7 - Median Normalised Risk Adjustment Ratio by Performance Decile, Varying the Assessment Period

Assessment Period	Performance Decile	10	9	8	7	6	5	4	3	2	1
(4,8)	Observations	2112	2293	2303	2365	2361	2434	2403	2441	2417	2445
	Median Normalised RAR	-0.0163**	0.0259**	0.0425**	0.0593**	0.0571**	0.0463**	-0.0008**	-0.0156**	-0.0452	-0.1382**
	Wilcoxon Statistic	-4.3230	-8.8680	-10.1317	-11.3619	-11.3571	-11.2073	-7.1557	-4.7867	-1.6422	-7.1910
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1006	0.0000
(5,7)	Observations	2117	2279	2321	2382	2338	2435	2416	2422	2434	2430
	Median Normalised RAR	-0.0173**	0.0470**	0.0603**	0.0492**	0.0402**	0.0397**	-0.0001**	-0.0253**	-0.0585	-0.1336**
	Wilcoxon Statistic	-3.2537	-9.9317	-10.8222	-10.7923	-9.2358	-9.6500	-5.4474	-2.8691	-0.0705	-7.5317
	p-Value	0.0011	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0041	0.9438	0.0000
(6,6)	Observations	2132	2275	2304	2378	2363	2427	2397	2438	2432	2426
	Median Normalised RAR	-0.0088**	0.0726**	0.0475**	0.0624**	0.0470**	0.0441**	-0.0036**	-0.0397	-0.0484	-0.1449**
	Wilcoxon Statistic	-2.9985	-10.3075	-9.2600	-10.6714	-9.5400	-8.6747	-5.2503	-0.6152	-0.3410	-8.1947
	p-Value	0.0027	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.5384	0.7331	0.0000
(7,5)	Observations	2158	2288	2317	2371	2359	2428	2391	2427	2412	2423
	Median Normalised RAR	-0.0134**	0.0430**	0.0354**	0.0406**	0.0347**	0.0364**	-0.0011**	-0.0053**	-0.0412	-0.1496**
	Wilcoxon Statistic	-3.7883	-7.3760	-8.3569	-8.5266	-8.1039	-8.1704	-5.2824	-4.1589	-1.8652	-7.1575
	p-Value	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0622	0.0000
(8,4)	Observations	2199	2295	2328	2366	2355	2417	2376	2402	2423	2413
	Median Normalised RAR	0.0323**	0.0288**	0.0089**	0.0233**	0.0450**	0.0022**	0.0106**	0.0113**	-0.0420	-0.1461**
	Wilcoxon Statistic	-7.0864	-7.5212	-6.1737	-7.2004	-7.8144	-5.8398	-6.2301	-4.5616	-1.7225	-4.9008
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0850	0.0000

*The table presents the normalised risk adjustment ratio by performance decile as well as the test statistics for a Wilcoxon signed rank test of this median. Values significant at the 5% level are denoted with * and those significant at 1% by **.*

Table 3.8 - Median Normalised Risk Adjustment Ratio by Moneyness Varying the Assessment Period

Assessment Period	Moneyness	0.70-0.75	0.75-0.80	0.80-0.85	0.85-0.90	0.90-0.95	0.95-1.00	1.00-1.05	1.05-1.10	1.10-1.15	1.15-1.20	1.20-1.25	1.25-1.30
(4,8)	Observations	209	310	498	795	1533	3347	7943	4528	1828	802	359	223
	Median Normalised RAR	-0.0040*	-0.0206	-0.0643	0.0000**	-0.0018**	0.0228**	0.0597**	-0.0077**	-0.0713	-0.0551	-0.1348**	-0.1303*
	Wilcoxon Statistic	-1.99	-0.45	-0.24	-3.11	-5.04	-9.26	-21.42	-8.19	-0.65	-1.41	-3.19	-2.13
	p-Value	0.05	0.65	0.81	0.00	0.00	0.00	0.00	0.00	0.52	0.16	0.00	0.03
(5,7)	Observations	246	311	479	805	1387	3190	7029	4935	2095	1016	520	265
	Median Normalised RAR	-0.0392	0.0019	-0.0277	0.0248**	0.0120**	0.0281**	0.0499**	0.0000**	-0.0690	-0.0831*	-0.0699*	-0.1458**
	Wilcoxon Statistic	-0.42	-0.64	-1.88	-3.11	-4.68	-9.77	-17.97	-8.31	-1.14	-2.51	-2.15	-3.31
	p-Value	0.68	0.52	0.06	0.00	0.00	0.00	0.00	0.00	0.26	0.01	0.03	0.00
(6,6)	Observations	244	300	460	810	1358	2796	6292	5140	2420	1197	691	342
	Median Normalised RAR	-0.0037	-0.0332	-0.0171*	-0.0074*	0.0207**	0.0481**	0.0437**	0.0133**	-0.0678	-0.0665*	-0.1334**	-0.1387**
	Wilcoxon Statistic	-1.13	-0.44	-2.04	-2.51	-4.74	-9.45	-15.71	-9.40	-0.34	-1.98	-3.98	-2.95
	p-Value	0.26	0.66	0.04	0.01	0.00	0.00	0.00	0.00	0.74	0.05	0.00	0.00
(7,5)	Observations	261	361	528	828	1452	2637	5700	4976	2547	1314	780	421
	Median Normalised RAR	0.0395	-0.0116	0.0507**	0.0264**	-0.0079**	0.0118**	0.0276**	0.0212**	-0.0211**	-0.0436	-0.1118	-0.1123**
	Wilcoxon Statistic	-1.84	-1.53	-3.62	-3.56	-3.51	-6.50	-12.73	-10.25	-2.61	-0.59	-1.50	-3.03
	p-Value	0.07	0.13	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.55	0.13	0.00
(8,4)	Observations	284	361	554	829	1380	2607	5193	4881	2698	1417	825	504
	Median Normalised RAR	0.1052**	0.1201**	0.0158**	0.0035**	0.0046**	0.0220**	0.0290**	0.0032**	0.0005**	-0.0431	-0.0689	-0.0863
	Wilcoxon Statistic	-2.99	-5.04	-2.72	-3.06	-3.85	-6.53	-11.76	-8.27	-5.02	-0.60	-0.42	-1.65
	p-Value	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.55	0.67	0.10

*The table presents the normalised risk adjustment ratio by performance level of moneyness as well as the test statistics for a Wilcoxon signed rank test of this median. Values significant at the 5% level are denoted with * and those significant at 1% by **.*

3.4.4 SIZE AND AGE EFFECTS

The previous analysis has shown that managers do appear to change their risk taking behaviour according to both relative performance and as a function of the value of their incentive option, with the former having the largest impact. As suggested by the theoretical literature on this topic, the implicit terms of the compensation contract do appear to inhibit excessive risk taking by fund managers who find themselves substantially below their high-water mark.

In the next section of the chapter I examine whether fund characteristics such as size and age have any impact on risk taking behaviour.

3.4.4.1 SIZE

Using a Probit regression Liang (2000) shows that fund size is an important factor in determining fund survival with smaller funds more likely to liquidate. With this in mind I now examine whether small and large funds differ in their risk taking behaviour in response to relative performance and dependent upon the moneyness of their incentive option. Using the fund size data reported in Table 3.1, I split the sample by defining large funds as those which are in the top quartile of assets and small funds as in the bottom quartile of assets under management. I then carry out the same contingency analysis as in the previous section on these sub-samples.

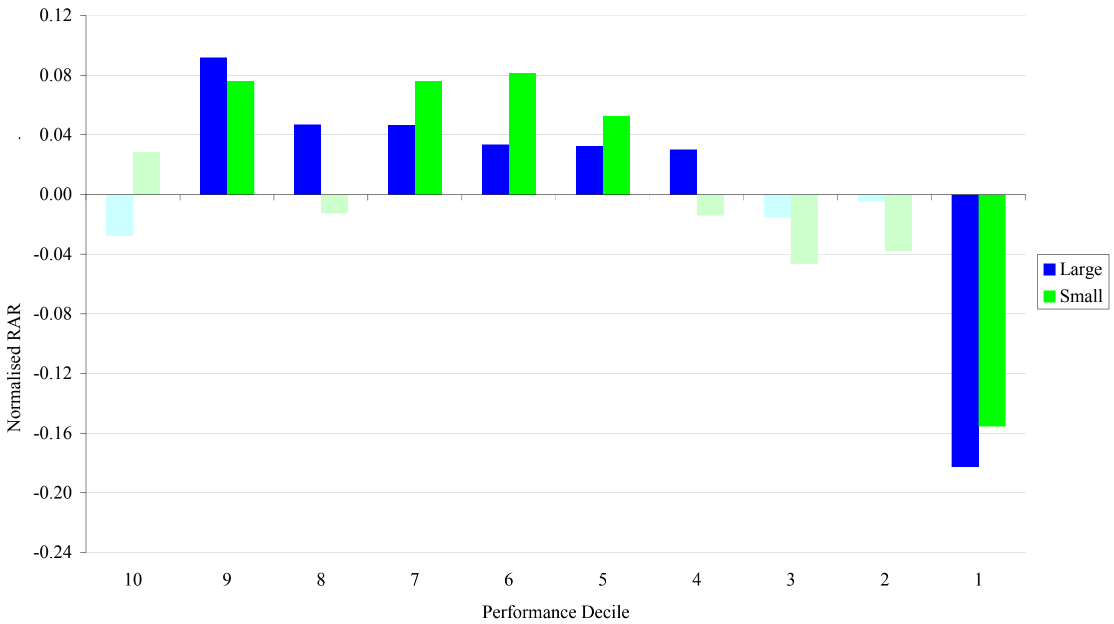
In Table 3.9 and Figure 3.5 I present the results for the effect of relative performance on Normalised RAR for both large and small funds. The pattern of risk taking is similar for both the large and small fund samples with a normalised RAR of below zero for the first to third deciles and above zero for the fifth to ninth deciles. It is interesting to note that for the fifth, sixth, seventh deciles the median normalised RAR for the small fund sample is more positive, which suggests that smaller funds are more likely to increase risk, however the difference is not statistically significant.

Table 3.9 - Median Normalised Risk Adjustment Ratio by Performance Decile and Size

	Performance Decile	10	9	8	7	6	5	4	3	2	1
Large	Observations	321	314	303	335	343	356	360	332	350	320
	Median Normalised RAR	-0.0279	0.0917**	0.0469**	0.0465**	0.0333*	0.0324**	0.0299**	-0.0154	-0.0045	-0.1826**
	Wilcoxon Statistic	-1.1079	-4.1535	-3.4364	-3.0948	-2.2909	-3.3899	-3.8732	-0.4925	-1.5033	-5.9635
	p-Value	0.2679	0.0000	0.0006	0.0020	0.0220	0.0007	0.0001	0.6224	0.1328	0.0000
	Performance Decile	10	9	8	7	6	5	4	3	2	1
Small	Observations	316	285	299	296	269	292	300	335	333	335
	Median Normalised RAR	0.0282	0.0758**	-0.0124	0.0759**	0.0814**	0.0528**	-0.0141	-0.0465	-0.0380	-0.1553**
	Wilcoxon Statistic	-1.7392	-3.3250	-1.8508	-3.8803	-4.1628	-3.5853	-1.6791	-0.2421	-0.0849	-3.3331
	p-Value	0.0820	0.0009	0.0642	0.0001	0.0000	0.0003	0.0931	0.8087	0.9323	0.0009
	Wilcoxon Rank Sum Test for Equal Medians p-value	0.7541	0.6050	0.2444	0.4129	0.1448	0.7060	0.1202	0.4364	0.2374	0.2824

*The table presents the normalised risk adjustment ratio by performance decile, the test statistics for a Wilcoxon signed rank test of this median as well as the p-values for the Wilcoxon Rank Sum test of equal medians between the two samples. Values significant at the 5% level are denoted with * and those significant at 1% by **.*

Figure 3.5 - Median Normalised Risk Adjustment Ratio Performance Decile and Size



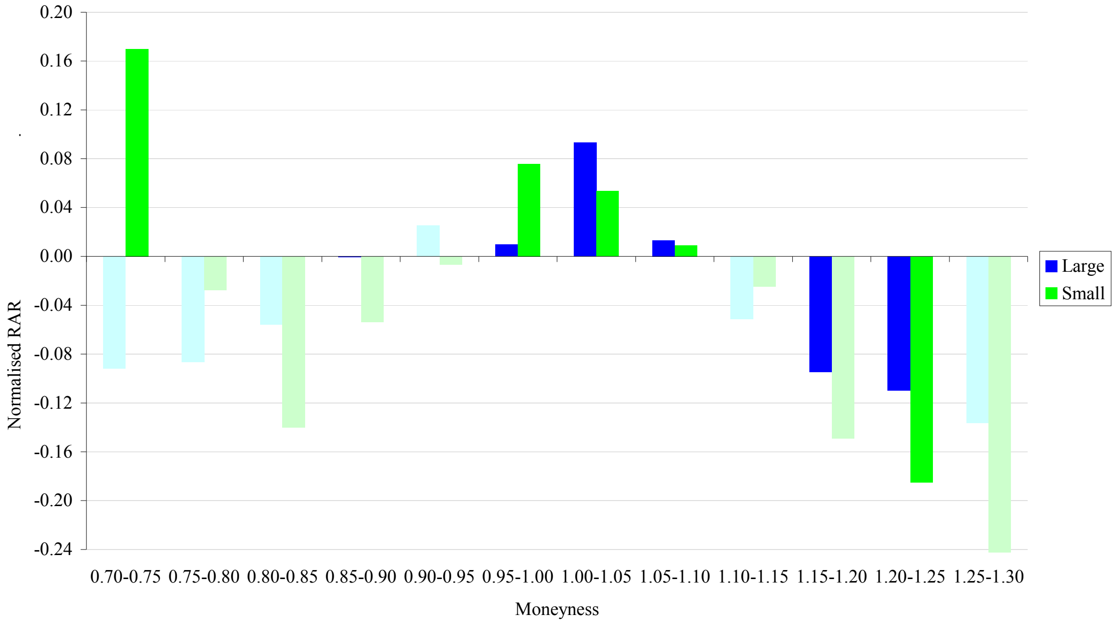
This figure shows the normalised risk adjustment ratio by performance decile and size with statistically significant values in bold colour and others in faint

Table 3.10 - Median Normalised Risk Adjustment Ratio by Moneyness and Size

	Moneyness	0.70-0.75	0.75-0.80	0.80-0.85	0.85-0.90	0.90-0.95	0.95-1.00	1.00-1.05	1.05-1.10	1.10-1.15	1.15-1.20	1.20-1.25	1.25-1.30
Large	Observations	23	38	55	93	181	363	933	804	350	147	94	40
	Median Normalised RAR	-0.0918	-0.0864	-0.0559	-0.0007	0.0251	0.0097*	0.0930**	0.0133**	-0.0513	-0.0948*	-0.1097*	-0.1362
	Wilcoxon Statistic	-0.2433	-1.1674	-0.2932	-0.8138	-0.9985	-2.4175	-7.7977	-3.7271	-0.2035	-1.9724	-2.0646	-1.0081
	p-Value	0.8078	0.2430	0.7693	0.4157	0.3180	0.0156	0.0000	0.0002	0.8387	0.0486	0.0390	0.3134
	Moneyness	0.70-0.75	0.75-0.80	0.80-0.85	0.85-0.90	0.90-0.95	0.95-1.00	1.00-1.05	1.05-1.10	1.10-1.15	1.15-1.20	1.20-1.25	1.25-1.30
Small	Observations	38	61	67	114	182	399	761	633	306	135	90	48
	Median Normalised RAR	0.1699*	-0.0276	-0.1402	-0.0537	-0.0066	0.0758**	0.0536**	0.0092**	-0.0246	-0.1492	-0.1851**	-0.2821
	Wilcoxon Statistic	-2.1246	-0.7219	-0.8808	-0.0410	-1.5926	-3.4845	-5.9742	-2.8281	-1.0474	-1.4451	-2.6000	-1.7566
	p-Value	0.0336	0.4704	0.3784	0.9673	0.1112	0.0005	0.0000	0.0047	0.2949	0.1484	0.0093	0.0790
	Wilcoxon Rank Sum Test for Equal Medians p-value	0.1427	0.5057	0.8209	0.4906	0.5770	0.4436	0.4111	0.5843	0.3613	0.7121	0.4522	0.2872

*The table presents the normalised risk adjustment ratio by level of moneyness, the test statistics for a Wilcoxon signed rank test of this median as well as the p-values for the Wilcoxon Rank Sum test of equal medians between the two samples. Values significant at the 5% level are denoted with * and those significant at 1% by **.*

Figure 3.6 - Median Normalised Risk Adjustment Ratio by Moneyness and Size



This figure shows the normalised risk adjustment ratio by performance decile and size with statistically significant values in bold colour and others in faint

In Table 3.10 and in Figure 3.6 I present the results for the effect that the moneyness of the incentive option has on Normalised RAR for both large and small funds. For the funds that are significantly above their high-water mark (moneyness greater than 1.15), the median normalised RAR is more negative for the small fund sample suggesting smaller funds are more susceptible to "locking in" behaviour though this difference is not statistically significant. For those funds that are at or slightly below their high-water marks the median normalised RAR for the small fund sample is more positive than for large funds suggesting smaller funds are more prone to risk shifting behaviour, however for funds that are significantly below their high-water mark (moneyness of between 0.80 and 0.90) this patter is reversed. This result would appear to be consistent with the literature because it could be the possibility of liquidation that prevents small funds from increasing risk once they are significantly below their high-water mark.

3.4.4.2 FUND AGE

Both Liang (2000) and Brown, Goetzmann, and Park (2001) identify age as an important factor in determining fund survival with younger funds more likely to liquidate. With this in mind I now examine whether young and old funds differ in their risk taking behaviour in response to relative and absolute returns. Using the fund age data reported in Table 3.1, I split the sample by defining old funds as those which are in the top quartile of fund age and small funds as in the bottom quartile of fund age. I then carry out the same analysis as in the previous section on these sub-samples.

Table 3.11 and Figure 3.7 present the results for the effect of relative performance on Normalised RAR for both young and old funds. The pattern of risk taking is almost identical for both the old and young fund samples with a normalised RAR of below zero for the first to third deciles and above zero for the fifth to ninth deciles and no statistical difference between the two samples for any decile. It is interesting to note that for the eighth, ninth and tenth deciles the median normalised RAR for the old fund sample is more positive suggesting that younger funds are less likely to increase risk following poor relative performance perhaps because they face a higher probability of liquidation.

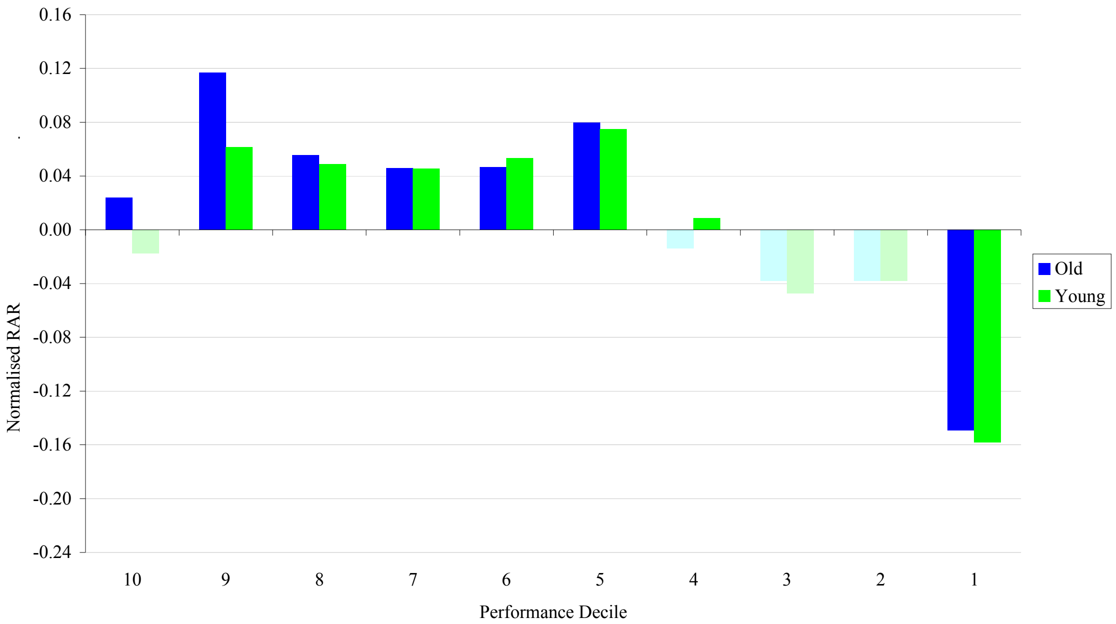
Table 3.11 - Median Normalised Risk Adjustment Ratio by Performance Decile and Age

	Performance Decile	10	9	8	7	6	5	4	3	2	1
Old	Observations	643	697	680	717	658	686	689	647	594	493
	Median Normalised RAR	0.0241**	0.1168**	0.0555**	0.0458**	0.0467**	0.0798**	-0.0140	-0.0380	-0.0379	-0.1492**
	Wilcoxon Statistic	-2.9036	-6.6506	-5.5035	-4.2515	-5.0717	-5.2879	-1.6818	-0.0684	-0.2484	-5.2388
	p-Value	0.0037	0.0000	0.0000	0.0000	0.0000	0.0000	0.0926	0.9455	0.8038	0.0000

	Performance Decile	10	9	8	7	6	5	4	3	2	1
Young	Observations	372	360	416	410	412	482	439	485	551	674
	Median Normalised RAR	-0.0174	0.0616**	0.0487**	0.0454**	0.0532**	0.0748**	0.0086**	-0.0474	-0.0380	-0.1582**
	Wilcoxon Statistic	-1.4823	-3.9925	-3.7809	-3.5777	-5.0333	-4.4316	-3.2604	-1.0448	-0.3694	-4.1649
	p-Value	0.1383	0.0001	0.0002	0.0003	0.0000	0.0000	0.0011	0.2961	0.7118	0.0000
	Wilcoxon Rank Sum Test for Equal Medians p-value	0.6967	0.4473	0.9403	0.6743	0.3229	0.9895	0.1812	0.7059	0.8948	0.7545

*The table presents the normalised risk adjustment ratio by level of moneyness, the test statistics for a Wilcoxon signed rank test of this median as well as the p-values for the Wilcoxon Rank Sum test of equal medians between the two samples. Values significant at the 5% level are denoted with * and those significant at 1% by **.*

Figure 3.7 - Median Normalised Risk Adjustment Ratio Performance Decile and Age



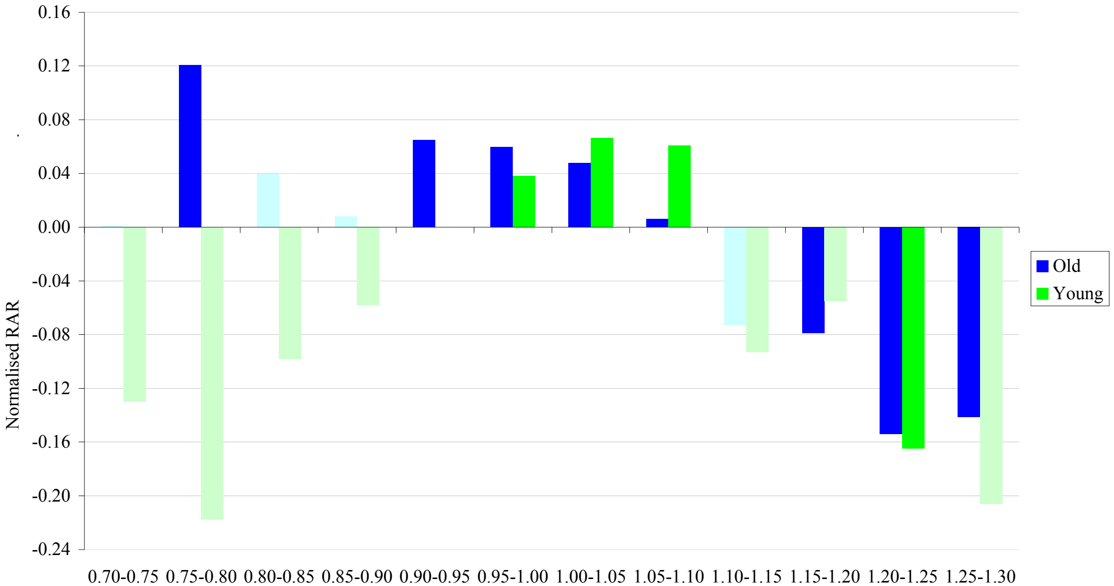
This figure shows the normalised risk adjustment ratio by performance decile and size with statistically significant values in bold colour and others in faint

Table 3.12 - Median Normalised Risk Adjustment Ratio by Moneyness and Age

	Moneyness	0.70-0.75	0.75-0.80	0.80-0.85	0.85-0.90	0.90-0.95	0.95-1.00	1.00-1.05	1.05-1.10	1.10-1.15	1.15-1.20	1.20-1.25	1.25-1.30
Old	Observations	107	116	161	268	409	780	1,666	1,388	602	309	162	75
	Median Normalised RAR	0.0009	0.1208**	0.0397	0.0078	0.0649**	0.0595**	0.0480**	0.0062**	-0.0729	-0.0787*	-0.1538**	-0.1415*
	Wilcoxon Statistic	-1.6122	-2.8045	-1.9520	-1.7680	-3.1199	-5.5015	-8.4206	-3.5949	-0.2641	-1.9637	-2.7501	-2.2759
	p-Value	0.1069	0.0050	0.0509	0.0771	0.0018	0.0000	0.0000	0.0003	0.7917	0.0496	0.0060	0.0229
	Moneyness	0.70-0.75	0.75-0.80	0.80-0.85	0.85-0.90	0.90-0.95	0.95-1.00	1.00-1.05	1.05-1.10	1.10-1.15	1.15-1.20	1.20-1.25	1.25-1.30
Young	Observations	21	29	53	119	192	508	1,259	1,034	569	277	170	91
	Median Normalised RAR	-0.1298	-0.2176	-0.0981	-0.0580	0.0000	0.0382**	0.0666**	0.0607**	-0.0929	-0.0552	-0.1649*	-0.2061
	Wilcoxon Statistic	-0.9559	-1.7190	-0.9107	-0.6205	-1.1812	-4.2391	-7.8290	-6.0565	-0.5757	-0.8951	-2.2383	-1.6304
	p-Value	0.3391	0.0856	0.3625	0.5349	0.2375	0.0000	0.0000	0.0000	0.5648	0.3707	0.0252	0.1030
	Wilcoxon Rank Sum Test for Equal Medians p-value	0.1532	0.0019**	0.7089	0.3289	0.6448	0.9980	0.5117	0.0247*	0.3855	0.6031	0.9021	0.6496

*The table presents the normalised risk adjustment ratio by level of moneyness, the test statistics for a Wilcoxon signed rank test of this median as well as the p-values for the Wilcoxon Rank Sum test of equal medians between the two samples. Values significant at the 5% level are denoted with * and those significant at 1% by **.*

Figure 3.8 - Median Normalised Risk Adjustment Ratio Moneyness and Age



This figure shows the normalised risk adjustment ratio by level of moneyness and size with statistically significant values in bold colour and others in faint

Table 3.12 and Figure 3.8 present the results for the effect of the moneyness of the incentive option has on Normalised RAR for both young and old funds. Once again there is no statistically significant difference between the two samples for any level of moneyness. However it is worth noting that for both levels of moneyness above 1.20 and below 0.90 the young fund sample has a more negative normalised RAR, implying that younger funds are more prone to "locking in" and less prone increasing risk following poor performance. Once again this result is consistent with the literature because if it is the threat of liquidation that is preventing excess increasing of risk, and younger funds have a higher probability of liquation, then they are less inclined to increase risk.

3.5 CHANGES IN ALPHA AND BETA

Having identified that hedge fund managers appear to adjust the risk profile of their funds in response their prior performance, in this section I examine whether it is the alpha, the beta or both components of the return that varies.

With a maximum of 6 data points in the pre and post assessment periods the use of multi-factor models is not practical. To overcome this problem I construct an equally weighted return index for each strategy from the funds in my sample and run the following regression for both the pre and post assessment periods

$$R_{ft} = \alpha + \beta S_t + \varepsilon_t \qquad (7)$$

where R_{ft} is the fund return in month t and S_t is the return on the relevant strategy index in month t.

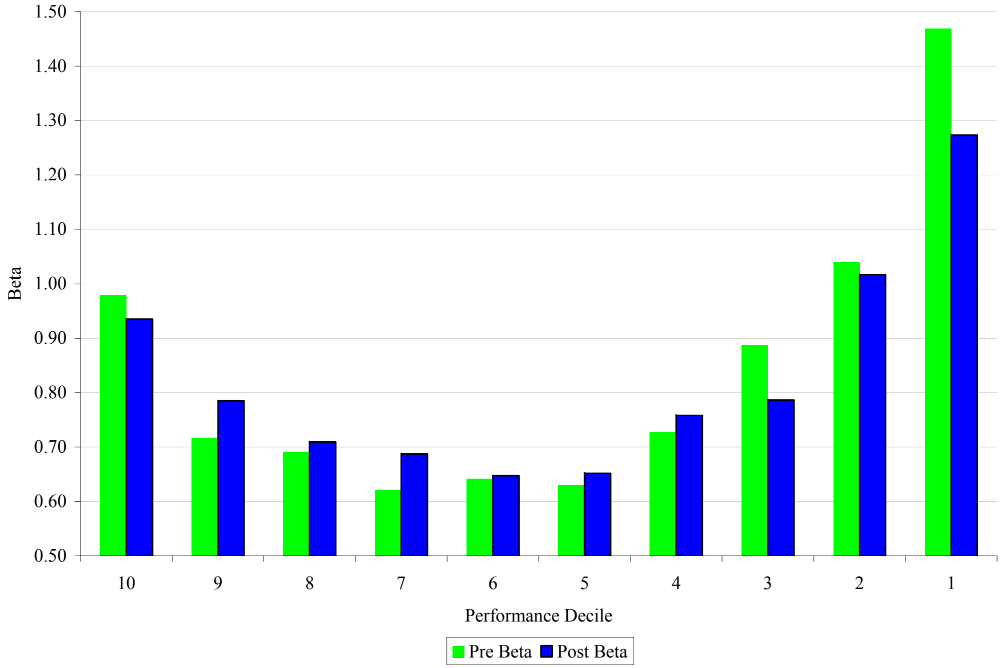
By construction, for the whole universe of funds in my sample the mean beta will be one & the mean alpha will be zero. However by applying the same disaggregated analysis I used for the standard deviation of returns in the previous section across different levels of relative and absolute performance I should be able to shed some light on how the components of return vary in the pre and post assessment periods. For each sub sample I calculate the median value of alpha and beta for both the pre and post assessment periods, I test the significance of each median using a Wilcoxon signed rank

Table 3.13 - Median Beta by Performance Decile

Assessment Period	Performance Decile	10	9	8	7	6	5	4	3	2	1
(6,6)	Observations	2,132	2,277	2,304	2,378	2,363	2,427	2,397	2,438	2,432	2,426
	Median Beta Pre Assessment	0.9799**	0.7167**	0.6911**	0.6205**	0.6418**	0.6298**	0.7275**	0.8871**	1.0403**	1.4689**
	Median Beta Post Assessment	0.9351**	0.7848**	0.7094**	0.6874**	0.6474**	0.6518**	0.7584**	0.7863**	1.0170**	1.2734**
	Change in Median	-0.0448	0.0681*	0.0183	0.0670*	0.0056	0.0219	0.0309	-0.1008**	-0.0233	-0.1955**

*The table presents the median beta calculated from expression (7) for the pre and post assessment periods by performance decile. The statistical significance of each median is tested by a Wilcoxon signed rank test and the difference between the medians by a Wilcoxon Rank Sum test.s. Values significant at the 5% level are denoted with * and those significant at 1% by **.*

Figure 3.9 - Median Beta by Performance Decile



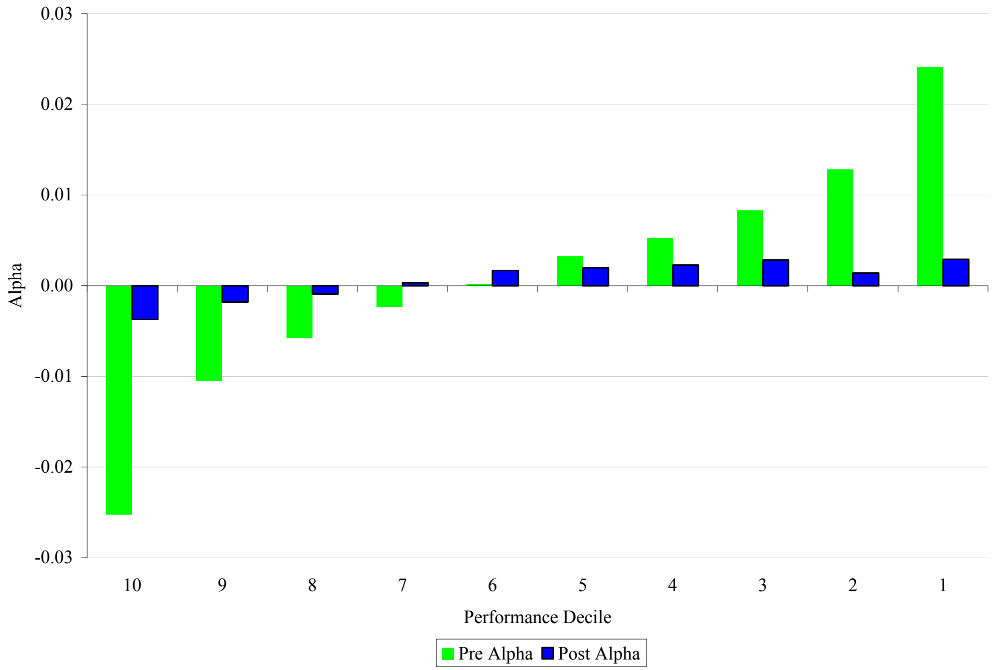
This figure shows median beta for the pre and post assessment period by performance decile

Table 3.14 - Median Alpha by Performance Decile

Assessment Period	Performance Decile	10	9	8	7	6	5	4	3	2	1
(6,6)	Observations	2,132	2,277	2,304	2,378	2,363	2,427	2,397	2,438	2,432	2,426
	Median Alpha Pre Assessment	-0.0252**	-0.0105**	-0.0057**	-0.0023**	0.0002	0.0032**	0.0052**	0.0083**	0.0128**	0.0241**
	Median Alpha Post Assessment	-0.0037**	-0.0018**	-0.0009**	0.0003	0.0017**	0.0020**	0.0023**	0.0028**	0.0014*	0.0029**
	Change in Median	0.0215**	0.0088**	0.0048**	0.0026**	0.0015**	-0.0012**	-0.0030**	-0.0054**	-0.0114**	-0.0212**

*The table presents the median alpha calculated from expression (7) for the pre and post assessment periods by performance decile. The statistical significance of each median is tested by a Wilcoxon signed rank test and the difference between the medians by a Wilcoxon Rank Sum test.s. Values significant at the 5% level are denoted with * and those significant at 1% by **.*

Figure 3.10 - Median Alpha by Performance Decile



This figure shows median alpha for the pre and post assessment period by performance decile and then test whether the medians in the pre and post assessment periods are equal using the Wilcoxon rank sum test.

Tables 3.13 and 3.14 present the results for alpha and beta categorised by performance deciles, the results are also presented graphically in figures 3.9 and 3.10.

Examining beta first, funds in the top 3 deciles have a lower beta in the post assessment period while funds in the fourth to the ninth deciles have a higher beta, the difference being statistically significant for the first, third, seventh and ninth deciles. This pattern of betas for the pre and post assessment periods is consistent with my previous results, the top performing funds reduce risk and the lower performing funds increase risk. The “U” shape of figure 3.9 also consistent with my previous findings with regard to the level of risk (see figure 3.2), higher beta funds are more likely to be at the extremes of performance while lower beta funds are more likely to be nearer the median.

Turning to alpha, for the pre assessment period alpha is positive and significant for the top five deciles while it is negative and significant for the bottom four deciles. This pattern is to be expected because I am sorting the funds by performance. For the post assessment period alpha is positive and significant for the top six deciles while it is negative and significant for the bottom three deciles, this would suggest that there is some persistence in alpha between the pre and post assessment periods. The change in alpha is statistically significant for all deciles, funds in the top six deciles exhibit a decrease in alpha (though remaining positive) while those funds in the bottom four deciles exhibit an increase in alpha (though remaining negative for deciles eight to ten).

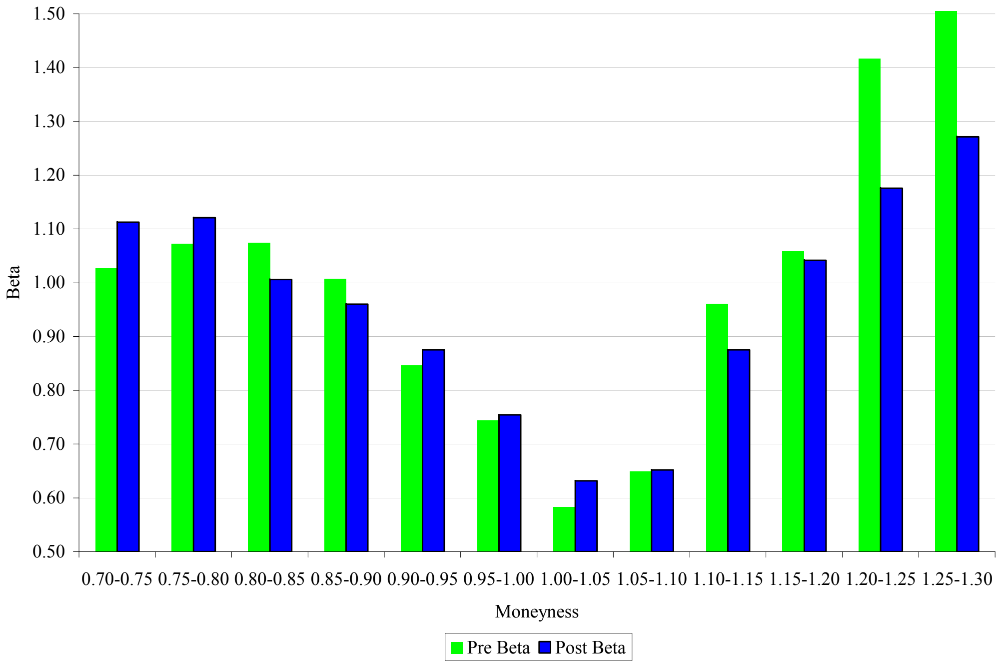
These results augment my previous findings for the changes in RAR across performance deciles showing that those funds that increase (decrease) risk not only increase (decrease) their beta but also increase (decrease) alpha.

Table 3.15 - Median Beta by Moneyness

Assessment Period	Moneyness	0.70-0.75	0.75-0.80	0.80-0.85	0.85-0.90	0.90-0.95	0.95-1.00	1.00-1.05	1.05-1.10	1.10-1.15	1.15-1.20	1.20-1.25	1.25-1.30
(6,6)	Observations	245	300	460	810	1,358	2,796	6,292	5,140	2,420	1,197	691	342
	Median Beta Pre Assessment	1.0272**	1.0721**	1.0745**	1.0076**	0.8463**	0.7437**	0.5829**	0.6488**	0.9610**	1.0582**	1.4170**	1.6421**
	Median Beta Post Assessment	1.1125**	1.1209**	1.0061**	0.9600**	0.8755**	0.7544**	0.6317**	0.6520**	0.8754**	1.0416**	1.1756**	1.2713**
	Change in Median	0.0854	0.0487	-0.0684	-0.0477	0.0291	0.0107	0.0488*	0.0032	-0.0856*	-0.0166	-0.2414*	-0.3708

*The table presents the median beta calculated from expression (7) for the pre and post assessment periods by level of moneyness. The statistical significance of each median is tested by a Wilcoxon signed rank test and the difference between the medians by a Wilcoxon Rank Sum test.s. Values significant at the 5% level are denoted with * and those significant at 1% by **.*

Figure 3.11 - Median Beta by Moneyness



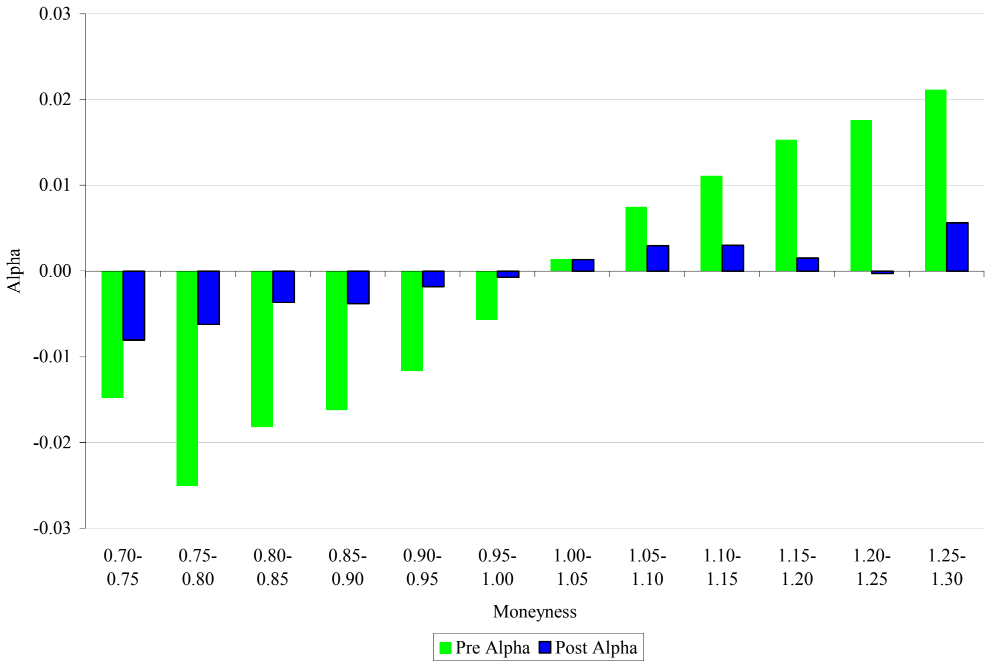
This figure shows median beta for the pre and post assessment period by level of moneyness

Table 3.16 - Median Alpha by Moneyness

Assessment Period	Moneyness	0.70-0.75	0.75-0.80	0.80-0.85	0.85-0.90	0.90-0.95	0.95-1.00	1.00-1.05	1.05-1.10	1.10-1.15	1.15-1.20	1.20-1.25	1.25-1.30
(6,6)	Observations	245	300	460	810	1,358	2,796	6,292	5,140	2,420	1,197	691	342
	Median Alpha Pre Assessment	-0.0147**	-0.0251**	-0.0182**	-0.0162**	-0.0117**	-0.0057**	0.0013**	0.0075**	0.0111**	0.0153**	0.0176**	0.0211**
	Median Alpha Post Assessment	-0.0081**	-0.0062**	-0.0037**	-0.0038**	-0.0018**	-0.0007**	0.0013**	0.0030**	0.0030**	0.0015	-0.0003	0.0056
	Change in Median	0.0067**	0.0188**	0.0146**	0.0124**	0.0099**	0.0050**	0.0000*	-0.0045**	-0.0081**	-0.0138**	-0.0179**	-0.0155**

*The table presents the median alpha calculated from expression (7) for the pre and post assessment periods by level of moneyness. The statistical significance of each median is tested by a Wilcoxon signed rank test and the difference between the medians by a Wilcoxon Rank Sum test.s. Values significant at the 5% level are denoted with * and those significant at 1% by **.*

Figure 3.12 - Median Alpha by Moneyness



This figure shows median alpha for the pre and post assessment period by level of moneyness

Tables 3.15 and 3.16 present the results for alpha and beta categorised by moneyness, the results are also presented graphically in figures 3.11 and 3.12.

Once again the pattern for beta is broadly consistent with my previous results for risk. For levels of moneyness above 1.10 beta is lower in the post assessment period and for moneyness between 0.9 and 1.10 beta is higher in the post assessment period, for these same levels of moneyness I found negative and positive normalised RAR.

Alpha for the pre assessment period is positive and significant for levels of moneyness above one while it is negative and significant for levels of moneyness below one; once again this pattern is to be expected because I am effectively sorting the funds by performance. Similar to the results for relative performance, the change in alpha between the pre and post assessment periods is statistically significant for all categories of moneyness, funds with levels of moneyness above 1.05 exhibit a decrease in alpha while those funds with levels of moneyness below 1.05 exhibit an increase in alpha. However the impact is more severe, in the post assessment period alpha is no longer statistically significant for funds with levels of moneyness above 1.15 and it remains negative and significant for levels of moneyness below one.

Once again these results illustrate that my previous findings for the changes in RAR relative to moneyness are driven by both alpha and beta, those funds that increase (decrease) risk not only increase (decrease) their beta but also increase (decrease) alpha.

3.6 CONCLUSIONS

In this chapter I have found evidence to suggest that hedge fund managers adjust the risk profile of their funds in response to their performance relative to their peers, with managers of relatively poor (strong) performing funds increasing (decreasing) the risk profile of their funds. This is in line with the findings of Brown, Harlow and Starks (1996) for mutual funs but somewhat surprising as hedge funds have generally been portrayed as pursuing absolute returns. This may well be a consequence of the actions of fund of fund managers and other investors who make their own investment decisions based upon the relative performances of the funds in which they seek to invest. It may well be an unintended consequence of the way in which investors choose to invest in a fund.

My results with regard to how hedge fund managers adjust the risk profile of their fund given the moneyness of their incentive option are more complex. Managers whose incentive option is well in the money decrease risk. Relatively speaking these managers are protecting the value of this option towards the end of the year. For investors who wish their managers to take risks in a consistent manner regardless of the month of the year, this result may come as a disappointment. It suggests that there is an element of "locking in" behaviour particularly towards the end of the calendar year. Perhaps of more interest is the risk taking behaviour of those fund managers who find their incentive option to be well out of the money. I find that these managers do not "put it all on black" in order to "win" back earlier losses and to increase the value of their incentive option. This should be good news for hedge fund investors. This conservative behaviour may be due to the implicit terms of the manager's contract. As Hodder and Jackwerth (2007) suggest, these implicit terms may include the risk of liquidation as investors withdraw funds and may also be due to the often substantial management stake in the fund that discourages the fund manager from "swinging the bat".

My analysis of the alpha and beta exposures of the funds shows that the changes in risk outlined above are driven by both alpha and beta. Those funds that increase (decrease) risk as measured by the risk adjustment ratio not only increase (decrease) their beta but also increase (decrease) alpha.

My results are of significance for the design of hedge fund manager compensation contracts. It would appear that the concern that incentive fees encourage excessive risk taking behaviour may be misplaced, however there does appear to be an incentive to "lock in" previous gains by reducing the risk profile of the fund. It is possible that this locking in behaviour could be reduced by introducing a rising scale of incentive fees.

CHAPTER 4

PORTFOLIOS OF HEDGE FUNDS: IN SEARCH OF THE OPTIMAL NUMBER

Abstract

Over 40% of the total assets of the hedge fund industry are controlled by Funds of Hedge Funds. The main reason for their popularity is the ability to form portfolios of hedge funds that diversify risk by spreading capital among several managers. Using the approach first proposed by Evans and Archer (1968) several researchers have demonstrated that the majority of the diversifiable time series standard deviation of returns can be eliminated by holding between 5 and 15 individual funds in a portfolio. However surveys of practitioner behaviour indicate that only a small proportion of funds of hedge funds hold portfolios of less than 15 funds and that many hold portfolios of over 30 funds. In this chapter I examine why there should be such a disparity between theory and practice. I illustrate that due to the nature of the original studies, the conclusions reached about the size of the portfolio required to reduce risk are inevitable and it is no coincidence that the number of hedge funds recommended is the same as the earlier recommendations about portfolios of equities. I go on to show empirically that there are statistically significant benefits to holding portfolios of a much larger size.

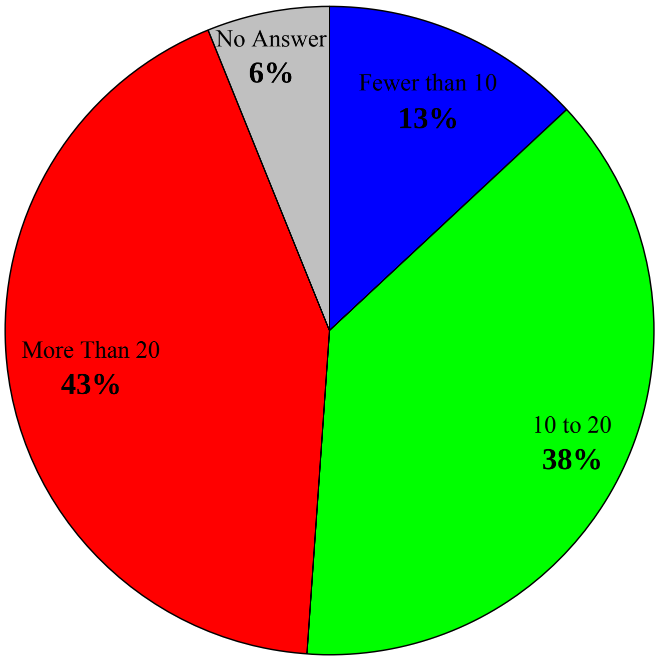
4.1 INTRODUCTION

Amin and Kat (2002) investigated the properties of naively diversified portfolios of hedge funds and concluded that no more than 15 funds were required to diversify away specific risk approach the population values for return and standard deviation of return.

Using broadly the same approach and techniques L'Habitant and Learned (2002) conclude that in terms of naive diversification, that most of the diversification benefits are achieved by forming fund of funds comprising just five to ten individual hedge funds.

However in a survey of 61 European alternative multi-management companies, representing a total volume of Euro 136 bn of alternative assets under management, the Edhec European Alternative Multimanagement Practices Survey (2003) found that practitioner behaviour appear to contradict this research. Figure 4.1 below shows the number of individual funds held by the fund of funds surveyed.

Figure 4.1 – Number Of Underlying Funds Held By Fund Of Fund Managers



Source Data: Edhec European Alternative Multimanagement Practices Survey (2003)

Only 13% of respondents hold fewer than 10 funds and while 38% of the respondents hold between 10 and 20 funds, 43% invest with more than 20 underlying funds.

In this chapter I examine why there should be such a disparity between academic theory and practitioner behaviour. I illustrate algebraically that due to the nature of the original studies, the conclusions reached about the size of the portfolio required to reduce risk are inevitable and it is no coincidence that the number of hedge funds recommended is the same as the earlier recommendations about portfolios of equities. I go on to examine empirically the traditional risk measure such as portfolio standard deviation, but rather than relying upon arbitrary analysis of charts in order to ascertain the point at which the marginal impact of increasing portfolio size is no longer significant, I instead introduce a bootstrap procedure to calculate confidence intervals for the difference in means for various portfolio sizes. I also consider alternative measures of risk including terminal wealth standard deviation, shortfall probability and illustrate that due to the distribution of individual hedge fund returns there are substantial benefits to holding portfolios of more than 15 funds that have been recommended by earlier authors.

4.2 NAÏVE CONCLUSIONS ABOUT THE BENEFITS OF NAÏVE DIVERSIFICATION

4.2.1 IS DIVERSIFICATION IN HEDGE FUNDS REALLY A FREE LUNCH?

As I will prove later, the standard deviation of a portfolio of assets will be lower than the mean standard deviation of the component assets while the mean return will be the same. For this reason diversification has been described as the only free lunch in finance. However, this lunch is only free if there are no costs involved in constructing the portfolio and if the mean return and standard deviation are the only two factors being considered.

In the case of hedge funds there are significant costs involved in constructing a portfolio. Firstly there is costly search, because hedge funds are not allowed to advertise the only way of finding hedge funds that are open to new investment is to subscribe to one or more of the industry databases. Once these eligible hedge funds have been identified there are costs involved in performing due diligence to ensure that the operational risk is minimised and the hedge fund manager is reliable. Finally once the portfolio has been constructed there are ongoing monitoring costs.

Several previous studies have also found that for portfolios of hedge funds, as the portfolio size increases so does the correlation with equities which will reduce their diversification benefits. In some cases they also found that increasing portfolio size can lead to lower skewness.

As a consequence of the above, even if mean variance analysis suggests that it is optimal to hold a portfolio of the entire universe of hedge funds a rational investor should only increase the number of hedge funds in their portfolio as long as the marginal benefit of adding them is greater than the marginal cost. In this chapter I attempt to measure the marginal benefit of increasing portfolio the portfolio size using various measures of risk, I also measure the cost in terms certain risks as well but the absolute costs are beyond the scope of my study. For this reason, in the absence of reliable data on the costs of search, due diligence and monitoring, my conclusions about the optimal size of a hedge fund portfolio might overstate the true optimal portfolio size.

4.2.2 IS IT NAÏVE TO EXAMINE NAÏVE DIVERSIFICATION?

Naïve diversification whereby an investor invests in N assets in equal proportions 1/N will (as I will later prove) lead to lower portfolio variance as the number of assets increases. However critics would point out that this strategy is sub-optimal and better results can be obtained by using some form of optimised diversification strategy, such as mean-variance optimisation. This criticism is valid if, and only if, the proposed optimisation method can be proven to be optimal, which in the case of hedge funds is unlikely to be the case for several reasons.

Firstly, as already mentioned, the most common optimisation method is mean-variance, which by definition ignores higher moments such as skew and kurtosis. It is well documented that hedge fund returns exhibit excess kurtosis and negative skewness and although as I demonstrated in chapter 2 that some of this is the effect of the incentive fees, ignoring these moments in the optimisation process could lead to portfolios that appear to be superior in terms of mean and variance but are in fact inferior in terms of skewness and kurtosis.

Even if higher moments are considered in the optimisation procedure, the results might not be superior to naïve diversification. All optimisation methods depend upon efficient and unbiased estimates of the inputs, for example, expected returns, expected variances and expected correlations While I cannot dispute that an optimised approach to diversification would be superior to naïve diversification if the true values of the inputs were know, this is unlikely to be the case. In a recent paper examining the performance of various optimisation strategies in stock portfolios DeMiguel, Garlappi, and Uppal (2007) found that naïve diversification often outperformed more complex strategies out of sample. The reason proposed by the authors was that the large estimation error for the inputs overwhelmed the gains from optimization and so simple allocation strategies outperformed. In the case of hedge funds these measurement errors are likely to be even larger due to the short histories, monthly reporting and dynamic nature of the trading strategies.

The aim of this chapter is to investigate the marginal benefits of diversification in hedge funds by increasing the portfolio size, while I accept that a naïve diversification strategy could in certain cases be improved upon, for the above reasons I believe it serves as a useful benchmark.

4.2.3 WHY IS 10-20 ALWAYS THE MAGIC NUMBER UNDER THE TRADITIONAL FRAMEWORK?

The standard deviation of a portfolio of n hedge funds (or any other asset) is simply

$$\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i \sigma_i w_j \sigma_j \rho_{i,j} \qquad (1)$$

where σ_p is the portfolio variance, σ_i is the variance of fund i, w_i is the weight invested in fund i and $\rho_{i,j}$ is the correlation between funds i and j and n is the total number of funds in the portfolio.

Equation (1) can be expanded because when $i = j$, $\rho_{i,j} = 1$ and $w_i \sigma_i w_j \sigma_j = w_i^2 \sigma_i^2$

$$\sigma_p^2 = \sum_{i=1}^{n} w_i^2 \sigma_i^2 + \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} w_i \sigma_i w_j \sigma_j \rho_{i,j} \tag{2}$$

In an equally weighted portfolio of n funds with equal weights of 1/n in each asset, then $\sigma_{ewp_n}^2$, the variance of an equally weighted portfolio becomes

$$\sigma_{ewp_n}^2 = \sum_{i=1}^{n} \frac{1}{n^2} \sigma_i^2 + \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} \frac{1}{n^2} \sigma_i \sigma_j \rho_{i,j} \tag{3}$$

As there are n terms in the first summation and n[n-1] in the second summation, if I define the mean standard deviation $\overline{\sigma}^2$ and mean covariance $\overline{\rho}\overline{\sigma}^2$ as

$$\overline{\sigma}_n^2 = \sum_{i=1}^{n} \frac{1}{n} \sigma_i^2 \tag{4}$$

$$\overline{\rho}_n \overline{\sigma}_n^2 = \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} \frac{1}{n[n-1]} \sigma_i \sigma_j \rho_{i,j} \tag{5}$$

equation (3) can be simplified to

$$\sigma_{ewp_n}^2 = \frac{1}{n} \overline{\sigma}_n{}^2 + \frac{n-1}{n} \overline{\rho}_n \overline{\sigma}_n{}^2 \tag{6}$$

Equation (6) shows that the expected variance of an equally weighted portfolio of n funds can be decomposed into two parts. The first component (represented by the first term on the right hand side of equation (6)) can be eliminated by increasing the number of funds in the portfolio, this is because as n→∞ then 1/n→0. The second component (represented by the second term on the right hand side of equation (6)) cannot be eliminated by increasing the number of funds in the portfolio, because as n→∞ then n-1/n→1 hence it converges to the product of the average correlation and average variance (the average co-variance).

In reality however the population size is never infinity and has some finite value. For finite population of N funds then equation (6) becomes

$$\sigma^2_{ewp_N} = \frac{1}{N}\overline{\sigma}_N^{\,2} + \frac{N-1}{N}\overline{\rho}_N\overline{\sigma}_N^{\,2} \tag{7}$$

and if a portfolio of n funds is randomly selected from the population N then

$$E\left(\sigma^2_{ewp_n}\right) = \frac{1}{n}\overline{\sigma}_N^{\,2} + \frac{n-1}{n}\overline{\rho}_N\overline{\sigma}_N^{\,2} \tag{8}$$

Researchers have generally measured the benefits of diversification by calculating the ratio of the variance (or standard deviation) of portfolios of increasingly large values of n funds to the base case of n=1. From equation 8, the expected variance of a portfolio composed of a single fund is

$$E\left(\sigma^2_{ewp_1}\right) = \overline{\sigma}_N^{\,2} \tag{9}$$

Hence if I divide equation (8) by equation (9) I obtain

$$\frac{E\left(\sigma^2_{ewp_n}\right)}{E\left(\sigma^2_{ewp_1}\right)} = \frac{1}{n} + \frac{n-1}{n}\overline{\rho}_N \tag{10}$$

and equation (10) can be rearranged to give

$$\frac{E\left(\sigma^2_{ewp_n}\right)}{E\left(\sigma^2_{ewp_1}\right)} = \overline{\rho}_N + \frac{1}{n}\left[1 - \overline{\rho}_N\right] \tag{11}$$

Three important conclusions can be drawn from equation (11).

Firstly, as n→∞ then 1/n→0, thus the variance a portfolio of n funds relative to a portfolio of a single fund will tend to $\overline{\rho}_N$. To put this another way, $\overline{\rho}_N$ is the relative expected variance that cannot be eliminated via naive diversification while $[1-\overline{\rho}]$ is the relative expected variance that can be eliminated completely through naive diversification if the population of funds in infinite.

Secondly, the expected proportion of variance reduction is inversely proportional to the size of the portfolio n. Even if the population N is infinite, a portfolio of size n=5 will eliminate 80% of the diversifiable risk, n=10 will eliminate 90% and n=20 will eliminate 95%. In fact the marginal reduction in variance from adding one additional fund to a portfolio of n funds can be calculated as

$$\left(\overline{\rho}_N+\frac{1}{n}[1-\overline{\rho}_N]\right)-\left(\overline{\rho}_N+\frac{1}{n+1}[1-\overline{\rho}_N]\right)=\frac{1}{[n^2+n]}[1-\overline{\rho}_N] \qquad (12)$$

from equation (12) it is clear that as n increases, $1/[n^2+n]$ decrease extremely rapidly, even in the extreme case of $\overline{\rho}=0$ if n=1 the marginal reduction is 50%, for n=5 this falls to 3.33% and by the time n=10 it is less than 1%.

Finally for a finite population of N funds, even holding all N funds will result in $[1-\overline{\rho}]$/N of the diversifiable risk remaining, thus the maximum amount that can be eliminated is $[(N-1)/N]$ similarly for a portfolio of n funds $[(n-1)/n]$ is eliminated, and hence the proportion of the maximum relative diversifiable risk eliminated with a portfolio size n is $[N(n-1)/n(N-1)]$. Table 4.1 shows the proportion of maximum relative diversifiable risk that is eliminated for selected portfolio sizes (n) from selected population sizes (N).

Table 4.1 – The Proportion of Diversifiable Risk Eliminated For Selected Portfolio and Population Sizes

		Population Size			
		100	500	1,000	10,000
Portfolio Size	5	81%	80%	80%	80%
	10	91%	90%	90%	90%
	15	94%	94%	93%	93%
	20	96%	95%	95%	95%
	50	99%	98%	98%	98%
	100	100%	99%	99%	99%
	500		100%	100%	100%
	1000			100%	100%

This table the proportion of maximum relative diversifiable risk that is eliminated for selected portfolio sizes (n) from selected population sizes (N).

From the above I can reach two major conclusions:

i) The marginal benefit of adding an additional fund to a portfolio of 20 funds as measured by the ratio of variance to that of a single fund will be less than 0.25% even if the correlation between the individual funds is zero

ii) If the universe of hedge funds is estimated to be approximately 10,000 then a portfolio of 20 funds will eliminate 95% of the total diversifiable risk.

From these two conclusions it is clear why previous researchers have found that 10-20 funds are enough to form an adequately diversified portfolio of hedge funds and that there is little benefit to diversifying further. It is also clear why the magic number of 10-20 coincides with the findings of Evans and Archer (1968) for portfolios of stocks.

However, despite the analysis and conclusions reached above there are two possible explanations which would rationally explain diversification beyond the 10-20 fund portfolio.

Firstly, equation (11) formalises the relationship between the *expected* variance of portfolio of n funds and a single fund i.e. what will be the average outcome. However some portfolios of n funds would have larger variance and others would have smaller variance. Since an investor will only have a single portfolio they might choose to diversify further in order to be more certain about their level of risk. Secondly, (and similarly) the above analysis is based on the fact that the *expected* return on an equally weighted portfolio of n assets will be identical to the expected return of a single fund, once again because there is uncertainty surrounding this expected return and an investor will only have a single portfolio they might choose to diversify further in order to be more certain about their return. For these two reasons researchers have also examined diversification in a terminal wealth framework.

4.2.4 WHY IS 10-20 ALWAYS THE MAGIC NUMBER UNDER THE ALTERNATIVE FRAMEWORK?

Authors such as Amo, Harasty and Hillion (2007) have examined how the dispersion of terminal wealth varies according to the size of portfolios of randomly selected hedge funds, where terminal wealth is defined as the wealth accumulated from an initial investment of $1. While this framework has a number of promising applications, it can lead to the same naïve conclusions illustrated above.

Consider a universe of single hedge funds which produce a mean terminal wealth μ_{TW} and have a terminal wealth standard deviation σ_{TW}. If equally weighted portfolios of n funds are randomly formed from the universe, then the expected terminal wealth standard deviation of portfolios of size n will simply be the standard error.

$$E\left(\sigma_{TW_n}\right) = \frac{\sigma_{TW}}{\sqrt{n}} \qquad (13)$$

If (as in the case of Amo et al. (2007)) the benefits of diversification are measured by calculating the ratio of the terminal wealth standard deviation of portfolios of increasingly large values of n funds to the base case of n=1, because $E\left(\sigma_{TW_1}\right) = \sigma_{TW}$

$$\frac{E\left(\sigma_{TW_n}\right)}{E\left(\sigma_{TW_1}\right)} = \frac{1}{\sqrt{n}} \qquad (14)$$

Since from equation (14) the expected proportion of terminal wealth standard deviation reduction is inversely proportional to the square root of the size of the portfolio n, a portfolio of size n=5 will eliminate 55% of the diversifiable risk, n=10 will eliminate 68% and n=20 will eliminate 78%. Once again marginal reduction in variance from adding one additional fund to a portfolio of n funds will fall quite rapidly. In fact by the time n=15, the marginal benefit will be less than 1% ($1/\sqrt{15} - 1/\sqrt{16} = 0.0082$).

From the above analysis it is apparent why Amo et al. (2007) found that "the marginal risk reduction is less than 5% from six funds onwards." And in fact the same conclusions could have been reached without resorting to simulations.

4.2.5 ARE 1,000 SIMULATIONS ADEQUATE?

Previous studies have examined between 500 and 1,000 simulations for each portfolio size. While this is adequate for reliable estimates of the mean values it might not identify the risk of extreme outcomes.

For example if there are 1,000 funds in the sample, then there are 4.76×10^{49} possible combinations of 25 funds, hence running 1,000 simulations will only identify 2.10×10^{-45} % of the population. With the availability of cheap computer power there is no excuse for not running more simulations.

4.3 DATA AND METHODOLOGY

4.3.1 DATA

A combination of the TASS live and graveyard databases covering the period from January 1994 to December 2006 is used to obtain the data in order to minimise survivorship bias. From this combined database I extract monthly net of fee returns and strategy details for all hedge funds that are denominated in US Dollars, have assets in excess of $10m and report monthly performance. In order to minimise back-fill bias I discard the first 12 data points for each fund. This procedure results in a total sample of 3,493 hedge funds of which 1,485 are from the live database and 2,008 are from the graveyard database covering twelve years of performance data from January 1995 through to December 2006.

Only 27 funds survived the entire period from January 1995 to December 2006 so I use a methodology similar to Amin and Kat (2002). For three different inception dates, January 1995, January 1999 and January 2003 I start by selecting all of the funds that were alive at that point. If a fund stops reporting performance, it is replaced by a fund that is randomly selected from the set of eligible funds following the same strategy and alive at the time of closure. The above procedure results in three different time series of returns covering the twelve year period from January 1995 to December 2006, the eight years from January 1999 to December 2006 and four years from January 2003 to December 2006. For simplicity I will still refer to the data series obtained from this procedure as fund returns. The size and strategy composition of these samples is shown in table 4.2.

Table 4.2 Summary Statistics of Hedge Fund Samples

	Sample Period Jan95 - Dec06	Sample Period Jan99 - Dec06	Sample Period Jan03 - Dec06
Convertible Arbitrage	14	40	96
Dedicated Short Bias	4	13	15
Emerging Markets	40	112	115
Equity Market Neutral	8	43	124
Event Driven	44	124	185
Fixed Income Arbitrage	14	47	77
Global Macro	29	59	62
Long Short Equity	124	344	616
Managed Futures	51	97	106
Multi-Strategy	11	37	86
Total	339	916	1482

This table presents summary information for the sample of hedge funds collected from the TASS database. Only funds that are denominated in US Dollars, report monthly performance and that have assets in excess of $10m are included. If a fund stops reporting performance, it is replaced by a fund that is randomly selected from the set of eligible funds following the same strategy and alive at the time of closure

I am implicitly assuming that in the case of fund closure, investors are able to roll from one fund to another at the reported month end NAV and at zero cost. Although it is likely that this may understate the true cost of fund closure to the investor, a recent paper by Hodder, Jackwerth and Kolokolova (2008) shows that this difference might be small. Hodder et al. find that the mean return for funds de-listing from the ALTVEST database for January 1994 to June 2006 as -1.86% per month versus an average hedge fund return of 1.01%.

4.3.2 METHODOLOGY

Using the "fund returns" generated above I create equally weighted portfolios of increasing size n (n=1, 2, 3, ... 50, 100, 150, 200, 250, 300, all funds) by randomly selecting (without replacement) funds from the data set. For each portfolio, I build a time series of returns and use it to generate various statistics which are detailed below, I also calculate the terminal wealth achieved from an initial investment of $1 in the various portfolios. For each portfolio size, this process is repeated either 2,000 times or the maximum number of possible combinations whichever is smaller. I then repeat the whole process (including generating the "fund returns" to allow for different random replacements) 25 times, thus obtaining either the exhaustive set or 50,000 observations of each statistic. This is necessary not only to estimate the mean behaviour of a portfolio of size n, but also to examine the cross sectional variation in the results. For each statistic detailed below, I not only calculate the mean value but also the maximum, minimum, 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentile in order to quantify the risk around the mean value.

4.3.3 TIME SERIES STATISTICS

As well as calculating the standard measures of return and risk such as compound annual return, time-series standard deviation, skewness and kurtosis I also calculate various other statistics for each portfolio size.

Value at risk (VAR) measures the potential loss in value of a portfolio over a specific period for a specific confidence interval. For each size of portfolio I calculate 1 month VAR with 95% and 99% confidence intervals. Rather than relying on assumptions about the underlying distribution of returns I empirically measure the 5^{th} or 1^{st} percentile of the monthly return series for each simulation and basket size.

The major limitation of VAR as a risk measure is that it only considers one particular point of the return distribution, no information is provided about how large the loss can be when it exceeds the VAR level. Conditional VAR (CVAR) addresses this issue, CVAR is defined at the expected loss given the fact that the VAR level has been exceeded. Once again I measure this value empirically by calculating the mean values below the 5th or 1st percentile of the monthly return series.

Tracking Error is a measure of how closely a portfolio follows an index to which it is benchmarked, it is calculated by equation 15

$$TrackingError = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(R_{t,Portfolio} - R_{t,Benchmark}\right)^2} \tag{15}$$

where n is the number of periods, $R_{t,Portfolio}$ is the portfolio return at time t and $R_{t,Benchmark}$ is the benchmark return at time t. Though this statistic is easily calculated the choice of an appropriate benchmark is not so straightforward. As I am assuming that an investor is targeting the return of an *average fund* I use the portfolio of all funds in the sample as the benchmark, though similar results were obtained using the Credit Suisse Tremont hedge fund index.

The statistics above are all designed to help understand the risk profile of a basket of hedge funds. However, investors will also be interested to understand how this basket behaves relative to traditional asset classes. I therefore calculate the correlation over the full sample of each portfolio of hedge funds with the return on the S&P 500 composite index.

Previous authors have often relied upon arbitrary analysis of charts of the standard deviation (and other measures) in order to ascertain the point at which the marginal impact of increasing portfolio size is no longer significant. Rather than relying upon such arbitrary analysis I calculate 95% and 99% confidence intervals for the difference in means for portfolio sizes of n and n-1, where the null hypothesis is equal means. Due to the non-normality that is inherent in the data I use a bootstrap methodology. I draw 50,000 observations with replacement for each statistic and portfolio size 1,000 times and use the empirical distribution of the resulting sample means to test the hypothesis. If I can reject the null hypothesis then I am able to conclude that increasing the portfolio size by one fund has had a statistically significant impact upon the mean of the specific test statistic.

4.3.4 TERMINAL WEALTH STATISTICS

In considering the number of mutual funds necessary to reduce risk to its undiversifiable minimum, O'Neal (1997) argued that investors should not only consider the time series properties of their portfolios (as I do above by calculating these statistics), but also their terminal values and more specifically the distribution of that terminal value.

The intuition behind this is as follows. One could be unfortunate enough to get in to a taxi and enjoy a very smooth ride, but ultimately not arrive at one's chosen destination. A traveller may instead be willing to put up with a bumpy cab ride that does get them to their chosen destination. In an investment context then investors should care at least as much about the dispersion of their terminal wealth as they do the volatility of that wealth over time. Since long-term investors like pension funds should be focussed on the end result, or the value of their "terminal wealth" I follow O'Neal and calculate a set of additional statistics to explore the impact of diversification hedge funds on the distribution of terminal wealth outcomes. These include: a measure of short fall probability; the mean of this shortfall; and also the semi-deviation of portfolio returns.

As described earlier, I calculate the terminal wealth created from an initial investment of \$1 for each simulation and portfolio size. From this I calculate the mean terminal wealth (TWM) as well as the terminal wealth standard deviation (TWSD) and the other higher moments such as skewness and kurtosis.

Shortfall probability is calculated by equation (16)

$$Shortfall\ \Pr obability = \frac{Number\ Of\ Obseravtions\ Below\ TWM}{Total\ Number\ Of\ Observations} \tag{16}$$

A major limitation of the shortfall probability as a measure of risk is that it does not account for the magnitude that these returns fall short of the mean (similar to VAR). For this reason I also calculate the mean shortfall using equation (17).

$$MeanShortfall = \sum_{i=1}^{n} \frac{\min\{0,(TW_i - TWM)\}}{n_{TW_i < TWM}} \tag{17}$$

Where TW_i is the terminal wealth for observation i, TWM is the mean terminal wealth and $n_{TW_i < TWM}$ is the number of observations where $TW_i < TWM$.

An alternative measure of downside risk is the semi-deviation, like the standard deviation this will give greater weight to those observations that are farthest from the mean, it is calculated from equation (18)

$$SemiDeviaiton = \sqrt{\sum_{i=1}^{n} \frac{[\min\{0,(TW_i - TWM)\}]^2}{n_{TW_i < TWM}}} . \tag{18}$$

4.4 RESULTS

4.4.1 TIME-SERIES STATISTICS

Table 4.3 presents the mean values of all the major time series statistics described above for selected portfolio sizes (full results are available on request).

As expected, the mean portfolio return does not vary with portfolio size but only with the sample period. Clearly there is uncertainty around this mean value which I will investigate further in the terminal wealth framework below.

Risk, as measured by the time series standard deviation of returns, declines rapidly initially as the number of funds in the portfolio is increased but the rate of decrease levels off quite quickly. These results are exactly as predicted by equations (6) and (11), they are presented graphically in figure 4.2 which shows the familiar “L” shape.

Table 4.3 – Summary Time Series Statistics

Panel A: Sample Period January 1995 - December 2006

Portfolio Size	Mean Return	Mean Standard Deviaiton	Reduction	Mean Skew	Mean Kurtosis	Mean 1 Month VAR 95%	Mean 1 Month VAR 99%	Mean 1 Month CVAR 95%	Mean 1 Month CVAR 99%	Mean Tracking Error All Funds	Mean Correlation S&P500
1	11.6%	16.5%	100.0%	-0.18	9.06	-6.3%	-12.1%	-9.9%	-17.0%	4.6%	25.8%
2	11.6%	13.3%**	80.6%	-0.17	7.52**	-5.0%**	-9.6%**	-7.8%**	-13.4%**	3.4%**	32.9%**
3	11.6%	11.9%**	72.3%	-0.17	6.88**	-4.4%**	-8.5%**	-6.9%**	-12.0%**	2.9%**	37.4%**
4	11.6%	11.1%**	67.6%	-0.17	6.43**	-4.0%**	-7.9%**	-6.4%**	-11.0%**	2.6%**	40.9%**
5	11.6%	10.6%**	64.5%	-0.17	6.21**	-3.8%**	-7.4%**	-6.0%**	-10.5%**	2.3%**	43.4%**
6	11.6%	10.2%**	62.0%	-0.18	5.96**	-3.6%**	-7.1%**	-5.7%**	-10.0%**	2.2%**	45.5%**
7	11.6%	9.9%**	60.3%	-0.17	5.84**	-3.5%**	-6.8%**	-5.5%**	-9.7%**	2.0%**	47.2%**
8	11.6%	9.7%**	59.0%	-0.17	5.72**	-3.4%**	-6.6%**	-5.4%**	-9.4%**	1.9%**	48.4%**
9	11.6%	9.5%**	57.8%	-0.18	5.62**	-3.3%**	-6.4%**	-5.2%**	-9.2%**	1.8%**	49.6%**
10	11.6%	9.4%**	56.8%	-0.17	5.51**	-3.2%**	-6.3%**	-5.1%**	-9.0%**	1.7%**	50.5%**
11	11.6%	9.2%**	56.0%	-0.17	5.45*	-3.1%**	-6.1%**	-5.0%**	-8.9%**	1.6%**	51.5%**
12	11.6%	9.1%**	55.4%	-0.17	5.38**	-3.1%**	-6.0%**	-4.9%**	-8.8%**	1.6%**	52.2%**
13	11.6%	9.0%**	54.8%	-0.17	5.31*	-3.0%**	-5.9%**	-4.9%**	-8.7%**	1.5%**	52.8%**
14	11.6%	9.0%**	54.3%	-0.17	5.25	-3.0%**	-5.8%**	-4.8%**	-8.6%*	1.5%**	53.4%**
15	11.6%	8.9%**	53.9%	-0.17	5.20**	-3.0%**	-5.8%**	-4.8%**	-8.5%**	1.4%**	53.9%**
20	11.6%	8.6%**	52.3%	-0.17	5.00*	-2.8%**	-5.5%**	-4.6%**	-8.3%*	1.2%**	55.8%**
30	11.6%	8.3%**	50.4%	-0.16	4.70**	-2.6%**	-5.1%**	-4.3%**	-8.0%	1.0%**	58.0%**
40	11.6%	8.2%	49.5%	-0.15	4.50	-2.5%	-4.9%	-4.2%	-7.8%	0.9%**	59.2%**
50	11.6%	8.1%	49.0%	-0.15	4.34	-2.4%	-4.7%	-4.1%	-7.7%	0.8%**	60.0%**
All	11.6%	7.8%	47.1%	-0.09	4.30	-1.5%	-2.3%	-3.8%	-7.4%	0.0%	62.7%

Panel B: Sample Period January 1999 - December 2006

Portfolio Size	Mean Return	Mean Standard Deviaiton	Reduction	Mean Skew	Mean Kurtosis	Mean 1 Month VAR 95%	Mean 1 Month VAR 99%	Mean 1 Month CVAR 95%	Mean 1 Month CVAR 99%	Mean Tracking Error All Funds	Mean Correlation S&P500
1	13.7%	15.3%	100.0%	0.30	7.38	-5.8%	-10.7%	-8.3%	-12.2%	4.4%	22.9%
2	13.7%	12.7%**	83.0%	0.30	6.55**	-4.7%**	-8.5%**	-6.6%**	-9.6%**	3.4%**	29.3%**
3	13.8%	11.6%**	75.8%	0.32	6.11**	-4.2%**	-7.5%**	-5.8%**	-8.4%**	3.0%**	33.5%**
4	13.8%	10.9%**	71.2%	0.33**	5.83**	-3.8%**	-6.9%**	-5.4%**	-7.7%**	2.7%**	36.4%**
5	13.8%	10.4%**	68.2%	0.35*	5.65**	-3.6%**	-6.5%**	-5.1%**	-7.2%**	2.5%**	38.7%**
6	13.7%	10.1%**	65.8%	0.35	5.45**	-3.5%**	-6.2%**	-4.8%**	-6.9%**	2.3%**	40.5%**
7	13.7%	9.9%**	64.4%	0.36	5.40**	-3.4%**	-5.9%**	-4.7%**	-6.6%**	2.2%**	42.0%**
8	13.7%	9.6%**	63.0%	0.37**	5.23*	-3.3%**	-5.7%**	-4.5%**	-6.4%**	2.1%**	43.1%**
9	13.7%	9.4%**	61.7%	0.36	5.13**	-3.2%**	-5.6%**	-4.4%**	-6.2%**	2.0%**	44.2%**
10	13.7%	9.3%**	61.0%	0.38	5.12**	-3.2%**	-5.4%**	-4.3%**	-6.0%**	1.9%**	44.9%**
11	13.7%	9.2%**	60.1%	0.38**	5.00	-3.1%**	-5.3%**	-4.2%**	-5.9%**	1.8%**	45.9%**
12	13.7%	9.1%**	59.4%	0.37	4.93**	-3.0%**	-5.2%**	-4.1%**	-5.8%**	1.8%**	46.5%**
13	13.7%	9.0%**	59.0%	0.37	4.89**	-3.0%**	-5.1%**	-4.1%**	-5.7%**	1.7%**	47.1%**
14	13.7%	8.9%**	58.4%	0.38	4.84	-3.0%**	-5.0%**	-4.0%**	-5.6%**	1.7%**	47.5%**
15	13.8%	8.9%**	58.0%	0.38	4.76*	-2.9%**	-5.0%**	-4.0%**	-5.5%**	1.6%**	48.1%**
20	13.7%	8.6%*	56.2%	0.36	4.48*	-2.8%*	-4.7%*	-3.8%**	-5.2%*	1.4%**	50.0%**
30	13.7%	8.3%	54.3%	0.34	4.13*	-2.7%**	-4.4%**	-3.6%**	-4.9%**	1.2%**	52.0%**
40	13.7%	8.1%	53.1%	0.33**	3.92**	-2.6%**	-4.2%**	-3.4%*	-4.6%*	1.1%**	53.3%
50	13.7%	8.0%	52.3%	0.32	3.79	-2.6%	-4.1%	-3.3%	-4.5%	1.0%**	54.2%
All	13.8%	7.8%	49.2%	0.26	3.28	-2.4%	-3.2%	-3.0%	-3.6%	0.0%	58.1%

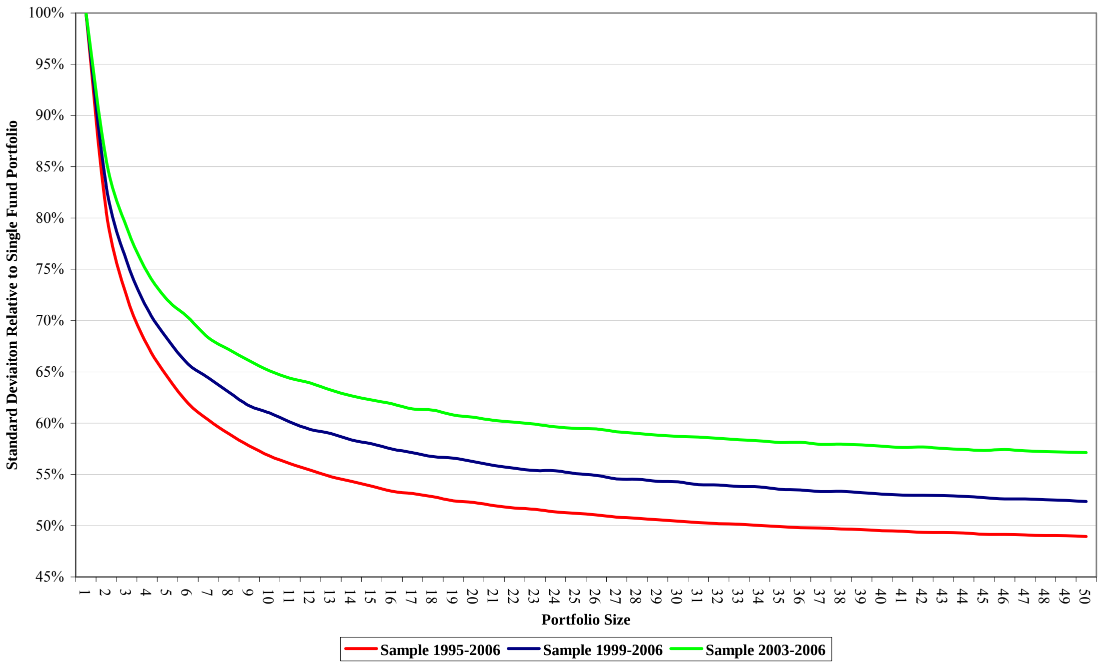
Panel C: Sample Period January 2003 - December 2006

Portfolio Size	Mean Return	Mean Standard Deviaiton	Reduction	Mean Skew	Mean Kurtosis	Mean 1 Month VAR 95%	Mean 1 Month VAR 99%	Mean 1 Month CVAR 95%	Mean 1 Month CVAR 99%	Mean Tracking Error All Funds	Mean Correlation S&P500
1	13.6%	9.8%	100.0%	0.12	4.54	-3.5%	-5.7%	-5.0%	-5.7%	2.8%	31.3%
2	13.5%	8.3%**	85.6%	0.07**	4.01**	-2.9%**	-4.7%**	-4.1%**	-4.7%**	2.2%**	40.4%**
3	13.6%	7.7%**	79.1%	0.05**	3.84**	-2.6%**	-4.2%**	-3.7%**	-4.2%**	1.9%**	45.3%**
4	13.5%	7.3%**	74.7%	0.02**	3.72**	-2.4%**	-3.9%**	-3.4%**	-3.9%**	1.7%**	48.8%**
5	13.6%	7.0%**	72.0%	0.00**	3.61**	-2.3%**	-3.7%**	-3.2%**	-3.7%**	1.6%**	51.2%**
6	13.6%	6.9%**	70.3%	-0.03**	3.52**	-2.3%**	-3.6%**	-3.1%**	-3.6%**	1.5%**	53.1%**
7	13.6%	6.7%**	68.3%	-0.05**	3.44**	-2.2%**	-3.4%**	-3.0%**	-3.4%**	1.4%**	54.7%**
8	13.6%	6.6%**	67.2%	-0.07**	3.36**	-2.2%**	-3.4%**	-3.0%**	-3.4%**	1.3%**	56.0%**
9	13.6%	6.4%**	66.1%	-0.08**	3.32**	-2.1%**	-3.3%**	-2.9%**	-3.3%**	1.2%**	57.0%**
10	13.6%	6.4%**	65.1%	-0.10**	3.26**	-2.1%**	-3.2%**	-2.8%**	-3.2%**	1.2%**	57.7%**
11	13.6%	6.3%**	64.4%	-0.11**	3.21**	-2.1%**	-3.2%**	-2.8%**	-3.2%**	1.1%**	58.6%**
12	13.6%	6.2%**	63.9%	-0.12**	3.17**	-2.0%**	-3.1%**	-2.8%**	-3.1%**	1.1%**	59.2%**
13	13.6%	6.2%**	63.2%	-0.14**	3.13**	-2.0%**	-3.1%**	-2.7%**	-3.1%**	1.1%**	59.8%**
14	13.6%	6.1%**	62.7%	-0.15**	3.10**	-2.0%**	-3.0%**	-2.7%**	-3.0%**	1.0%**	60.4%**
15	13.6%	6.1%**	62.3%	-0.16**	3.06**	-2.0%**	-3.0%**	-2.7%**	-3.0%**	1.0%**	60.7%**
20	13.6%	5.9%**	60.6%	-0.20**	2.95**	-1.9%*	-2.9%**	-2.6%**	-2.9%**	0.9%**	62.4%**
30	13.6%	5.7%	58.7%	-0.25**	2.83**	-1.9%	-2.7%	-2.4%	-2.7%	0.7%**	64.5%**
40	13.6%	5.6%	57.7%	-0.29	2.77*	-1.9%	-2.6%	-2.4%	-2.6%	0.6%**	65.5%**
50	13.6%	5.6%	57.1%	-0.31	2.73**	-1.9%	-2.6%	-2.4%	-2.6%	0.6%**	66.3%
All	13.6%	7.8%	54.4%	-0.42	2.59	-1.9%	-2.3%	-2.1%	-2.3%	0.0%	69.6%

*This table presents mean values for various time series statistics for portfolio sizes from 1 to 50 funds. Panel A presents the results for the period January 1995 to December 2006, Panel B presents the results for the period starting in January 1999 and ending in December 2006 and Panel C presents the results for the period starting in January 2003 and ending in December 2006. All results are calculated from either 50,000 random selections or the exhaustive set of possible combinations using the data set presented in table 2. A bootstrap procedure is used to test whether adding 1 additional fund to the portfolio makes a statistically significant change in the mean value, those significant at the 5% level are denoted with * and those significant at 1% by **.*

For the twelve year sample period, holding a portfolio of all 339 funds would have a time series standard deviation of 47.1% of the average for the single fund portfolios, a reduction of 52.9%. A portfolio of 20 funds would on average provide 47.7% of this 52.9% reduction, or 90% which is almost exactly what equation (11) would have predicted.

Figure 4.2 – Time Series Standard Deviation



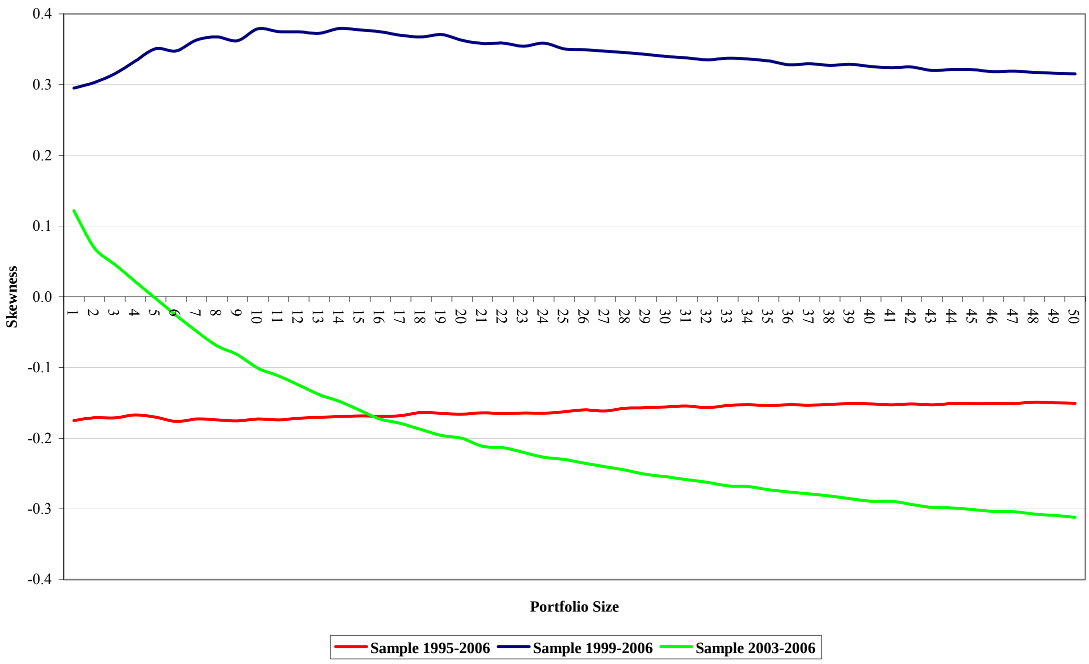
This figure present graphically the results for the mean standard deviation of portfolio sizes from 1 to 50 funds for the 3 different sample periods using the data from table 4.3.

In terms of the statistical significance of the reduction in standard deviation, the results vary slightly according to the sample period. For the twelve year sample period holding there is no statistically significant decrease in the standard deviation for increasing portfolio sizes above 32 funds, for the eight year sample the cut-off is 24 funds and for the four year sample it is 28 funds.

As the sample period shortens (and the number of funds in the sample increases) the benefits of diversification appear to decline, implying that the correlation between the funds has increased. This is in fact the case, for the twelve year sample of 339 funds the average correlation is 15.8% while for the four year sample of 1,482 funds the average correlation is 19.6%.

All of the above would imply that there is little benefit to holding portfolios of more than 20-30 funds which although higher than previous academic estimates does not explain why almost a quarter of fund-of-funds hold portfolios of greater than 30 funds. However as already mentioned there is significant uncertainty surrounding the mean values for each of these statistics. For the twelve year sample period, a 20 fund portfolio has a mean time series standard deviation of 8.6% but the 10th percentile value is 10.7%, thus a naive investor has a 10% chance of choosing a portfolio of 20 funds that will result in a standard deviation of over 2% higher than the mean. In fact to be 90% certain of not choosing a portfolio with a standard deviation greater than 8.6% an investor would have to hold a portfolio of between 100 and 150 funds.

Figure 4.3 – Skewness



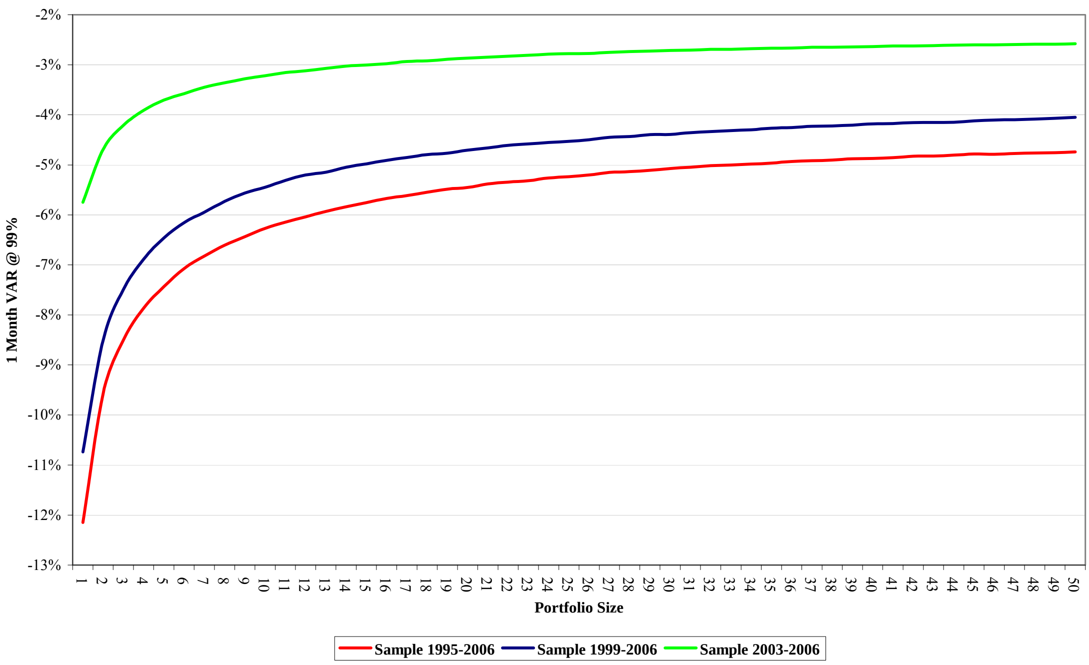
This figure present graphically the results for the mean skewness of portfolio sizes from 1 to 50 funds for the 3 different sample periods using the data from table 4. 3.

With regard to the skewness of the resulting portfolios, once again my results appear to depend upon the sample period chosen, the results are presented graphically in figure 4.3. For the twelve year period the average skewness of the individual funds is negative and there does not appear to be any statistically significant change as the portfolio size increases. For the eight year sample period the average skewness is positive and once again there does not appear to be any statistically significant change as the portfolio size increases. For the four year sample period the average skewness is positive, but increasing the portfolio size results in increasingly negative skewness with the change being statistically significant up to portfolios of over 30 funds.

One of reasons practitioners give for holding larger portfolios is to decrease the risk of an extreme loss. One measure of this is kurtosis, a value greater than 3 indicates that the tails of the distribution are fatter than the standard normal distribution and hence there is a greater probability of extreme outcomes. For all three of my sample periods, individual funds on average exhibit excess kurtosis, ranging from a value of 9.06 for the twelve year sample to 4.54 for the four year sample. As portfolio size is increased kurtosis falls for all three samples though and the rate of this fall is statistically significant even for portfolio sizes up to 50 funds in the four year sample period.

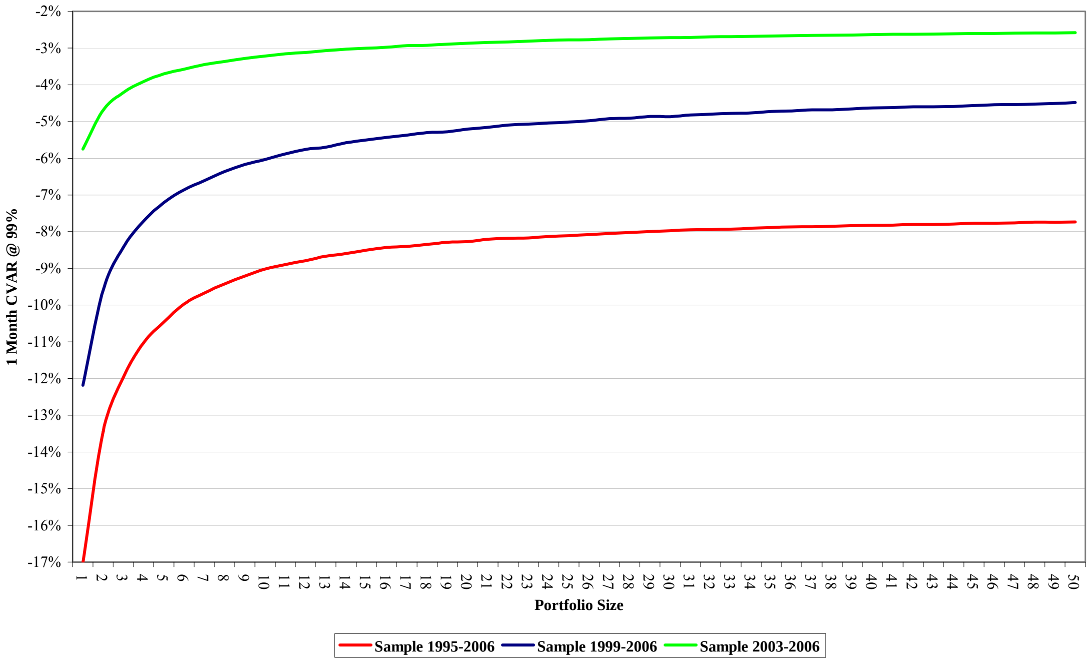
Perhaps slightly more intuitive measures of the risk of an extreme loss are VAR and CVAR. I report these measures for a monthly horizon at 95% and 99% confidence levels and the results for the 99% confidence interval are presented graphically in figures 4.4 and 4.5.

Figure 4.4 – 1 Month Value At Risk 99% Confidence



This figure present graphically the results for the mean 1-month Value At Risk at a 99% confidence level for portfolio sizes from 1 to 50 funds for the 3 different sample periods using the data from table 4.3.

Figure 4.5 – 1 Month Conditional Value At Risk 99% Confidence

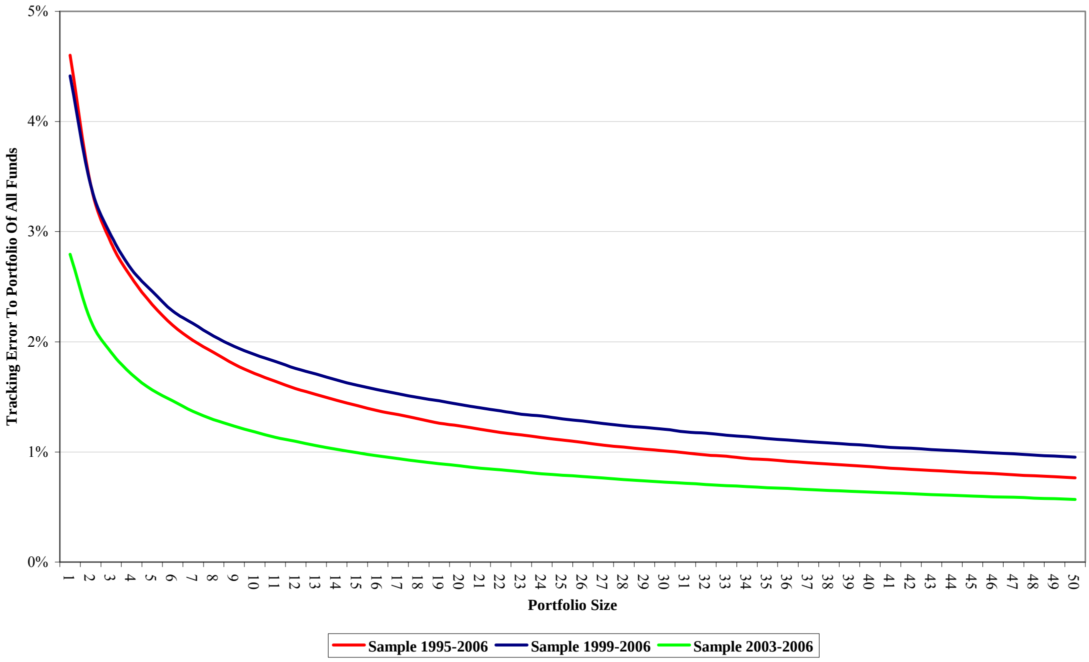


This figure present graphically the results for the mean 1-month Conditional Value At Risk at a 99% confidence level for portfolio sizes from 1 to 50 funds for the 3 different sample periods using the data from table 4.3.

Once again, as one would expect, for all three sample periods these measures decrease as the portfolio size increases. The point at which the reduction becomes statistically insignificant varies according to the sample period, in the case of 99% 1 month VAR this occurs at 39 funds, 40 funds and 25 funds for the twelve, eight and four year samples respectively. Similar results are obtained for CVAR. These results suggest that an investor who is concerned with minimising the risk of an extreme loss would be advised to hold a portfolio of at approximately 40 funds which is much larger than the size suggested when only considering risk measured in terms of standard deviation.

The tracking error measures how closely a portfolio follows an index to which it is benchmarked. If we assume that investors consider the whole population of hedge funds as the benchmark and they are attempting to replicate this benchmark by holding a smaller portfolio of hedge funds, obviously the larger the portfolio becomes the closer it will track the benchmark, but at which point does the improvement in tracking error become insignificant? From table 4.3, the improvement in mean tracking error is significant at a 99% confidence level in all three sample periods for portfolio sizes up to 50 funds Figure 4.6 shows my results graphically.

Figure 4.6 – Tracking Error

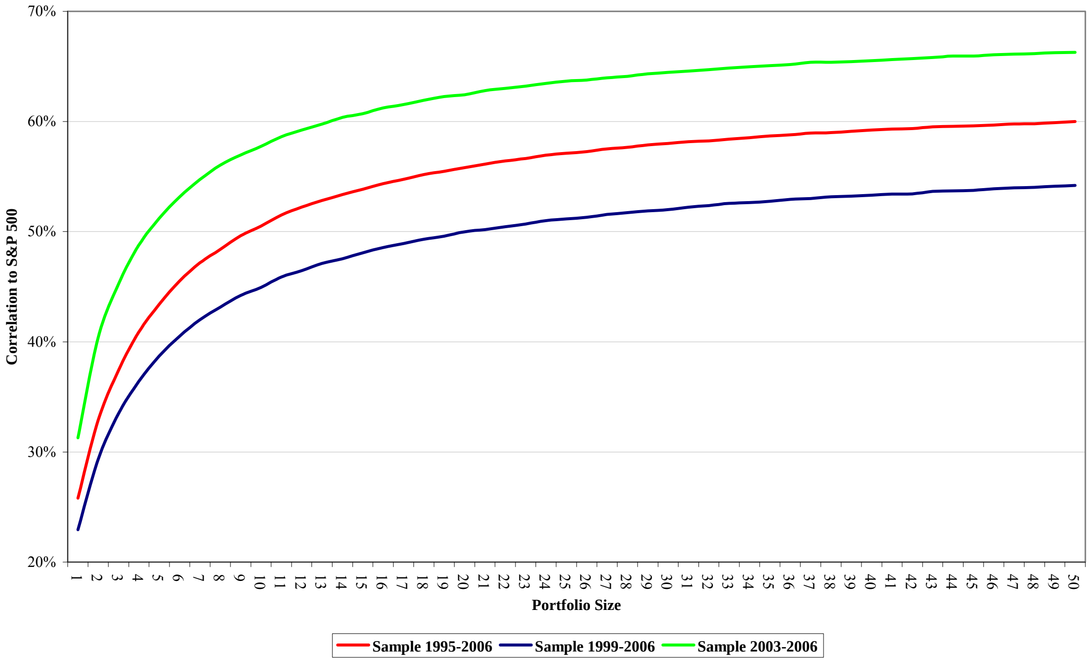


This figure present graphically the results for the mean tracking error for portfolio sizes from 1 to 50 funds for the 3 different sample periods using the data from table 4.3.

Thus far all of my results have indicated that there are benefits to holding portfolios of hedge funds of sizes much larger than the 10 to 20 suggested in the previous literature. In fact my results would indicate that portfolio sizes of between 30 and 40 funds would be more appropriate for an investor concerned about either the time series standard deviation or the risk of an extreme loss (and even larger portfolios if the investor is concerned with tracking a benchmark).

These results are all based on different measures of risk; however it is also important to understand how these portfolios might behave relative to an asset class that they may be designed to replace or to which they may be combined. For this reason I also calculate the average correlation of the portfolios with equities, as proxied by the S&P 500 index. The results from table 4.3 (illustrated in figure 4.7) show that as the portfolio size is increased so does the correlation with the S&P 500 index and the increase is statistically significant up to portfolio sizes of between 39 and 50 funds depending upon the sample period.

Figure 4.7 – Correlation to the S&P 500 Index



This figure present graphically the mean correlation between the hedge fund portfolios and the S&P 500 for portfolio sizes from 1 to 50 funds for the 3 different sample periods using the data from table 3.

This is clearly a cost of diversification as generally investors will hold hedge funds in addition to a traditional portfolio, thus as the correlation rises the diversification benefits of hedge funds falls.

4.4.2 TERMINAL WEALTH STATISTICS

All of the terminal wealth statistics outlined in section 4.3 are calculated for the end point of 31st December 2006 with the three different start dates of January 1995, 1999 and 2003. The results for selected portfolio sizes (full results are available on request) are presented in table 4.4. Unlike the previously calculated time series statistics, the majority of the terminal wealth statistics are point estimates as opposed to means, so it is unnecessary to calculate confidence intervals via a bootstrap.

Table 4.4 – Summary Terminal Wealth Statistics

Panel A: Sample Period January 1995 - December 2006

Portfolio Size	Mean Terminal Weatlh (TWM)	Median Terminal Weatlh	Maximum Terminal Weatlh	Minimum Terminal Weatlh	Terminal Wealth Standard Deviation (TWSD)	Reduction	Terminal Wealth Skewness	Terminal Wealth Kurtosis	Shortfall Probability	Mean Shortfall	Semi-Deviation
1	$3.73	$3.16	$46.55	$0.01	$2.80	100.0%	3.20	24.24	63.33%	-$1.45	$1.71
2	$3.72	$3.32	$31.27	$0.07	$1.96**	69.9%	2.18	12.90	60.80%	-$1.14	$1.35
3	$3.73	$3.41	$21.26	$0.17	$1.62**	57.9%	1.82	9.53	59.76%	-$0.98	$1.16
4	$3.73	$3.47	$20.91	$0.71	$1.39**	49.7%	1.56	8.06	58.61%	-$0.88	$1.04
5	$3.73	$3.50	$15.52	$0.88	$1.24**	44.4%	1.39	6.97	58.03%	-$0.81	$0.95
6	$3.72	$3.53	$15.19	$0.95	$1.13**	40.5%	1.34	6.79	57.89%	-$0.75	$0.89
7	$3.73	$3.57	$13.25	$1.26	$1.05**	37.3%	1.17	5.94	56.90%	-$0.70	$0.84
8	$3.74	$3.59	$14.06	$1.35	$0.98**	35.1%	1.13	5.88	56.27%	-$0.66	$0.79
9	$3.73	$3.60	$10.65	$1.11	$0.93**	33.1%	1.04	5.21	56.00%	-$0.63	$0.76
10	$3.73	$3.61	$10.91	$1.55	$0.88**	31.3%	1.04	5.38	56.12%	-$0.60	$0.72
11	$3.73	$3.62	$11.00	$1.35	$0.83**	29.8%	1.00	5.25	55.64%	-$0.58	$0.69
12	$3.73	$3.62	$9.88	$1.47	$0.80**	28.5%	0.90	4.72	55.41%	-$0.56	$0.67
13	$3.72	$3.63	$8.95	$1.65	$0.77**	27.3%	0.87	4.56	55.76%	-$0.54	$0.65
14	$3.72	$3.63	$9.12	$1.65	$0.74**	26.4%	0.83	4.54	55.19%	-$0.53	$0.63
15	$3.73	$3.65	$9.26	$1.77	$0.71**	25.4%	0.80	4.35	54.82%	-$0.50	$0.61
20	$3.73	$3.66	$7.34	$1.75	$0.62**	22.1%	0.70	3.94	54.17%	-$0.45	$0.54
30	$3.73	$3.69	$8.08	$2.12	$0.50*	17.8%	0.55	3.76	53.11%	-$0.37	$0.45
40	$3.73	$3.70	$6.07	$2.37	$0.42**	15.2%	0.48	3.50	52.64%	-$0.32	$0.39
50	$3.73	$3.71	$6.00	$2.36	$0.37**	13.4%	0.41	3.36	52.52%	-$0.28	$0.34
All	$3.73	$3.73	$3.92	$3.63	$0.07	2.5%	1.20	4.48	53.25%	-$0.03	$0.04

Panel B: Sample Period January 1999 - December 2006

Portfolio Size	Mean Terminal Weatlh (TWM)	Median Terminal Weatlh	Maximum Terminal Weatlh	Minimum Terminal Weatlh	Terminal Wealth Standard Deviation (TWSD)	Reduction	Terminal Wealth Skewness	Terminal Wealth Kurtosis	Shortfall Probability	Mean Shortfall	Semi-Deviation
1	$2.80	$2.05	$134.04	$0.00	$4.21	100.0%	9.44	132.11	75.61%	-$1.05	$1.21
2	$2.80	$2.14	$74.90	$0.11	$3.08**	73.1%	7.20	80.27	75.27%	-$0.90	$1.02
3	$2.82	$2.20	$46.91	$0.46	$2.47**	58.6%	5.19	40.34	74.05%	-$0.82	$0.92
4	$2.81	$2.25	$36.36	$0.47	$2.12**	50.3%	4.56	31.89	73.39%	-$0.77	$0.86
5	$2.81	$2.28	$35.55	$0.75	$1.90**	45.1%	4.36	31.27	72.33%	-$0.73	$0.82
6	$2.79	$2.31	$29.41	$0.77	$1.70**	40.4%	4.01	26.95	72.09%	-$0.70	$0.78
7	$2.79	$2.33	$23.87	$0.78	$1.56**	37.0%	3.53	21.06	71.18%	-$0.67	$0.75
8	$2.79	$2.35	$27.94	$0.89	$1.48**	35.1%	3.36	19.65	70.80%	-$0.65	$0.73
9	$2.79	$2.37	$20.51	$1.07	$1.40**	33.2%	3.22	18.39	69.91%	-$0.63	$0.71
10	$2.79	$2.39	$23.09	$0.94	$1.32**	31.4%	2.96	15.65	70.13%	-$0.61	$0.69
11	$2.80	$2.41	$15.49	$1.05	$1.27**	30.2%	2.81	13.89	69.52%	-$0.60	$0.67
12	$2.80	$2.42	$16.55	$1.03	$1.22**	28.9%	2.69	13.37	68.94%	-$0.58	$0.66
13	$2.80	$2.44	$15.54	$1.24	$1.16**	27.6%	2.63	13.09	68.34%	-$0.57	$0.64
14	$2.80	$2.45	$13.52	$1.30	$1.12**	26.5%	2.51	11.99	68.34%	-$0.56	$0.63
15	$2.80	$2.46	$15.02	$1.23	$1.08**	25.7%	2.39	11.29	67.71%	-$0.55	$0.62
20	$2.80	$2.51	$11.63	$1.41	$0.93**	22.1%	2.03	8.73	66.03%	-$0.51	$0.57
30	$2.80	$2.57	$9.04	$1.51	$0.76**	18.0%	1.64	6.70	63.13%	-$0.45	$0.51
40	$2.80	$2.62	$8.97	$1.56	$0.65**	15.5%	1.43	5.88	60.77%	-$0.41	$0.47
50	$2.80	$2.66	$7.01	$1.70	$0.58**	13.8%	1.26	5.14	59.49%	-$0.38	$0.44
All	$2.80	$2.80	$2.90	$2.74	$0.04	0.9%	0.88	3.37	52.26%	-$0.02	$0.03

Panel C: Sample Period January 2003 - December 2006

Portfolio Size	Mean Terminal Weatlh (TWM)	Median Terminal Weatlh	Maximum Terminal Weatlh	Minimum Terminal Weatlh	Terminal Wealth Standard Deviation (TWSD)	Reduction	Terminal Wealth Skewness	Terminal Wealth Kurtosis	Shortfall Probability	Mean Shortfall	Semi-Deviation
1	$1.67	$1.45	$18.47	$0.24	$0.94	100.0%	6.82	83.80	68.18%	-$0.36	$0.42
2	$1.66	$1.51	$10.33	$0.36	$0.65**	68.5%	4.61	40.54	66.19%	-$0.29	$0.34
3	$1.66	$1.54	$8.04	$0.65	$0.54**	57.5%	3.84	28.16	64.93%	-$0.26	$0.30
4	$1.66	$1.55	$7.02	$0.74	$0.46**	49.2%	3.36	22.88	64.23%	-$0.24	$0.28
5	$1.66	$1.57	$6.57	$0.89	$0.41**	43.9%	2.99	18.45	63.03%	-$0.22	$0.26
6	$1.67	$1.58	$5.45	$0.82	$0.39**	41.0%	2.69	15.31	62.48%	-$0.21	$0.24
7	$1.66	$1.58	$6.29	$0.88	$0.36**	37.9%	2.60	14.47	62.33%	-$0.19	$0.23
8	$1.67	$1.59	$4.92	$0.97	$0.33**	35.0%	2.39	12.90	61.47%	-$0.19	$0.22
9	$1.66	$1.60	$5.30	$1.05	$0.31**	33.0%	2.23	11.62	61.35%	-$0.18	$0.21
10	$1.67	$1.60	$4.94	$1.08	$0.30**	31.7%	2.17	11.23	61.09%	-$0.17	$0.20
11	$1.67	$1.61	$4.47	$1.07	$0.29**	30.3%	2.09	10.58	60.43%	-$0.17	$0.19
12	$1.67	$1.61	$4.06	$1.06	$0.27**	29.0%	1.98	9.63	60.31%	-$0.16	$0.19
13	$1.67	$1.61	$4.14	$1.12	$0.26**	27.7%	1.87	9.05	59.97%	-$0.16	$0.18
14	$1.67	$1.61	$4.11	$1.14	$0.25**	26.7%	1.83	8.83	59.84%	-$0.15	$0.18
15	$1.67	$1.62	$3.91	$1.16	$0.24**	25.9%	1.84	8.86	59.98%	-$0.15	$0.17
20	$1.67	$1.62	$3.42	$1.19	$0.21**	22.3%	1.50	6.79	58.98%	-$0.13	$0.16
30	$1.66	$1.64	$2.73	$1.26	$0.17**	18.1%	1.21	5.35	57.95%	-$0.11	$0.13
40	$1.67	$1.64	$2.72	$1.30	$0.15**	15.6%	1.06	4.86	56.81%	-$0.10	$0.12
50	$1.67	$1.65	$2.50	$1.33	$0.13*	13.9%	0.91	4.29	55.82%	-$0.09	$0.11
All	$1.67	$1.66	$1.68	$1.66	$0.00	0.4%	0.97	3.75	51.82%	-$0.00	$0.00

This table presents terminal wealth statistics for portfolio sizes from 1 to 50 funds assuming an initial investment of $1. Panel A presents the results for the period January 1995 to December 2006, Panel B presents the results for the period starting in January 1999 and ending in December 2006 and Panel C presents the results for the period starting in January 2003 and ending in December 2006. All results are calculated from either 50,000 random selections or the exhaustive set of possible combinations using the data set presented in table 2

As one would expect the mean terminal wealth (TWM) is independent of the size of the portfolio but does depend upon the sample period. As the average returns were positive for all periods, TWM is largest for the twelve year sample and smallest for the four year sample period. For portfolios of individual funds, the difference between the maximum and minimum terminal wealth values is extremely wide with the minimum being close to zero for all three sample periods, this is an indication of how risky simply choosing a single fund can be. The risk of extreme outcomes gradually reduces as portfolio size is increased but even with a portfolio of 20 funds the minimum terminal wealth is less than 50% of the average for the twelve and eight year sample periods.

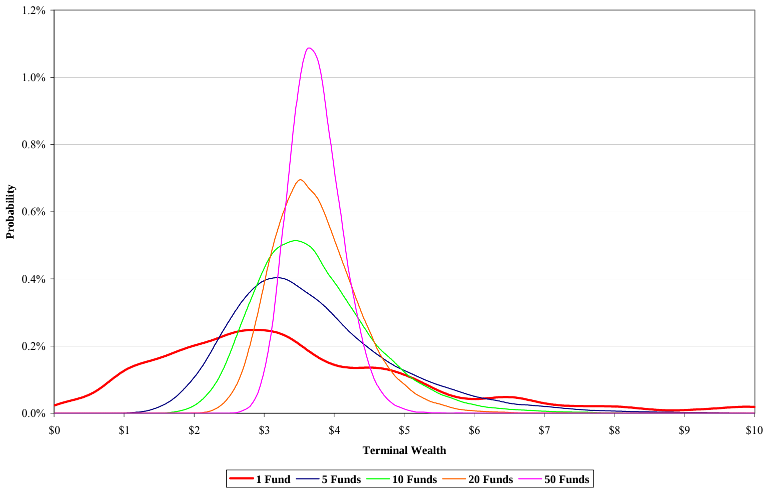
For all three sample periods the terminal wealth standard deviation (TWSD) declines rapidly initially as the number of funds in the portfolio is increased but the rate of decrease levels off quite quickly. This is exactly as predicted by equations (13) and (14), because the TWSD is simply a function of the square root of the portfolio size. For a portfolio size of 20 funds, equation (14) predicts that the TWSD relative to the single fund case should be $1/\sqrt{20} \approx 22\%$, which is the result I find for all three sample periods.

An F-test is used to determine the statistical significance of the TWSD reduction as portfolio size increases. When comparing two distributions, the ratio of the variances is distributed $F(d_1,d_2)$ where d_1 and d_2 are the degrees of freedom for the respective samples. I am able to reject the null hypothesis of equal variances for all portfolio sizes considered; more specifically the TWSD of the larger portfolio is always significantly less at the 1% level than the TWSD of the smaller portfolio. This result contrasts with the results for the time series standard deviation presented above and implies that there are significant benefits to diversifying beyond the 30 fund portfolio level.

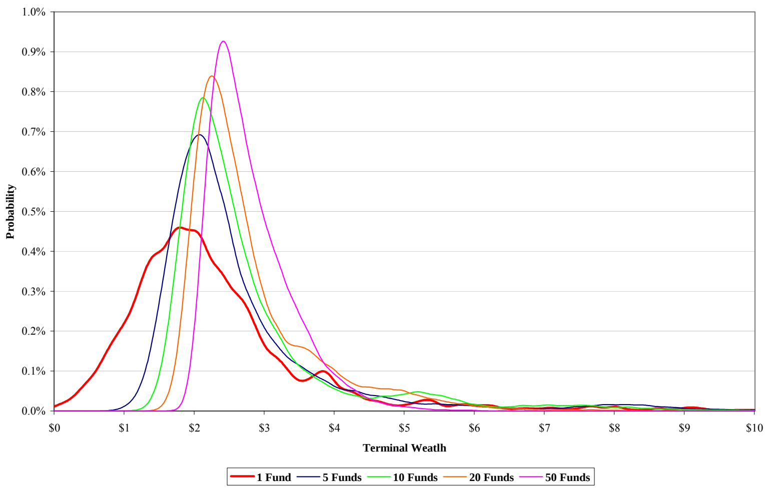
For all three sample periods the median terminal wealth is below the mean value which indicates that the distribution is positively skewed (as confirmed by the skewness measure). This has extremely important implications for the construction of portfolio as it indicates that the TWM is influenced by a small number of high performing funds.

Figure 4.8 – Probability Density Functions For Selected Portfolio Sizes

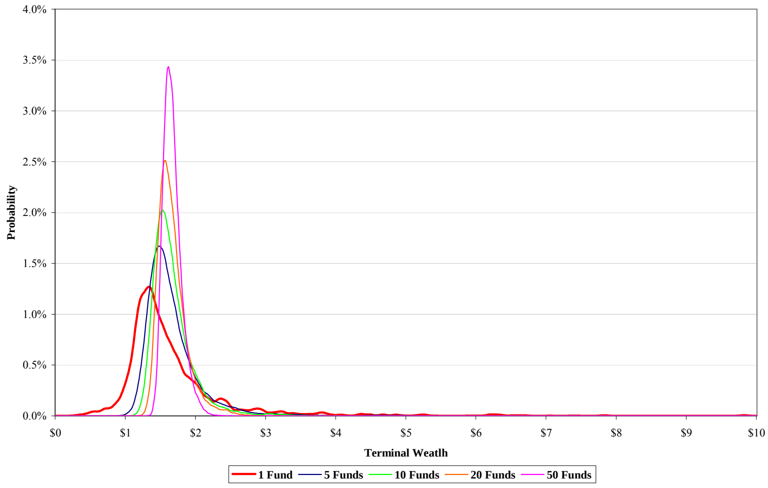
Sample Period January 1995 - December 2006



Sample Period January 1999 - December 2006



Sample Period January 2003 - December 2006



These figures depict the probability density functions of the terminal wealth achieved from an initial investment of $1 over the three sample periods.

Figure 4.8 shows the probability density function for the individual funds and selected portfolio sizes. The long right hand tails of the three distributions shows the positive skewness.

This fact is also illustrated by the shortfall probability. The benchmark I use is the mean return all of the funds in the sample, because more of the randomly selected funds have a return below the mean than above (as illustrated above) the shortfall probability is always greater than 50%. The shortfall probability declines in an almost linear fashion as the portfolio size is increase for all three sample periods but does not approach 50% until a portfolio of all funds is held.

As previously mentioned, the major shortcoming of the shortfall probability is that it does not take account of the magnitude by which returns fall short of the mean, for this reason I also calculate the mean shortfall. As with many of the previous risk measures, the mean shortfall decreases as the portfolio size is increased and this rate of decrease declines fairly rapidly. The mean shortfall is reduced to almost 50% of the single fund portfolio level by increasing the portfolio size to between seven and twelve funds depending upon the sample period chosen. However these shortfalls are still substantial, take for example a portfolio size of 20 funds in the twelve year sample period where the mean shortfall is $0.45, this equates to an annual shortfall of 1.19% p.a. Thus a naïve investor who formed an equally weighted portfolio of 20 hedge funds has a 53% chance of underperforming the mean by an average of 1.19% p.a.

All of the above would imply that there are indeed benefits to holding portfolios of hedge funds that are much larger than the ten to fifteen funds that have been previously suggested as the optimum size. The main reason for this is that previous studies have ignored the uncertainty that exists around the mean return; although the mean return remains unchanged as portfolio size is increased the uncertainty around that mean is reduced. If, as in the case of my sample of hedge funds, the distribution of individual fund returns is positively skewed then there is a more than 50% probability that a portfolio of funds chosen at random will have a return below the mean.

To better illustrate this effect I repeat all of the above analysis on a sample of mutual fund returns drawn from the Morningstar database. Using the same sample period as before (January 1995 to December 2006), I extract all live and dead actively managed large cap US mutual funds which results in a sample of 1,934 funds of which 1,407 are live and 527 are dead. Summary time series and terminal wealth statistics for selected portfolio sizes are presented in table 4.5 which are directly comparable with tables 4.3 and 4.4.

Table 4.5 – Summary Time Series and Terminal Wealth Statistics For Mutual Fund Sample

Sample Period January 1995 - December 2006

	Panel A: Summary Time Series Statistics						Panel B: Summary Terminal Wealth Statistics						
Portfolio Size	Mean Return	Mean Standard Deviaiton	Reduction	Mean Skew	Mean Kurtosis	Mean 1 Month VAR 95%	Mean Terminal Weatlh (TWM)	Median Terminal Weatlh	Terminal Wealth Standard Deviation	Reduction	Terminal Wealth Skewness	Terminal Wealth Kurtosis	Shortfall Probability
1	9.9%	15.9%		-0.58	4.48	-7.1%	$3.10	$3.07	$1.19		0.67	0.26	53.3%
2	9.9%	14.9%**	93.6%	-0.60**	4.16**	-6.6%	$3.10	$3.07	$0.84**	70.6%	0.47	0.33	51.7%
3	9.9%	14.5%**	91.3%	-0.63**	4.11**	-6.5%	$3.10	$3.07	$0.69**	57.7%	0.37	0.37	51.6%
4	9.9%	14.3%**	90.2%	-0.65**	4.10**	-6.4%	$3.10	$3.07	$0.59**	49.6%	0.32	0.41	51.6%
5	9.9%	14.2%**	89.4%	-0.67**	4.09*	-6.4%	$3.10	$3.08	$0.53**	44.6%	0.28	0.43	51.5%
6	9.9%	14.1%**	88.9%	-0.69**	4.09	-6.4%	$3.10	$3.08	$0.48**	40.6%	0.27	0.46	51.5%
7	9.9%	14.1%**	88.6%	-0.70**	4.08	-6.4%	$3.10	$3.08	$0.45**	37.4%	0.23	0.47	51.3%
8	9.9%	14.0%**	88.2%	-0.70**	4.08	-6.3%	$3.10	$3.08	$0.42**	35.1%	0.24	0.48	51.4%
9	9.9%	14.0%**	88.0%	-0.71**	4.08	-6.3%	$3.10	$3.08	$0.39**	33.1%	0.22	0.50	51.2%
10	9.9%	14.0%**	87.8%	-0.71**	4.08*	-6.4%	$3.10	$3.09	$0.37**	31.2%	0.19	0.51	50.9%
11	9.9%	14.0%*	87.7%	-0.72**	4.08	-6.4%	$3.10	$3.09	$0.35**	29.7%	0.18	0.52	51.1%
12	9.9%	13.9%*	87.6%	-0.72**	4.07	-6.4%	$3.10	$3.08	$0.34**	28.5%	0.17	0.52	51.4%
13	9.9%	13.9%*	87.6%	-0.73**	4.07	-6.4%	$3.10	$3.08	$0.32**	27.2%	0.19	0.53	51.6%
14	9.9%	13.9%**	87.4%	-0.73**	4.07	-6.4%	$3.10	$3.09	$0.31**	26.4%	0.17	0.53	50.7%
15	9.9%	13.9%	87.4%	-0.73**	4.07	-6.4%	$3.10	$3.09	$0.30**	25.2%	0.17	0.54	51.4%
20	9.9%	13.8%	87.1%	-0.74**	4.07	-6.4%	$3.10	$3.09	$0.26**	21.8%	0.15	0.56	51.1%
30	9.9%	13.8%	86.8%	-0.75**	4.07	-6.4%	$3.10	$3.09	$0.21**	17.5%	0.10	0.58	50.6%
40	9.9%	13.8%	86.7%	-0.75	4.06	-6.4%	$3.10	$3.09	$0.18**	15.0%	0.10	0.59	50.6%
50	9.9%	13.8%	86.6%	-0.76	4.06*	-6.5%	$3.10	$3.09	$0.16**	13.1%	0.06	0.60	50.6%
All	9.9%	13.7%	86.3%	-0.77	4.06	-6.5%	$3.10	$3.09	$0.00	0.4%	2.55	0.63	50.4%

*This table presents selected mean values for various time series and terminal wealth statistics for portfolio sizes from 1 to 50 funds. A bootstrap procedure is used to test whether adding 1 additional fund to the portfolio makes a statistically significant change in the mean value, those significant at the 5% level are denoted with * and those significant at 1% by **. All results are calculated from either 50,000 random selections or the exhaustive set of possible combinations.*

The time series statistic results in Panel A for mutual funds are strikingly different from those previously presented for hedge funds in table 4.3. The mutual funds in the sample are much more highly correlated and hence the reduction in time-series standard deviation in much less pronounced, in fact there is no statistically significant reduction beyond portfolios of 14 funds whereas for hedge funds there was for portfolio sizes up to 30 funds.

The terminal wealth statistics presented in panel B are also somewhat different for mutual funds compared to hedge funds. Although the distribution of individual fund return is still exhibits positive skew and excess kurtosis (skewness = 0.67 and excess kurtosis = 0.26) the effect is much smaller than for hedge funds (skewness = 3.2 and excess kurtosis = 25.24). This is reflected in the shortfall probability which is 53.3% for portfolios of one fund compared to 63.33% for hedge funds. In fact a portfolio of just 2 mutual funds has a lower shortfall probability than a portfolio of 50 hedge funds.

These results clearly demonstrate that a much smaller portfolio of mutual funds compared to hedge funds is required to be adequately diversified and that this is driven by the statistical properties of the underlying funds, namely their correlation, skewness and kurtosis.

4.5 EXAMINING THE EFFECT OF REBALANCING

Thus far all of my results have been calculated for portfolios that are not rebalanced, hence although the portfolio weights are equal at the point at inception they will vary significantly over time. As pointed out by Gorton and Rouwenhorst (2005) rebalancing is actually an embedded trading strategy whereby an investor “sells” assets with strong prior performance and “buys” assets with poor prior performance. If returns are not independent over time, this trading strategy can either lose or make money depending on the time series properties of the underlying assets.

I now repeat the previous analysis with annual rebalancing to equal portfolio weights. More frequent rebalancing would be impractical due to the various lock-up and redemption restrictions that most hedge funds apply to their investors. The results are presented in tables 4.6 and 4.7 which are directly comparable to tables 4.3 and 4.4.

The first and most striking result is that rebalancing does not appear to have been a profitable trading strategy in any of the three sample periods considered. This is illustrated by the fact that the mean return declines as the portfolio size is increased. The reason for this probably lies in the performance persistence of the underlying funds. Authors including Agarwal and Naik (2000) and Edwards and Caglayan (2001) have found evidence of performance persistence for both winners and losers. Rebalancing the portfolios annually means selling part of the best performing funds and buying the worst performing funds. If either the best performing funds continue to outperform or the worst performing funds continue to under perform (i.e. persistence) then this will clearly not be a profitable strategy.

Table 4.6 – Summary Time Series Statistics For Annually Rebalanced Portfolios

Panel A: Sample Period January 1995 - December 2006

Portfolio Size	Mean Return	Mean Standard Deviaiton	Reduction	Mean Skew	Mean Kurtosis	Mean 1 Month VAR 95%	Mean 1 Month VAR 99%	Mean 1 Month CVAR 95%	Mean 1 Month CVAR 99%	Mean Tracking Error All Funds	Mean Correlation S&P500
1	11.6%	16.5%	100.0%	-0.18	9.08	-6.3%	-12.2%	-9.9%	-17.1%	4.6%	26.0%
2	11.6%	13.1%**	79.3%	-0.09**	7.32**	-4.9%**	-9.3%**	-7.6%**	-12.9%**	3.4%**	32.2%**
3	11.6%	11.5%**	69.9%	-0.06**	6.51**	-4.2%**	-8.0%**	-6.5%**	-11.1%**	2.8%**	36.3%**
4	11.6%	10.6%**	64.4%	-0.04**	6.05**	-3.8%**	-7.2%**	-5.9%**	-10.0%**	2.4%**	39.3%**
5	11.5%	10.0%**	60.8%	-0.03	5.73**	-3.6%**	-6.7%**	-5.4%**	-9.3%**	2.2%**	41.8%**
6	11.6%	9.6%**	58.1%	-0.03	5.52**	-3.4%**	-6.3%**	-5.1%**	-8.8%**	2.0%**	43.9%**
7	11.6%	9.2%**	55.9%	-0.03	5.34**	-3.2%**	-6.0%**	-4.9%**	-8.5%**	1.9%**	45.8%**
8	11.5%	9.0%**	54.5%	-0.02	5.22**	-3.1%**	-5.8%**	-4.7%**	-8.1%**	1.7%**	47.0%**
9	11.5%	8.8%**	53.2%	-0.03	5.09**	-3.0%**	-5.6%**	-4.6%**	-7.9%**	1.7%**	48.3%**
10	11.5%	8.6%**	52.3%	-0.03	5.01**	-2.9%**	-5.4%**	-4.5%**	-7.8%**	1.6%**	49.2%**
11	11.6%	8.5%**	51.3%	-0.03	4.95**	-2.9%**	-5.3%**	-4.4%**	-7.6%**	1.5%**	50.3%**
12	11.6%	8.4%**	50.6%	-0.03	4.86**	-2.8%**	-5.2%**	-4.3%**	-7.5%**	1.4%**	51.1%**
13	11.5%	8.3%**	50.0%	-0.03	4.81**	-2.8%**	-5.1%**	-4.2%**	-7.4%**	1.4%**	51.8%**
14	11.5%	8.2%**	49.4%	-0.03	4.76**	-2.7%**	-5.0%**	-4.1%**	-7.3%**	1.3%**	52.3%**
15	11.5%	8.1%**	48.9%	-0.03*	4.71**	-2.7%**	-4.9%**	-4.1%**	-7.2%*	1.3%**	52.9%**
20	11.5%	7.8%**	47.2%	-0.04	4.57**	-2.5%**	-4.6%**	-3.9%**	-7.0%**	1.1%**	55.1%**
30	11.5%	7.5%**	45.4%	-0.04	4.41*	-2.4%**	-4.3%**	-3.6%**	-6.7%**	0.9%**	57.5%*
40	11.5%	7.3%**	44.4%	-0.03	4.32	-2.3%**	-4.1%**	-3.5%**	-6.6%	0.8%**	59.0%
50	11.5%	7.2%	43.9%	-0.04*	4.29*	-2.2%**	-4.0%**	-3.4%	-6.6%	0.7%**	59.8%
All	11.5%	6.9%	41.8%	-0.03	4.13	-2.1%	-3.7%	-3.2%	-6.5%	0.0%	63.0%

Panel B: Sample Period January 1999 - December 2006

Portfolio Size	Mean Return	Mean Standard Deviaiton	Reduction	Mean Skew	Mean Kurtosis	Mean 1 Month VAR 95%	Mean 1 Month VAR 99%	Mean 1 Month CVAR 95%	Mean 1 Month CVAR 99%	Mean Tracking Error All Funds	Mean Correlation S&P500
1	13.7%	15.3%	100.0%	0.30	7.41	-5.8%	-10.7%	-8.3%	-12.2%	4.3%	22.9%
2	12.5%	12.4%**	80.7%	0.36**	6.69**	-4.5%**	-8.1%**	-6.3%**	-9.2%**	3.3%**	28.9%**
3	12.3%	10.9%**	71.5%	0.38**	6.23**	-3.9%**	-6.9%**	-5.4%**	-7.9%**	2.7%**	32.9%**
4	12.2%	10.1%**	66.2%	0.42	5.91**	-3.5%**	-6.2%**	-4.9%**	-7.0%**	2.4%**	35.8%**
5	12.1%	9.5%**	62.2%	0.43**	5.64**	-3.2%**	-5.7%**	-4.5%**	-6.4%**	2.2%**	38.1%**
6	12.2%	9.1%**	59.7%	0.45**	5.44**	-3.1%**	-5.3%**	-4.2%**	-5.9%**	2.0%**	40.0%**
7	12.1%	8.8%**	57.5%	0.46**	5.29**	-2.9%**	-5.0%**	-4.0%**	-5.6%**	1.9%**	41.6%**
8	12.0%	8.5%**	55.8%	0.47**	5.16**	-2.8%**	-4.8%**	-3.8%**	-5.3%**	1.8%**	42.9%**
9	12.0%	8.3%**	54.5%	0.48	5.05**	-2.7%**	-4.6%**	-3.7%**	-5.1%**	1.7%**	44.0%**
10	12.0%	8.2%**	53.4%	0.49*	4.96**	-2.7%**	-4.4%**	-3.6%**	-4.9%**	1.6%**	45.1%**
11	12.0%	8.0%**	52.4%	0.50**	4.88**	-2.6%**	-4.3%**	-3.5%**	-4.8%**	1.5%**	46.1%**
12	12.0%	7.9%**	51.6%	0.50	4.81**	-2.5%**	-4.2%**	-3.4%**	-4.6%**	1.5%**	46.9%**
13	12.0%	7.8%**	50.9%	0.50	4.75**	-2.5%**	-4.1%**	-3.3%**	-4.5%**	1.4%**	47.7%**
14	12.0%	7.7%**	50.3%	0.51**	4.70	-2.4%**	-4.0%**	-3.2%**	-4.4%**	1.4%**	48.2%**
15	12.0%	7.6%**	49.8%	0.51	4.68**	-2.4%**	-3.9%**	-3.2%**	-4.3%**	1.3%**	48.8%**
20	12.0%	7.3%**	47.9%	0.53	4.54	-2.3%**	-3.6%**	-3.0%**	-4.0%**	1.1%**	51.0%**
30	12.0%	7.0%**	45.8%	0.55	4.42	-2.1%**	-3.3%**	-2.7%**	-3.6%**	0.9%**	53.7%**
40	11.9%	6.8%**	44.7%	0.56	4.37	-2.0%**	-3.1%**	-2.6%**	-3.3%**	0.8%**	55.1%*
50	11.9%	6.7%	44.0%	0.57	4.32	-2.0%	-3.0%**	-2.5%*	-3.2%**	0.7%**	55.9%**
All	11.9%	6.3%	41.4%	0.62	4.08	-1.9%	-2.3%	-2.2%	-2.4%	0.0%	59.9%

Panel C: Sample Period January 2003 - December 2006

Portfolio Size	Mean Return	Mean Standard Deviaiton	Reduction	Mean Skew	Mean Kurtosis	Mean 1 Month VAR 95%	Mean 1 Month VAR 99%	Mean 1 Month CVAR 95%	Mean 1 Month CVAR 99%	Mean Tracking Error All Funds	Mean Correlation S&P500
1	13.6%	9.7%	100.0%	0.11	4.53	-3.5%	-5.7%	-5.0%	-5.7%	2.7%	31.3%
2	12.9%	8.1%**	82.9%	0.10**	4.04**	-2.8%**	-4.5%**	-3.9%**	-4.5%**	2.1%**	40.1%**
3	12.8%	7.3%**	74.6%	0.09**	3.84**	-2.4%**	-3.9%**	-3.4%**	-3.9%**	1.8%**	45.4%**
4	12.7%	6.8%**	69.8%	0.06**	3.69**	-2.2%**	-3.6%**	-3.1%**	-3.6%**	1.6%**	48.8%**
5	12.7%	6.5%**	66.6%	0.04**	3.58**	-2.1%**	-3.3%**	-2.9%**	-3.3%**	1.4%**	51.6%**
6	12.6%	6.2%**	64.0%	0.02**	3.48**	-2.0%**	-3.1%**	-2.8%**	-3.1%**	1.3%**	53.8%**
7	12.6%	6.1%**	62.5%	0.00**	3.42**	-1.9%**	-3.0%**	-2.7%**	-3.0%**	1.2%**	55.5%**
8	12.6%	5.9%**	60.8%	-0.01**	3.33**	-1.9%**	-2.9%**	-2.6%**	-2.9%**	1.1%**	56.9%**
9	12.5%	5.8%**	59.5%	-0.03**	3.26**	-1.8%**	-2.8%**	-2.5%**	-2.8%**	1.1%**	57.9%**
10	12.5%	5.7%**	58.8%	-0.05**	3.19**	-1.8%**	-2.8%**	-2.5%**	-2.8%**	1.0%**	59.0%**
11	12.6%	5.6%**	57.9%	-0.06**	3.15**	-1.8%**	-2.7%**	-2.4%**	-2.7%**	1.0%**	60.0%**
12	12.5%	5.6%**	57.2%	-0.08**	3.09**	-1.8%**	-2.7%**	-2.4%**	-2.7%**	0.9%**	60.8%**
13	12.5%	5.5%**	56.6%	-0.09**	3.05**	-1.7%**	-2.6%**	-2.3%**	-2.6%**	0.9%**	61.4%**
14	12.5%	5.5%**	56.1%	-0.11**	3.01**	-1.7%**	-2.6%**	-2.3%**	-2.6%**	0.9%**	62.0%**
15	12.5%	5.4%**	55.5%	-0.11**	2.98**	-1.7%**	-2.5%**	-2.3%**	-2.5%**	0.8%**	62.5%**
20	12.5%	5.3%**	54.0%	-0.16**	2.85**	-1.7%**	-2.4%**	-2.2%**	-2.4%**	0.7%**	64.6%**
30	12.4%	5.1%*	52.1%	-0.21**	2.74**	-1.6%	-2.3%**	-2.1%*	-2.3%*	0.6%**	66.8%**
40	12.4%	5.0%	51.2%	-0.24	2.69	-1.6%	-2.2%*	-2.0%*	-2.2%*	0.5%**	68.1%**
50	12.4%	4.9%	50.8%	-0.26	2.66	-1.6%	-2.1%	-2.0%	-2.1%	0.5%**	68.8%**
All	12.4%	4.7%	48.5%	-0.33	2.57	-1.7%	-1.8%	-1.7%	-1.8%	0.0%	72.1%

*This table presents mean values for various time series statistics for portfolio sizes from 1 to 50 funds which are rebalanced annually to equal weights. Panel A presents the results for the period January 1995 to December 2006, Panel B presents the results for the period starting in January 1999 and ending in December 2006 and Panel C presents the results for the period starting in January 2003 and ending in December 2006. All results are calculated from either 50,000 random selections or the exhaustive set of possible combinations using the data set presented in table 4. 2. A bootstrap procedure is used to test whether adding 1 additional fund to the portfolio makes a statistically significant change in the mean value, those significant at the 5% level are denoted with * and those significant at 1% by **.*

Table 4.7 – Summary Terminal Wealth Statistics For Annually Rebalanced Portfolios

Panel A: Sample Period January 1995 - December 2006

Portfolio Size	Mean Terminal Weatlh (TWM)	Median Terminal Weatlh	Maximum Terminal Weatlh	Minimum Terminal Weatlh	Terminal Wealth Standard Deviation (TWSD)	Reduction	Terminal Wealth Skewness	Terminal Wealth Kurtosis	Shortfall Probability	Mean Shortfall	Semi-Deviation
1	$3.73	$3.16	$46.55	$0.01	$2.80	100.0%	3.20	24.24	63.33%	-$1.45	$1.71
2	$3.73	$3.34	$43.93	$0.12	$2.07**	73.8%	3.02	26.15	59.34%	-$1.14	$1.35
3	$3.72	$3.44	$39.15	$0.34	$1.63**	58.2%	2.04	16.07	57.40%	-$0.98	$1.17
4	$3.72	$3.50	$18.94	$0.36	$1.39**	49.6%	1.45	7.95	56.36%	-$0.88	$1.05
5	$3.71	$3.53	$17.74	$0.74	$1.23**	43.9%	1.26	6.74	55.62%	-$0.80	$0.96
6	$3.71	$3.56	$13.31	$0.71	$1.12**	39.9%	1.09	5.67	55.25%	-$0.74	$0.89
7	$3.72	$3.58	$13.35	$0.88	$1.03**	36.8%	0.99	5.14	54.73%	-$0.69	$0.84
8	$3.71	$3.58	$12.01	$1.15	$0.96**	34.2%	0.90	4.85	54.64%	-$0.65	$0.79
9	$3.71	$3.60	$10.84	$1.30	$0.91**	32.3%	0.86	4.66	54.07%	-$0.62	$0.75
10	$3.71	$3.62	$10.17	$1.19	$0.86**	30.6%	0.78	4.37	53.71%	-$0.59	$0.72
11	$3.71	$3.63	$10.64	$1.33	$0.82**	29.4%	0.77	4.36	53.43%	-$0.56	$0.68
12	$3.71	$3.63	$10.07	$1.47	$0.78**	28.0%	0.72	4.25	53.36%	-$0.54	$0.66
13	$3.71	$3.64	$8.67	$1.50	$0.75**	26.7%	0.67	4.06	52.75%	-$0.53	$0.64
14	$3.71	$3.64	$8.70	$1.52	$0.72**	25.8%	0.66	3.93	52.83%	-$0.50	$0.61
15	$3.71	$3.64	$8.24	$1.65	$0.70**	24.9%	0.64	3.85	53.22%	-$0.49	$0.60
20	$3.71	$3.66	$7.30	$1.72	$0.60**	21.4%	0.54	3.62	52.29%	-$0.43	$0.52
30	$3.70	$3.67	$6.39	$2.17	$0.48**	17.1%	0.40	3.31	51.53%	-$0.35	$0.43
40	$3.71	$3.68	$6.05	$2.27	$0.41**	14.6%	0.35	3.30	51.37%	-$0.30	$0.37
50	$3.70	$3.69	$5.78	$2.54	$0.36**	12.9%	0.33	3.24	51.04%	-$0.27	$0.33
All	$3.70	$3.70	$3.81	$3.57	$0.06**	2.3%	-0.29	2.41	40.00%	-$0.06	$0.06

Panel B: Sample Period January 1999 - December 2006

Portfolio Size	Mean Terminal Weatlh (TWM)	Median Terminal Weatlh	Maximum Terminal Weatlh	Minimum Terminal Weatlh	Terminal Wealth Standard Deviation (TWSD)	Reduction	Terminal Wealth Skewness	Terminal Wealth Kurtosis	Shortfall Probability	Mean Shortfall	Semi-Deviation
1	$2.80	$2.05	$134.04	$0.00	$4.21	100.0%	9.44	132.11	75.61%	-$1.05	$1.21
2	$2.57	$2.17	$47.97	$0.16	$1.78**	42.3%	4.66	43.85	74.33%	-$0.88	$1.01
3	$2.53	$2.22	$36.07	$0.37	$1.33**	31.5%	3.92	38.90	74.10%	-$0.79	$0.90
4	$2.52	$2.26	$14.88	$0.53	$1.06**	25.1%	2.50	13.77	73.90%	-$0.74	$0.84
5	$2.49	$2.29	$16.00	$0.68	$0.92**	21.8%	2.46	15.52	74.20%	-$0.69	$0.79
6	$2.50	$2.31	$16.57	$0.74	$0.84**	19.8%	2.17	13.04	74.30%	-$0.66	$0.76
7	$2.49	$2.33	$12.33	$0.76	$0.75**	17.8%	1.92	10.54	74.99%	-$0.64	$0.72
8	$2.48	$2.35	$9.26	$0.79	$0.69**	16.4%	1.74	8.94	75.61%	-$0.61	$0.70
9	$2.48	$2.35	$10.74	$0.87	$0.65**	15.5%	1.68	9.23	76.29%	-$0.59	$0.67
10	$2.48	$2.37	$11.07	$1.08	$0.61**	14.5%	1.55	8.31	76.44%	-$0.58	$0.66
11	$2.48	$2.37	$7.83	$1.14	$0.57**	13.6%	1.37	6.69	77.08%	-$0.56	$0.64
12	$2.48	$2.38	$8.13	$1.11	$0.55**	13.1%	1.35	6.78	77.27%	-$0.54	$0.62
13	$2.48	$2.38	$7.13	$1.21	$0.53**	12.6%	1.28	6.28	77.75%	-$0.53	$0.61
14	$2.47	$2.39	$7.69	$1.25	$0.51**	12.1%	1.29	6.64	78.63%	-$0.52	$0.60
15	$2.47	$2.39	$7.29	$1.20	$0.49**	11.6%	1.21	6.15	78.98%	-$0.52	$0.59
20	$2.47	$2.41	$5.63	$1.30	$0.42**	9.9%	1.00	5.01	81.02%	-$0.48	$0.54
30	$2.47	$2.42	$5.30	$1.49	$0.34**	8.1%	0.78	4.19	84.94%	-$0.43	$0.49
40	$2.46	$2.43	$4.61	$1.58	$0.29**	6.9%	0.70	4.09	87.74%	-$0.40	$0.45
50	$2.46	$2.44	$4.12	$1.70	$0.26**	6.1%	0.61	3.76	89.94%	-$0.39	$0.43
All	$2.46	$2.45	$2.49	$2.41	$0.02**	0.4%	-0.28	2.82	100.00%	-$0.33	$0.33

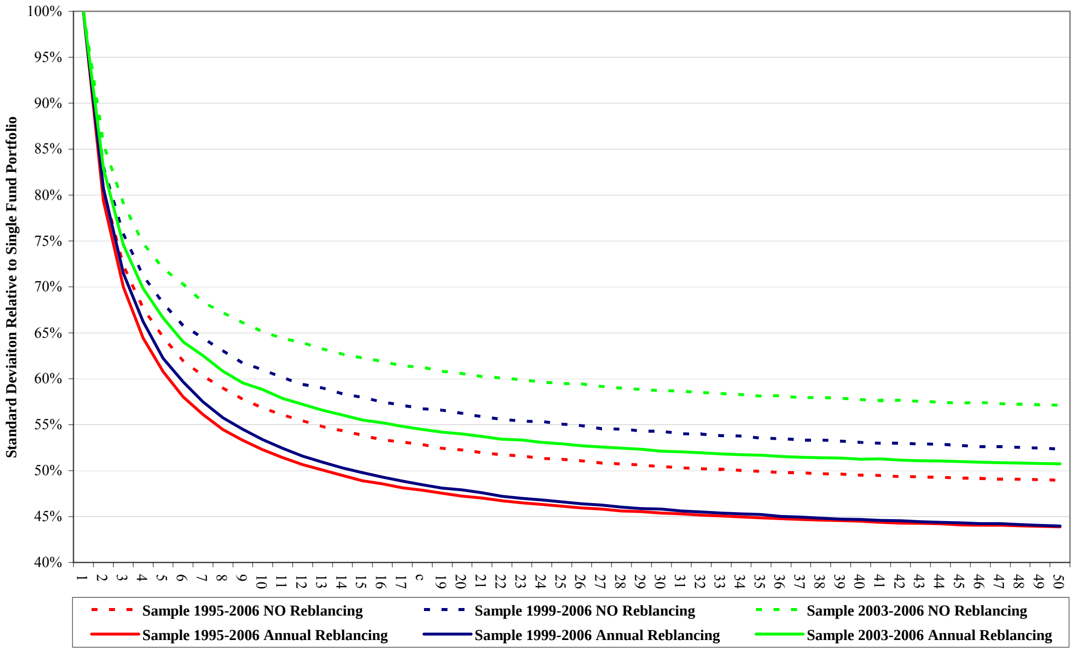
Panel C: Sample Period January 2003 - December 2006

Portfolio Size	Mean Terminal Weatlh (TWM)	Median Terminal Weatlh	Maximum Terminal Weatlh	Minimum Terminal Weatlh	Terminal Wealth Standard Deviation (TWSD)	Reduction	Terminal Wealth Skewness	Terminal Wealth Kurtosis	Shortfall Probability	Mean Shortfall	Semi-Deviation
1	$1.67	$1.45	$18.47	$0.24	$0.94	100.0%	6.82	83.80	68.18%	-$0.36	$0.42
2	$1.63	$1.50	$10.32	$0.57	$0.54**	57.3%	3.26	22.92	66.72%	-$0.30	$0.35
3	$1.62	$1.53	$7.15	$0.65	$0.42**	44.1%	2.36	14.04	66.76%	-$0.26	$0.31
4	$1.61	$1.54	$5.35	$0.70	$0.35**	37.4%	1.99	10.96	66.12%	-$0.24	$0.28
5	$1.61	$1.55	$4.51	$0.85	$0.31**	33.0%	1.67	8.37	66.81%	-$0.22	$0.26
6	$1.61	$1.56	$4.26	$0.89	$0.28**	29.5%	1.44	6.99	66.90%	-$0.21	$0.24
7	$1.61	$1.56	$3.86	$0.96	$0.26**	27.2%	1.29	6.16	66.89%	-$0.20	$0.23
8	$1.61	$1.57	$3.71	$0.97	$0.24**	25.3%	1.26	6.23	67.05%	-$0.19	$0.22
9	$1.60	$1.57	$3.23	$0.93	$0.22**	23.6%	1.09	5.24	67.37%	-$0.18	$0.21
10	$1.60	$1.57	$3.46	$1.04	$0.21**	22.5%	1.09	5.44	67.50%	-$0.17	$0.20
11	$1.60	$1.57	$3.20	$1.04	$0.20**	21.4%	1.03	5.11	68.10%	-$0.17	$0.20
12	$1.60	$1.57	$3.02	$1.05	$0.19**	20.2%	0.97	4.87	68.18%	-$0.16	$0.19
13	$1.60	$1.58	$2.99	$1.08	$0.18**	19.6%	0.96	4.83	68.82%	-$0.16	$0.19
14	$1.60	$1.58	$2.84	$1.08	$0.17**	18.5%	0.83	4.32	68.94%	-$0.16	$0.18
15	$1.60	$1.58	$2.89	$1.12	$0.17**	18.0%	0.85	4.46	69.78%	-$0.15	$0.18
20	$1.60	$1.58	$2.57	$1.15	$0.15**	15.5%	0.75	4.18	71.05%	-$0.14	$0.16
30	$1.60	$1.59	$2.28	$1.22	$0.12**	12.6%	0.59	3.69	73.51%	-$0.12	$0.14
40	$1.60	$1.59	$2.17	$1.26	$0.10**	10.9%	0.50	3.52	75.82%	-$0.11	$0.13
50	$1.60	$1.59	$2.07	$1.30	$0.09**	9.6%	0.42	3.29	77.72%	-$0.10	$0.12
All	$1.60	$1.60	$1.60	$1.59	$0.00**	0.3%	0.07	2.25	100.00%	-$0.07	$0.07

This table presents terminal wealth statistics for portfolio sizes from 1 to 50 funds which are rebalanced annually to equal weights assuming an initial investment of $1. Panel A presents the results for the period January 1995 to December 2006, Panel B presents the results for the period starting in January 1999 and ending in December 2006 and Panel C presents the results for the period starting in January 2003 and ending in December 2006. All results are calculated from either 50,000 random selections or the exhaustive set of possible combinations using the data set presented in table 4.2

Rebalancing does however appear to reduce the volatility of the resulting portfolios. Figure 4.9 compares the rebalanced and not rebalanced portfolios.

Figure 4.9 – Time Series Standard Deviation For Annually Rebalanced versus Non-Rebalanced Portfolios



This figure present graphically the results for the mean standard deviation of portfolio sizes from 1 to 50 funds for both non-rebalanced and annually rebalanced portfolios for the 3 different sample periods using the data from tables 3 and 5.

So although there appears to be a cost to this rebalancing strategy in terms of the mean return there is a corresponding benefit in the reduced standard deviation of the resulting portfolio.

4.6 CONCLUSIONS

In this chapter I have demonstrated that only using time series standard deviation to measure the benefits of diversification in portfolios of hedge funds is flawed. I have algebraically proven (and demonstrated empirically) that approximately 90% of the diversifiable time series standard deviation will be removed with a portfolio of 20 funds. However significant risk still remains in forming portfolios of this size, both in terms of the range of uncertainty around this mean value and in a terminal wealth framework.

I have used a bootstrap procedure to demonstrate that there is a statistically significant reduction in standard deviation for portfolio sizes up to between 24 and 32 funds, depending on the sample period chosen. There is also a statistically significant reduction in the risk of an extreme loss (as measured by either VAR or CVAR) for portfolio sizes up to 40 funds. Both of these are considerably larger than the 10 to 15 funds that have been suggested in previous literature and provide a possible explanation for the observed practitioner behaviour of holding much larger portfolios.

I have shown that in a terminal wealth framework there are benefits to holding portfolios of up to 50 funds as measured by either the terminal wealth standard deviation or the shortfall probability. For all three sample periods examined the distribution of individual hedge fund returns is positively skewed i.e. the mean is influenced by a small number of high performing funds, choosing a small portfolio risks not including these funds. I have demonstrated this effect by comparing the results for portfolios of mutual funds to hedge funds.

I have also investigated the effect of regular rebalancing of portfolios. Due to the existence of some performance persistence in the underlying funds it would appear that for all sample periods examined, annual rebalancing would not have been a profitable strategy. However this reduction in mean return is somewhat counterbalanced by a reduction in time series standard deviation.

In summary, my work in this chapter shows that there are indeed benefits to holding portfolios of hedge funds much larger than the 10-15 that have been suggested in the literature and provides an explanation as to why 43% of practitioners actually hold portfolios of more than 20 funds. In terms of an optimal number of hedge funds to hold in a portfolio, one must be careful not to confuse statistical significance with economic significance. My results suggest that a portfolio of between 40 and 50 funds would provide the optimal diversification benefits, however if monitoring costs are high then this number might be reduced.

CHAPTER 5

DO HEDGE FUNDS DELIVER WHEN INVESTORS NEED IT MOST?

Abstract

Factor models that have been widely used for performance attribution and style analysis of mutual fund managers have had limited success when applied to hedge funds. This is because hedge funds follow dynamic trading strategies with non-linear relationships to the standard asset classes. In this chapter I attempt to overcome this problem by introducing time variation and non-linearity in two ways, firstly by using an asymmetric factor model where the factor exposures vary according to the state of economy and secondly by applying a two state Markov regime switching regression model. Adopting these approaches not only leads to an improvement the fit of the factor models, it also allows me to investigate if hedge funds alpha varies over time and to ascertain whether they deliver this alpha when investors need it most, namely in times of recession when the marginal utility of wealth is higher.

5.1 INTRODUCTION

Factor models such as that proposed by Sharpe (1990) have been used successfully in the traditional asset management world but have had only limited success in explaining hedge fund returns. For example, regressing fund returns on an eight factor model Fung and Hsieh (1997) found that 47% of mutual funds had r-squared higher than 75% while 48% of hedge funds had R-squared below 25%. The authors suggest that these low R-squared are due to hedge funds dynamic trading strategies which result in non-linear relationships to the standard asset classes. Some authors (for example Agarwal and Naik (2000a)) have considered models that employ factors that themselves have non-linear relationships with traditional asset classes such as options, but these approaches have been subject to criticism due to the arbitrary nature of their specification.

In this chapter I investigate two alternative approaches that introduce time variation and non-linearity in different ways. Firstly I use an asymmetric factor model where the factor exposures vary according to the state of economy and secondly I apply a two state Markov switching regression model. Adopting these approaches not only leads to an improvement the fit of the factor models, it also allows me to investigate if hedge funds alpha varies over time and to ascertain whether they deliver this alpha when investors need it most, namely in times of recession when the marginal utility of wealth is higher.

In the mutual fund literature, many authors such as Wermers (2000) have found that funds tend to underperform benchmark models on average. However using a conditional performance model Kosowski (2001) finds this underperformance is driven by their performance in times of expansion and that in recessions they actually deliver positive alpha. Though there is a broad literature on the unconditional performance of hedge funds including Agarwal and Naik (2000b) and Ibbotson and Chen (2005) who find statistically significant positive alpha none of these authors consider conditional performance measures.

In this chapter by examining the performance of hedge funds conditional upon the state of the economy I attempt to answer whether hedge funds deliver when investors need it most, namely in recessions when the marginal utility of wealth is higher. My results for the asymmetric factor model where the states are explicitly classified as expansion and recession based on the NBER data contrast sharply with the findings of Kosowski (2001). In this case the positive alphas of hedge fund strategies that have been previously documented in the literature by authors such as Agarwal and Naik (2000b) and Ibbotson and Chen (2005) appear to stem from expansion periods when funds have statistically significant positive alpha and not recession periods when alpha is not statistically different from zero. However, the results of the two state Markov switching regression model, where the states are determined as those which best fit the data identifies one regime with positive alpha (and low volatility) which coincides with the two recessions in my sample period. Thus it would appear that hedge funds might deliver when investors need it most.

The rest of this chapter is organised as follows, section 2 outlines the data and methodology, section 3 presents the results and section 4 concludes.

5.2 DATA AND METHODOLOGY

5.2.1 DATA

For the empirical analysis in this chapter, I use hedge-fund index returns provided by Credit Suisse/Tremont for the period from January 1994 to October 2008. The Credit Suisse/Tremont indices are asset-weighted indices of funds with a minimum of $10 million of assets under management, a minimum one-year track record, and current audited financial statements. An aggregate index is computed from this universe, as well as sub-indexes based on investment style. Indices are computed and rebalanced on a monthly frequency and the universe of funds is redefined on a quarterly basis.

The construction methodology means that these indices are free from survivorship bias and backfill bias is minimized by excluding the first twelve months of returns. There will however be some selection bias as outlined in chapter 1 because of the minimum size and age restrictions, though the effect is likely to be small. The performance of these indices is reported net of all fees and expenses, however because I do not have access to the fee structure of the underlying funds it is not possible to calculate gross returns. As a result of this my results will be subject to the biases outlined in chapter 2, namely that the betas will be understated when the underlying funds are above their high-water mark.

As outlined in chapters 1 and 2 a large number of factors have been identified as being significant drivers of hedge fund returns. In this chapter I use the same 11 candidate factors used in chapter 2. Table 5.1 presents the list of candidate factors to be used in the regressions and performance attribution.

Table 5.1 Explanatory Factors

Name	Description	Datastream Mnemonic
MKT	Dow Jones Wilshire 5000 Composite Total Return	WILEQTY
SMB	Dow Jones Wilshire Small Cap Minus Dow Jones Wilshire Large Cap (Both Total Return)	WILDJSC & WILDJLC
USD	Finex-US Dollar Index Return	NDXCS00
CMDTY	GSCI Commodity Total Return	GSCITOT
BOND	Lehman US Agggregate Total Return	LHAGGBD
CREDIT	Lehman US Credit Intermediate Bond Index Minus Lehman Government Intermediate (Both Total Return)	LHCRPIN & LHGOVIN
SLOPE	Lehman US Treasury: 20+ Year Index Minus Lehman Short Treasury Index (Both Total Return)	LHTR20Y & LHSHORT
EMERGING	MSCI Emerging Markets Index Total Return	MSEMKFL
GLOBAL_STOCKS	JP Morgan Global Broad Excluding U.S. Total Return	JPMBXUS
GLOBAL_BONDS	MSCI World Excluding U.S. Total Return	MSWFXU
DVIX	Change In CBOE VIX Index	CBOEVIX

This table presents the set of candidate factors to be used for the hedge fund performance attribution with their DataStream mnemonic

5.2.2 LINEAR FACTOR MODEL

As a first step and for the basis of comparison the non-conditional exposures of the hedge fund indices are evaluated by running the following regression

$$R_t = \alpha + \sum_{i=1}^{n} \beta_{i,t} F_{i,t} + \varepsilon_t \qquad (1)$$

Where R_t is the return of the hedge fund index and $F_{i,t}$ are the returns on the candidate factors. Rather than including all 11 factors for every strategy, I undertake a procedure to identify the significant factors for each strategy individually. This is because of the heterogeneous nature of hedge fund strategies and the advantage is that it avoids the use of superfluous factors in the regressions. For each hedge fund strategy index I run regressions for all possible combinations of one to eleven factors, a total of 211 = 2,048 regressions, in order to identify the most parsimonious model, which I define as the one with the lowest Akaike Information Criterion (AIC). This set of factors is then used for all subsequent analysis.

The limitation of this model is that is constrains the relationship between the hedge fund returns and the factor returns to be linear, therefore it is unreliable if the relationship is non-linear. Authors such as Fung and Hsieh (1997) suggest that the dynamic trading strategies employed by hedge funds will result in non-linear relationships between their returns and traditional asset classes and hence in the following sections I propose two more flexible approaches in order to capture thias non linearity.

5.2.3 ASYMMETRIC FACTOR MODEL

In order to examine whether hedge fund returns and exposures vary with the business cycle I run the following two regressions:

$$R_t = \alpha(S_t) + \sum_{i=1}^{n} \beta_{i,t} F_{i,t} + \varepsilon_t \qquad (2)$$

$$R_t = \alpha(S_t) + \sum_{i=1}^{n} \beta_{i,t}(S_t) F_{i,t} + \varepsilon_t \qquad (3)$$

Where S_t is an indicator variable state variable which takes the value of zero or one conditional upon the current state at time t. I define the two states as expansion and recession using the business cycle dates taken from the NBER website. Within the 178 months of my sample period there are two recessions, the first starts in April 2001 and lasts until November 2001 (8 months) and the second starts January 2008 and lasts until the end of the sample period in October 2008 (10 months). Thus I have 160 months that are classified as expansion and 18 months that are classified as recession.

Expression (2) only allows the alpha of the hedge funds to vary conditional upon the state variable S_t while expression (3) allows both the alpha and the betas or factor exposures to vary.

This approach introduces time variation and non-linearity in the exposures via the factor weights being state dependent and because these states are defined as recessions and expansions, it could identify whether managers add value when investors' marginal utility of wealth is high. However the approach is open to criticism because of the way in which the states are imposed which could be seen as arbitrary. In order to overcome this I propose a third approach where the states are endogenously determined by the model.

5.2.4 MARKOV REGIME SWITCHING MODEL

A Markov switching regime model can be thought of as a special case of the simple mixture of distributions model. In a mixture of distributions model, each time t is considered as an independent random draw from two (or more) distributions. However, in a Markov switching model, the evolution of an unobserved state variable S_t which follows a first order Markov chain determines which of the 2 (or more) states (distributions) we are in at time t. Hence because the current regime s_t only depends on the regime one period ago $s_{t-1,}$ the stochastic process can described by the transition probabilities of moving from one state to another, in a two regime example these are defined as

$$\begin{aligned} P(S_t = 2 \mid S_t = 1) &= p_{12} \\ P(S_t = 1 \mid S_t = 1) &= p_{11} = (1 - p_{12}) \\ P(S_t = 1 \mid S_t = 2) &= p_{21} \\ P(S_t = 2 \mid S_t = 2) &= p_{22} = (1 - p_{21}) \end{aligned} \tag{4}$$

Since the pioneering work of Hamilton (1989) who applied Markov switching to US GDP, regime switching has been applied to a variety of financial data. Schaller and Van Norden (1997) considered excess market returns and found robust evidence of switching behaviour, Marsh (2000) considered high frequency foreign exchange data, and found the data to be well approximated by Markov models, Brooks and Katsaris (2005) successfully modelled periodically collapsing bubbles and Kosowski (2001) examined the performance of mutual funds conditional upon the business cycle.

In this chapter I consider a 2 regime model, where the transition probabilities between regimes are fixed as, these transition probabilities form the transition matrix P.

$$P = \begin{pmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{pmatrix} \tag{5}$$

The Markov chain is represented by the random vector ξ_t, whose i-th element equals one if St = i and zero otherwise. Thus, in a two-state Markov chain $\xi_t = (0,1)'$ if $S_t = 2$. However the Markov chain is assumed to be unobservable, thus we can never be sure about the regime at time *t*, we can only assign probabilities of being in one regime or another. The conditional expectation of ξ_{t+1} given *t* is denoted by $\hat{\xi}_{t+1|t}$ and is calculated by multiplying ξ_t by P:

$$\hat{\xi}_{t+1|t} = P \bullet \hat{\xi}_{t|t} \tag{6}$$

If I assume normality of the errors $\varepsilon_{i,t}$ for each of the 2 regimes, a vector of the conditional densities of the two regimes, η_t can be calculated from expression (7).

$$\eta_t = \begin{bmatrix} f(y_t \mid s_t = 1, x_t, \psi_{t-1}; \theta) \\ f(y_t \mid s_t = 2, x_t, \psi_{t-1}; \theta) \end{bmatrix} = \begin{bmatrix} \dfrac{1}{\sqrt{2\pi\sigma_1}} \exp\left\{ \dfrac{-(y_t - \alpha_1 - x'\beta_1)^2}{2\sigma_1^{\ 2}} \right\} \\ \dfrac{1}{\sqrt{2\pi\sigma_2}} \exp\left\{ \dfrac{-(y_t - \alpha_2 - x'\beta_2)^2}{2\sigma_2^{\ 2}} \right\} \end{bmatrix} \tag{7}$$

where $\theta = (P, \alpha_1, \alpha_2 \beta_1, \beta_2, \sigma_1, \sigma_2)$ and $\psi_{t-1} = (y_{t-1}, y_{t-2}, \ldots\ldots\ldots x_{t-1}, x_{t-2,\ldots\ldots})$ denotes the information up to time t − 1.

Hamilton (1994) illustrates that the optimal inference and forecast for each date t, ($\hat{\xi}_{t|t}$ and $\hat{\xi}_{t+1|t}$ respectively) in the sample can be found by iterating on equations (8) and (9).

$$\hat{\xi}_{t|t} = \frac{\left(\hat{\xi}_{t|t-1} \otimes \eta_t\right)}{1'\left(\hat{\xi}_{t|t-1} \otimes \eta_t\right)} \tag{8}$$

$$\hat{\xi}_{t+1|t} = P \bullet \hat{\xi}_{t|t} \tag{9}$$

where $\otimes$ indicates the Hadamard product (elementwise multiplication)

The vector $\hat{\xi}_{t|t}$ is referred to as the filtered probability and is the best estimate for the Markov chain at time t given all information up to time t. The log likelihood for the observed data for the value of θ used to perform the iterations can then be calculated from equation (10)

$$\ell(\theta) = \sum_{t=1}^{T} \log\left(1'\left(\hat{\xi}_{t|t-1} \otimes \eta\right)\right) \tag{10}$$

The set of optimal parameters θ can be obtained by maximising the log likelihood function under the restriction that probabilities sum to one (P'1 = 1) and standard deviations are greater than zero $(\sigma_i > 0)$.

Maximizing this function will give the optimal values for θ and hence the alphas, betas, standard deviations and transition probabilities which best describe the underlying process.

Once the optimisation is complete, smoothed inferences can be calculated using an algorithm developed by Kim (1993). The smoothed probabilities are found by iterating on the following equation backwards starting from the last value of $\hat{\xi}_{T|T}$

$$\hat{\xi}_{t|T} = \hat{\xi}_{t|t} \otimes \left\{P' \bullet \left[\hat{\xi}_{t+1|T} (\div) \hat{\xi}_{t+1|t}\right]\right\} \tag{11}$$

where $(\div)$ indicates elementwise division

I have written code in MATLAB to estimate the regime switching regression using the optimisation toolbox which is available on request

5.3 RESULTS

5.3.1 RETURNS AND STANDARD DEVIATION

Table 5.2 presents the mean and standard deviation for the hedge fund indices returns and the factor returns for the 1994-2008 period as well as sub-periods defined by the NBER as recessions and expansions.

Table 5.2 Hedge Fund and Factor Returns

Panel A: Hedge Fund Index Returns

	Mean Monthly Return			Monthly Standard Deviation		
	All	Expansion	Recession	All	Expansion	Recession
Convertible Arbitrage	0.48%	0.70%	-1.44%	1.98%	1.36%	4.37%
Dedicated Short Bias	0.04%	0.02%	0.23%	4.92%	4.87%	5.47%
Emerging Markets	0.66%	0.94%	-1.76%	4.60%	4.56%	4.34%
Equity Market Neutral	0.75%	0.81%	0.27%	0.84%	0.83%	0.85%
Event Driven	0.82%	0.96%	-0.49%	1.74%	1.62%	2.24%
Fixed Income Arbitrage	0.34%	0.51%	-1.14%	1.68%	1.07%	4.02%
Global Macro	1.03%	1.14%	0.05%	3.07%	3.08%	2.86%
Long Short Equity	0.83%	1.05%	-1.15%	2.96%	2.89%	2.97%
Managed Futures	0.62%	0.64%	0.42%	3.45%	3.39%	4.01%
All Hedge Funds	0.76%	0.93%	-0.73%	2.28%	2.21%	2.41%

Panel B: Factor Returns

	Mean Monthly Return			Monthly Standard Deviation		
	All	Expansion	Recession	All	Expansion	Recession
MKT	0.66%	0.95%	-2.00%	4.40%	4.01%	6.55%
SMB	0.08%	0.03%	0.57%	3.11%	3.14%	2.85%
USD	-0.04%	-0.12%	0.60%	2.22%	2.12%	2.94%
CMDTY	0.74%	1.13%	-2.70%	6.36%	5.76%	9.83%
BOND	0.49%	0.51%	0.24%	1.09%	1.07%	1.23%
CREDIT	-0.03%	0.05%	-0.75%	0.77%	0.45%	1.91%
SLOPE	0.29%	0.30%	0.17%	2.66%	2.66%	2.75%
EMERGING	0.90%	1.34%	-2.95%	6.09%	5.59%	8.70%
GLOBAL STOCKS	0.45%	0.89%	-3.46%	4.68%	4.05%	7.53%
GLOBAL BONDS	0.51%	0.55%	0.17%	2.30%	2.29%	2.42%
DVIX	0.27%	0.10%	1.81%	4.19%	3.60%	7.66%

This table presents summary statistic for the Credit Suisse Tremont Hedge Fund indices and return factors from January 1994 to October 2008. Recession and expansion periods are based on NBER business cycle dates. Panel A presents the mean and standard deviation for the hedge fund indices while Panel B presents the mean and standard deviation for the factor returns.

Panel A shows that the mean monthly return for all of the hedge fund strategy indices is positive for the sample period and consequently so is the index of all funds. However, it would appear that for all strategies apart from dedicated short bias the monthly return is lower in those months categorised as recession than in those categorised as expansion. More worryingly is that for five of the strategy indices and for the overall hedge fund index the mean return during recessions has actually been negative. A similar pattern is observed in the standard deviation, with eight out of the ten indices exhibiting a higher standard deviation in recessions than in expansions. Clearly this is not good news for investors because although the historical return has been positive, it implies that historically hedge funds have provided lower returns with higher volatility during periods when the marginal utility of wealth is high i.e. hedge funds have not delivered when investors have needed it most.

The results for the factor returns presented in Panel B exhibit a similar pattern; eight of the eleven factors have lower returns in recessions than in expansions with the exceptions being SMB, USD and DVIX. Only the SMB factor has a lower standard deviation in recessions than expansions with all ten of the other factors having a higher standard deviation.

5.3.2 LINEAR FACTOR MODEL

The procedure outlined in section 5.2.2 was carried out in order to identify the most parsimonious factor model to explain the hedge fund returns and the results are presented in table 5.3.

Table 5.3 Static Model

	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long Short Equity	Managed Futures	All Hedge Funds
Alpha	0.0030	0.0092**	-0.0009	0.0050**	0.0071**	0.0024**	0.0028	0.0006	0.0034*	0.0014
MKT		-0.9823**						0.3861**		0.1367**
SMB		-0.4301**	0.1221**		0.0870**			0.3227**		0.1466**
USD		-0.3937**		0.1677**	0.1290**	-0.3588*		0.1383*		0.3028**
CMDTY	0.0330*			0.0209**		0.0363**	0.0630*	0.0625**	0.1015**	0.0507**
BOND	0.6834**		0.5300**	0.3934**		0.6963**	1.8839**	0.7990**		0.8276**
CREDIT	1.8729**	1.4249**			0.6732**	1.2819**				0.4105**
SLOPE	-0.3480**			-0.1560**		-0.2166**	-0.3055*	-0.1979		-0.1746
EMERGING			0.6336**		0.0746**					0.0570
GLOBAL_STOCKS	0.0433			0.0664**	0.1221**	0.0454*	0.2262**	0.1590**		0.1470**
GLOBAL_BONDS	-0.1174*	-0.3318*	-0.2206*	0.1340*		-0.4528**	-0.5112**		0.3213**	
DVIX	0.1014**		0.1196*			0.1098*	0.1196	0.1581**	0.1503**	0.1334**
σ_ε	0.0126	0.0263	0.0274	0.0074	0.0108	0.0112	0.0268	0.0166	0.0326	0.0154
Adjusted R^2	0.5912	0.7146	0.6446	0.2333	0.6115	0.5553	0.2378	0.6849	0.1071	0.5432
Log Likelihood	529.63	398.29	390.71	624.73	555.73	551.37	395.36	481.22	358.86	495.83

*This table presents the results of the factor selection process outlined in section 5.2.2 using expression (1) and the factor from table 5.1. In each case the model with the lowest Akaike Information Criterion (AIC) was chosen. The figures in the body of the table are the resulting coefficients. Values significant at the 10% level are denoted with * and those significant at 5% by **.*

The first result of interest in table 5.3 is that the ability of a simple static factor model to adequately explain the returns of the Credit Suisse Tremont hedge fund indices varies significantly across the strategies. The adjusted r-squared range from 10.71% for managed futures up to 71.46% for dedicated short bias with an r-squared of 54.32% for all hedge funds.

The number of relevant factors also varies according to strategy, the most parsimonious model for managed futures only contains three factors while for both fixed income arbitrage and long short equity an eight factor model is selected. The broad hedge fund index that includes all strategies is best described by a model that contains ten of the eleven candidate factors. As I found in chapter two, the significant factors are in line with what one would expect. Equity based factors such as MKT and GLOBAL_STOCKS are identified as significant for those strategies that involve equities such as long/short equity and dedicated short bias, while fixed income based factors such as BOND, CREDIT and SLOPE are identified as significant for fixed income strategies such as convertible arbitrage and fixed income arbitrage.

Alpha is found to be positive and significant for five out of the nine individual strategies but not for convertible arbitrage, emerging markets, global macro, long-short equity or for the broad hedge fund index of all strategies. This implies that investors could have obtained similar returns to the Credit Suisse hedge fund indices by simply holding a static combination of the factors identified as significant (which are all investable) and consequently hedge funds do not appear to have added much value.

With these results in mind I now turn to the examination of conditional factor models with the states determined by NBER business cycle data in order to determine whether hedge funds deliver alpha in either expansions or recessions.

5.3.3 ASYMMETRIC FACTOR MODEL

Using the factors models identified above for each individual hedge fund index I run the regression described by expression (2) in order to determine the state dependent alphas, the results are presented in table 5.4.

Table 5.4 Asymmetric Alpha Model

		Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long Short Equity	Managed Futures	All Hedge Funds
Alpha	Expansion	0.0036*	0.0105**	-0.0007	0.0052**	0.0074**	0.0027**	0.0025	0.0014	0.0033	0.0016
	Recession	-0.0014	-0.0029	-0.0027	0.0036**	0.0050*	0.0000	0.0048	-0.0041	0.0037	-0.0005
MKT			-0.9879**						0.3883**		0.1371**
SMB			-0.4132**	0.1244**		0.0900**			0.3294**		0.1496**
USD			-0.3625**		0.1685**	0.1291**	-0.3595*		0.1332*		0.3015**
CMDTY		0.0315*			0.0201**		0.0354**	0.0641*	0.0592**	0.1018**	0.0498**
BOND		0.6863**		0.5266**	0.3866**		0.6981**	1.8989**	0.7701**		0.8327**
CREDIT		1.8117**	1.2750*			0.6508**	1.2479**				0.3821*
SLOPE		-0.3470**			-0.1546**		-0.2160**	-0.3094*	-0.1889		-0.1747
EMERGING				0.6309**		0.0750**					0.0574
GLOBAL_STOCKS		0.0345			0.0639**	0.1188**	0.0405	0.2315**	0.1445**		0.1425*
GLOBAL_BONDS		-0.1137*	-0.3088*	-0.2217*	0.1357*		-0.4514**	-0.5140**		0.3215**	
DVIX		0.0923**		0.1193*			0.1048*	0.1224	0.1528**	0.1500**	0.1298**
σ_ε		0.0126	0.0261	0.0275	0.2319	0.0109	0.0112	0.2338	0.0166	0.0327	0.0154
Adjusted R^2		0.5941	0.7191	0.6427	0.2319	0.6109	0.5549	0.2338	0.6860	0.1020	0.5412
Log Likelihood		530.77	400.23	390.75	625.09	556.09	551.82	395.42	482.05	358.86	495.97

*This table presents the results of the asymmetric alpha model described by expression (2). The two states are defined as expansion and recession using the business cycle dates taken from the NBER website. The figures in the body of the table are the resulting coefficients. Values significant at the 10% level are denoted with * and those significant at 5% by **.*

The improvement of this model over the static model in terms fit, as measured by either the adjusted r-squared or the log likelihood, is extremely marginal. However the difference between the alphas in the two states of the economy show some interesting, if slightly concerning patterns. In the expansion state, alpha is found to be positive and significant for five out of the nine individual strategies but not for, emerging markets, global macro, long-short equity, managed futures or for the broad hedge fund index of all strategies. In the recession state, alpha is only found to be positive and significant for two out of the nine individual strategies, namely equity market neutral and event driven and the alpha for the broad hedge fund index of all strategies is negative though not significantly different from zero. This result implies that hedge funds certainly do not deliver alpha when investors require it most, namely in recessions when the marginal utility of wealth is high.

In this model because the betas are assumed to be constant across the two states of the economy any successful market timing of the factors will be reflected in the alpha estimates, for this reason I now examine an asymmetric model where both the alpha and beta are state dependent. Once again using the same factors as above, I run the regression described by expression (3) in order to determine the state dependent alphas and betas, the results are presented in table 5.5.

Table 5.5 Asymmetric Alpha and Beta Model

		Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long Short Equity	Managed Futures	All Hedge Funds
Alpha	Expansion	0.0044**	0.0107**	-0.0011	0.0052**	0.0071**	0.0032**	0.0029	0.0012	0.0033	0.0017
	Recession	-0.0062*	-0.0048	-0.0089**	0.0045**	0.0019	-0.0048	-0.0032	-0.0021	0.0008	-0.0024
MKT	Expansion		-0.9758**						0.4686**		0.1788**
	Recession		-0.7321**						-0.4542**		-0.1866**
SMB	Expansion		-0.4200**	0.1272**		0.0951**			0.3669**		0.1695**
	Recession		-0.2047	0.1965		0.0417			0.0450		0.0833
USD	Expansion		-0.2597		0.2375**	0.1518**	-0.0948		0.1327*		0.3435**
	Recession		0.3594		0.0199	-0.0787	-0.7964**		0.3321**		0.0659
CMDTY	Expansion	0.0193			0.0134		0.0249**	0.0547	0.0561**	0.1122**	0.0443**
	Recession	0.0901*			0.0354**		0.0583	0.1867**	0.0951*	0.1705**	0.0900**
BOND	Expansion	0.5314*		0.5268**	0.3451**		0.4031**	1.7798**	0.6419**		0.7164**
	Recession	1.8771**		0.3433	0.2296**		2.1586**	1.6594**	0.6589*		0.6506*
CREDIT	Expansion	1.3626**	0.0649			0.9678**	0.9125**				0.4429
	Recession	1.4495**	1.3564**			0.8616**	0.5325				0.5465**
SLOPE	Expansion	-0.2722**			-0.1501**		-0.1565**	-0.2253	-0.1150		-0.1244
	Recession	-0.4846**			-0.1154**		-0.3046	-0.4727**	-0.3309**		-0.2561**
EMERGING	Expansion			0.6771**		0.0689*					0.0485
	Recession			0.2383**		0.1547**					0.1236**
GLOBAL_STOCKS	Expansion	0.0526			0.0630**	0.1465**	0.0500*	0.3036**	0.1268**		0.1581*
	Recession	-0.0394			0.0424*	-0.1274	-0.0411	-0.2187*	0.4524**		-0.0053
GLOBAL_BONDS	Expansion	-0.1301*	-0.2475	-0.2632**	0.1916**		-0.2080	-0.6236**		0.3222**	
	Recession	-0.2199*	0.8996**	0.1494	0.0955**		-1.0660**	0.1324		0.3828**	
DVIX	Expansion	0.0981**		0.1497*			0.1139*	0.1537	0.1575**	0.0490	0.1411**
	Recession	0.0168		-0.2102**			-0.0298	-0.1272	-0.1959**	0.4096**	-0.0410
σ_ε		0.0123	0.0251	0.0270	0.0074	0.0105	0.0102	0.0264	0.0150	0.0323	0.0151
Adjusted R^2		0.6142	0.7396	0.6558	0.2303	0.6327	0.6296	0.2614	0.7428	0.1219	0.5638
Log Likelihood		539.07	409.63	396.72	628.09	563.86	572.52	401.89	504.17	362.42	506.01

*This table presents the results of the asymmetric alpha and beta model described by expression (3). The two states are defined as expansion and recession using the business cycle dates taken from the NBER website. The figures in the body of the table are the resulting coefficients. Values significant at the 10% level are denoted with * and those significant at 5% by **.*

Introducing asymmetry in both alpha and beta leads to a further improvement of fit, as measured by either the adjusted r-squared or the log likelihood over the previous models with r-squared ranging from 12.19% for managed futures up to 73.96% for dedicated short bias. The difference between the alphas in the two states of the economy becomes further polarised, with five out of the nine individual strategies exhibiting positive and significant alpha in expansions but only one strategy, equity market neutral exhibiting positive and significant alpha in recessions. In fact two of the strategies, convertible arbitrage and emerging markets actually show negative and significant alpha in the recession state. The alpha for the broad hedge fund index of all strategies is positive in expansions and negative in recessions though not significantly different from zero in either state. These results appear to confirm what I found above that hedge funds certainly do not deliver alpha when investors require it most, namely in recessions when the marginal utility of wealth is high.

These results contrast sharply the findings of Kosowski (2001) for mutual funds. In that paper the author found that the negative alphas of mutual funds that have been documented in the literature stem from expansion periods when funds have statistically significant negative alpha and not recession periods when alpha is positive. However my results imply that the positive alphas of hedge fund strategies that have been documented in the literature by authors such as Agarwal and Naik (2000b) and Ibbotson and Chen (2005) stem from expansion periods when funds have statistically significant positive alpha and not recession periods when alpha is negative. This in turn implies that hedge funds deliver when investors require it least i.e. in expansions when the marginal utility of wealth is lower rather than in recessions when it is higher.

Having introduced time variation and non-linearity in the exposures via the factor weights being state dependent with those states being defined as either recession or expansion, I now examine a two state Markov regime switching model where the states are endogenously determined.

5.3.4 MARKOV REGIME SWITCHING MODEL

Using the factors models identified above for each individual hedge fund index I run the MATLAB code described in section 5.2.4 in order to identify a two regime Markov regime switching model which best describes the state dependent return generating process, the results are presented in table 5.6.

The Markov regime switching model leads to a better fitting model than the previous asymmetric models with the log likelihood being higher for all of the individual strategy indices and for the broad index of all hedge funds. Two distinct regimes are identified for all strategies and in all cases except dedicated short bias the residual variance, as measured by σ_ε, is lower in regime one than in regime two. Regime one is more persistent than regime two for all strategies with higher values of P_{11} than P_{22}.

Seven out of the nine individual strategies exhibit positive and significant alpha in regime one (the more persistent, lower volatility regime) but only two strategies, equity market neutral and long-short equity exhibit positive and significant alpha in regime 2, in fact two of the strategies, dedicated short bias and fixed income arbitrage actually show negative and significant alpha in regime 2. Only one strategy, namely equity market neutral has positive and significant alpha in both regimes. The alpha for the broad hedge fund index of all strategies is positive and significant in regime one but not significantly different from zero in regime two.

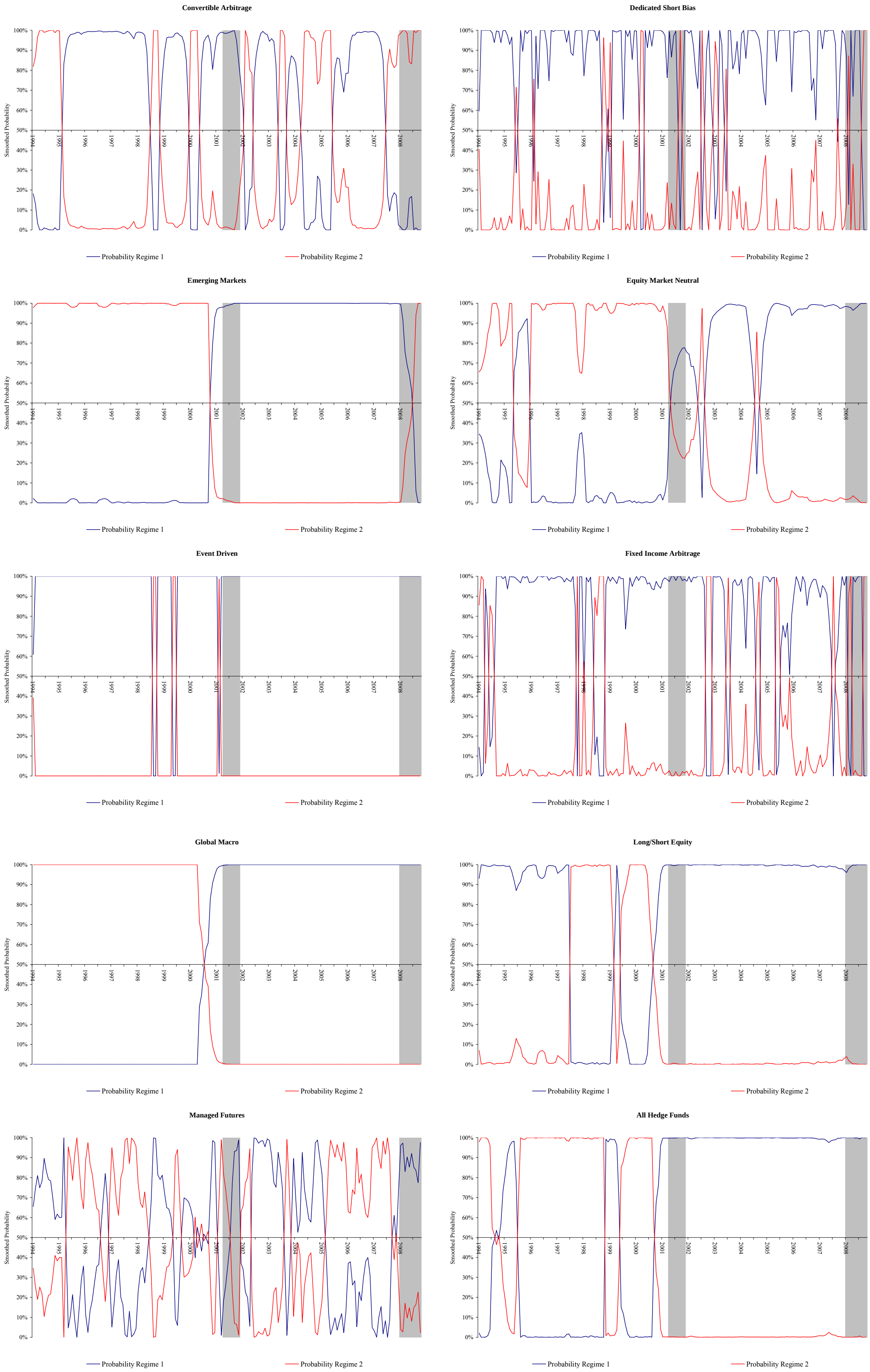
Table 5.6 Markov Regime Switching Model

		Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long Short Equity	Managed Futures	All Hedge Funds
Alpha	Regime 1	0.0086**	0.0148**	0.0034**	0.0041**	0.0078**	0.0062**	0.0038*	-0.0011	0.0031	0.0037**
	Regime 2	-0.0020	-0.0322**	-0.0018	0.0073**	-0.0227	-0.0124**	0.0038	0.0121**	0.0002	0.0064
MKT	Regime 1		-0.9247**						0.2205**		-0.0327
	Regime 2		-0.8643**						0.7048**		0.1394
SMB	Regime 1		-0.5691**	0.0360		0.0697**			0.1872**		0.0791**
	Regime 2		-0.1113	0.1719*		-2.0806			0.5516**		0.2039**
USD	Regime 1		-0.1653		-0.1447**	0.0819**	-0.0204		0.0824		-0.0881*
	Regime 2		0.6825**		0.4024**	3.2719	-0.8565**		0.1392		0.6582**
CMDTY	Regime 1	0.0119			0.0138*		0.0203**	0.0765**	0.0684**	0.1384**	0.0119
	Regime 2	0.0592*			0.0136		0.0865**	0.0639	0.0316	0.0785	0.0256
BOND	Regime 1	0.4393**		0.2643*	0.3308**		0.2763**	1.5512**	0.9435**		0.1389
	Regime 2	0.1915		0.3888	0.1078		1.6389**	1.3546	-0.2923		0.0338
CREDIT	Regime 1	1.0340**	-0.7780*			0.7421**	0.5628**				0.6301**
	Regime 2	1.8507**	1.5483**			1.5986	0.6642**				2.4221**
SLOPE	Regime 1	-0.2561**			-0.1246**		-0.1324**	-0.4717**	-0.2703**		-0.0865
	Regime 2	-0.0768			-0.0470		-0.3692*	0.1258	0.0545		0.1030
EMERGING	Regime 1			0.3872**		0.0465**					0.0564
	Regime 2			0.7788**		1.3991					0.1035
GLOBAL_STOCKS	Regime 1	0.0059			0.0250*	0.1085**	0.0308**	0.0407	0.1804**		0.1400**
	Regime 2	0.1151			0.0938**	-1.6409	0.2465**	0.4506**	0.2175**		0.1863*
GLOBAL_BONDS	Regime 1	-0.0228	-0.1164	0.0499	-0.0723		-0.0525	0.0207		0.8430**	
	Regime 2	-0.1705	0.8375**	-0.4422**	0.3096**		-1.2271**	-0.9944**		-0.3467*	
DVIX	Regime 1	0.0585**		-0.0122			0.0741**	-0.0015	0.1034**	0.3458**	0.0646*
	Regime 2	0.1255*		0.1647*			0.2865**	0.2004*	0.2856**	-0.1331	0.1708**
σ_ε	Regime 1	0.0056**	0.0194**	0.0112**	0.0042**	0.0082**	0.0050**	0.0120**	0.0116**	0.0243**	0.0075**
	Regime 2	0.0159**	0.0133**	0.0324**	0.0078**	0.0000	0.0084**	0.0332**	0.0127**	0.0288**	0.0156**
Transititon Probabilities	P_{11}	0.9288	0.8909	0.9877	0.9505	0.9826	0.9050	1.0000	0.9820	0.8135	0.9797
	P_{22}	0.8794	0.3946	0.9872	0.9426	0.3676	0.5663	0.9874	0.9284	0.8142	0.9503
Log Likelihood		570.92	419.01	444.14	646.00	616.92	628.04	448.31	519.96	367.87	551.77

*This table presents the results of the two state Markov regime switching model outlined in section 5.2.4 The two states are determined by maximum likelihood using MATLAB. The figures in the body of the table are the resulting coefficients. Values significant at the 10% level are denoted with * and those significant at 5% by **.*

All of the above indicates that hedge fund performance is generally superior in regime one i.e. lower volatility and positive alpha and that this regime is more persistent $P_{11} > P_{22}$. However the question remains as to when the individual regimes occur. In the Markov regime switching model, because the regimes are endogenously determined by the model rather than being arbitrarily imposed (as they were in my previous asymmetric models), the transition between the two regimes will most likely occur at different times for the different strategies. Using the smoothed probabilities calculated from expression (11) I can identify ex-post the probability of being in regime one or two at any point in time. These smoothed probabilities are presented graphically in figure 5.1.

Figure 5.1 Smoothed Probabilities



These figures depict the smoothed probabilities of being in regime 1 and regime 2 for the multi-factor Markov regime switching model of monthly returns of the Credit Suisse Tremont Indices. . NBER recession periods are represented by the shaded areas.

Examining figure 5.1 it is clear that my previous assertion about the possibility of variation in timing of the transition between regimes for the individual strategies was correct. Strategies such as convertible arbitrage, dedicated short bias and managed futures display frequent changes in regime while other strategies such as emerging markets and global macro appear much more stable.

The changes in regime do not appear to coincide with NBER recession periods which are represented by the shaded areas. However, the index of all hedge funds has been in regime one for both of the recession periods in my sample period. This implies that hedge funds have been in the positive alpha and low volatility regime when the marginal utility of wealth is high.

5.4 CONCLUSIONS

In this chapter I have demonstrated two alternative approaches that introduce time variation and non-linearity to factor models in order to examine the conditional performance of Credit Suisse Tremont hedge fund indices for the period January 1994 to October 2008. Firstly by using an asymmetric factor model where the factor exposures vary according to the state of economy and secondly by applying a two state Markov regime switching regression model. My results show that both of these approaches lead to models that better fit the returns of the hedge fund indices, as measured by the log likelihood, compared to a non-conditional linear factor model.

Using an asymmetric factor model where the states are explicitly classified as expansion and recession based on the NBER definitions, I find that the positive alphas of hedge fund strategies that have been previously documented in the literature by authors such as Agarwal and Naik (2000b) and Ibbotson and Chen (2005) appear to stem from expansion periods when funds have statistically significant positive alpha and not recession periods when alpha is not statistically different from zero. The implication of this result is that hedge funds do not deliver when investors need it most, namely in recessions when the marginal utility of wealth is high.

Using a two state Markov switching regression model, where the states are determined as those which best fit the data, I identify two distinct regimes. Regime one has positive alpha and lower volatility while regime two has no alpha and higher volatility. The timing of the transition between regimes does not coincide with the NBER classification of recessions and expansions and varies significantly across the strategies, however for the broad index all hedge funds regime one coincides with both of the recession periods in my sample. The implication of this result is that hedge funds do deliver when investors need it most, namely in recessions when the marginal utility of wealth is high.

At first glance these two results might appear to be contradictory, however it must be remembered that in the first asymmetric factor model I am imposing two states in what could be considered an arbitrary way. Although it is of economic significance for investors to consider the performance conditional upon the state of the economy there is no theoretical justification as to why hedge fund performance should vary across the two states. In contrast, the two state Markov regime switching model determines the states by what best fits the data and hence should be considered as more reliable.

Considering the above I can conclude that hedge funds have indeed delivered when investors need it most by being in the regime with positive alpha during the two recessions in my sample period. There have however been long periods in the zero alpha regime which raises the question what economic or market conditions drive the transition between the two regimes? This provides an interesting topic for further research.

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