

An Analysis of Hedge Fund Strategies



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An Analysis of Hedge Fund Strategies - Abstract

This PhD thesis analyses hedge fund strategies in detail by decomposing hedge fund performance figures. Our aim is to present hedge funds, to understand what managers expect to do and to understand how they make or destroy value over time. In order to achieve this objective, we develop a multi-factor performance analysis model, use it over several time periods and improve it over time. This model aims to determine both whether hedge funds create pure alpha over time (alpha over classical markets) and whether there is persistence in hedge fund returns over time. Following this, I analyse another specific aspect of hedge funds, their neutrality relative to equity markets in order to validate hedge fund managers' claims that they are market neutral. Finally, we develop new efficient frontier measures, which not only include returns and volatility, but also skewness and kurtosis in order to determine whether hedge funds are really beneficial to investors.

Introduction and Purpose

Hedge funds are private investment vehicles that can take long and short positions in various markets, using various investment strategies and these funds are accessible to large investors only. On the one hand, this definition is precise; on the other, it is very broad. This is clear and focused. From another point of view, the funds may use various kinds of securities on various markets. This part of the definition is much more open and allows almost anyone to classify his fund as a hedge fund as long as it is long and short...

Since the early 1990s, when around 2,000 hedge funds were managing assets totalling ca. \$60 billion, the subsequent growth in the number and asset base of hedge funds has never really been refuted. The industry only suffered from a relative slowdown in 1998, but since then has enjoyed a renewed vitality with an estimated total of 10,000 funds managing more than a trillion US dollars by the end of 2006. The growing trend of the sector remained remarkably sustained during the stock market collapse that started in March 2000, when the NASDAQ Composite Index reached an all-time high of 5,132, and finished three years later with a floor level of 1,253. In the meantime, the global net asset value (NAV) of hedge funds continued to grow at a steady rate of 10.6% (Van Hedge Funds Advisors International, 2002), contrasting with a decrease of 2.7% in the worldwide mutual fund industry (Investment Company Institute, 2003). More recently, in 2001, Capocci & Hübner (2004) estimated that there were 6.000 HF managing around \$400b. In 2007, Capocci, Duquenne & Hübner (2007) estimate that there are 10.000 HF managing around \$1trillion. This is a growth of 11% in the number of funds and 26% in assets over six years.

The purpose of this doctoral thesis is clearly established: to understand hedge fund strategies by looking at the performance numbers produced. Our first objective of the studies is to understand clearly hedge fund managers and to explain how they create alpha over time. This involves developing, testing and improving a performance analysis model to understand hedge fund performance, while developing and adapting a methodology to determine whether there is any persistence in hedge fund returns on the other. I achieve this objective in three complementary studies grouped in Part 1 (*An Analysis of Hedge Fund Performance, Hedge Fund Performance and Persistence in Bull and Bear Markets and Sustainability in Hedge Fund Performance: New Insights*).

The second objective of the thesis is clearly linked to the first. Since the purpose is to understand hedge fund strategies in detail, I perform a specific analysis on the most represented and the most interesting, market neutral funds. By definition, market neutral funds must have a limited exposure to the market. I check for this neutrality and analyse what kind of funds consistently outperform over time: the pure market neutral funds, market timers or funds with a more directional bias (see Part two: *An Analysis of Hedge Fund's Market Exposure*).

Finally, the third complementary objective for the thesis is to determine whether hedge fund strategies should be included in a classical portfolio of stocks and bonds. In Part three, *Diversifying Using Hedge Funds: A Utility-Based Approach*, we analyse the inclusion of hedge funds in a portfolio of stocks and bonds. The main originality of this study centres upon the development of a new efficient frontier, based not only on volatility but also on higher moments (skewness and kurtosis) and on a utility function that more closely corresponds to that of the investor without normality or other strong assumption. The specificities and main objectives of each study are reported in Table 1.

In the remainder of this introduction I present a global literature review. Then, I present the data issue before disserting on investing in hedge funds for the final investors. Finally, we present the three parts of the Thesis in detail.

Table 1: Studies Specificities and Objectives

	Specificity	Objective 1	Objective 2
An Analysis of Hedge Fund Performance	<ul style="list-style-type: none"> - Introduction of the extended multi-factor model - Analysis based on performance 	<ul style="list-style-type: none"> - Determine if HF strategies sign. outperform classical markets 	<ul style="list-style-type: none"> - Determine if HF strategies sign. and persis. outperform classical markets
Hedge Fund Performance and Persistence in Bull and Bear Markets	<ul style="list-style-type: none"> - Consider various market conditions & adapted model (high yield & mortgage factors) - Analysis based on performance 	<ul style="list-style-type: none"> - Determine if HF strategies sign. outperform classical markets in bull and/or bear market conditions 	<ul style="list-style-type: none"> - Determine if HF strategies sign. and persis. outperform classical markets in bull and/or bear market conditions
The Sustainability of Hedge Fund Performance	<ul style="list-style-type: none"> - Adapted model (option factors) - Adapted meth. based on performance & other risk-adj. measures 	<ul style="list-style-type: none"> - Determine if HF strategies sign. outperform classical markets using several risk-adjusted measures 	<ul style="list-style-type: none"> - Find a systematic way of buying HF in order to sign. and persis. outperform classical markets
The Neutrality of Market Neutral Funds	<ul style="list-style-type: none"> - Focus on market neutral funds (28% of the industry) - Focused on LT and ST periods and various market conditions 	<ul style="list-style-type: none"> - Determine the market exposure of market neutral funds 	<ul style="list-style-type: none"> - Determine if high/low beta market neutral funds outperform their high/low beta peers
Diversifying using Hedge Funds	<ul style="list-style-type: none"> - Analyse the impact of inserting HF in a classical portfolio taking abnormality into account - Distinguish between dir. undir HF and FoF 	<ul style="list-style-type: none"> - Develop a methodology to determine if a portfolio can be diversified with securities displaying abnormal return dist. charact. 	<ul style="list-style-type: none"> - Determine if bond and/or equity investors should include HF in their portfolio

This Table reports the specificities and the objectives of the studies grouped in this PhD Thesis. Part 1: The Persistence in Hedge Fund Performance contains three studies (An Analysis of Hedge Fund Performance, Hedge Fund Performance and Persistence in Bull and Bear Markets and the Sustainability of Hedge Fund Performance: new insights). Part 2: An Analysis of Hedge Fund's Market Exposure contains one study (The Neutrality of Market Neutral Funds). Part 3: Hedge Funds as Diversification Tools contains one study (Diversifying Using Hedge Funds: A Utility-Based Approach). For each Part we report the main specificity of the study and its first and second objective.

Global Literature Review

There have been many studies on hedge funds covering many different aspects of the industry. In each of the specific studies reported in the heart of the thesis, we perform literature reviews including studies whose results are directly linked to the subject under analysis. In this introduction, we provide a global literature review on hedge fund studies.

As illustrated in Figure 1, hedge fund academic studies can be classified into four global categories: 1. Hedge fund performance, 2. Hedge fund investment style, 3. Correlation analysis and diversification power and 4. Other studies. In the first global category, we report studies that are focused on hedge fund performance. There are three fields within this first category of hedge fund performance analysis. The first of these fields includes studies that compare the performance of hedge funds with equity and other indices (see for example Ackermann, McEnally and Ravenscraft, 1999; Brown, Goetzmann and Ibbotson, 1999; Liang, 1999; Amin and Kat, 2001; Liang, 2001; Barès, Gibson and Gyger, 2002; Liang, 2003; Agarwal and Naik, 2004). Results of such studies are mitigated. Some authors (Brown et al, 1999; Liang, 1999; Capocci et al., 2005) conclude that hedge funds have been able to outperform these indices, while others (Ackermann et al., 1999; Agarwal and Naik, 2004) are more cautious in their conclusion. Hübner and Papageorgiou (2006) find that there are three kinds of persistence in hedge fund returns. Firstly, that there is statistical evidence of positive persistence based on alphas for non-directional portfolios in the bullish period. Secondly, there is statistical evidence of negative persistence for directional portfolios in both the bullish and the bearish periods. Finally, the authors find statistical evidence of progressive positive

persistence based on alphas for funds of funds in both the bullish and the bearish periods.

The second field of hedge fund performance analysis compares the performance of hedge funds with mutual funds. In this context, Ackermann, McEnally and Ravenscraft (1999) and Liang (1999) find that hedge funds consistently achieve better performance than mutual funds, although they are lower and more volatile than the reference market indices considered.

The third field of hedge fund performance analysis includes the study of the persistence of hedge fund returns. Persistence is particularly important in the case of hedge funds because, as suggested by Brown, Goetzmann and Ibbotson (1999) and Liang (2000, 2001), the hedge fund industry has a higher attrition rate than is the case in mutual funds (see Brown, Goetzmann and Ibbotson, 1999). They prove that offshore hedge funds have positive risk adjusted returns, but they attribute this result to style effect and conclude that there is no proof of any particular alpha-generating capacity of some fund managers. Agarwal and Naik (2000) analyse the presence of persistence in hedge fund returns using a one-year moving average period. They find that there is proof of persistence in hedge fund performance, particularly for poorly performing funds that continue to underperform.

Figure 1: Four global categories of hedge fund academic studies

HEDGE FUND PERFORMANCE	HEDGE FUND INVESTMENT STYLE	CORRELATION ANALYSIS and DIVERSIFICATION POWER	OTHER STUDIES
- Comparison with classical markets (Ackermann et al., 1999; Brown et al., 1999; Liang, 1999; Amin and Kat, 2001; Liang, 2001; Barès et al., 2002; Liang, 2003; Agarwal and Naik, 2004).	- Sharpe style analysis (Fung and Hsieh, 1997; Brown et al., 1998; Brealy and Kaplanis, 2001, Brown and Goetzmann, 2001, Liang 2001; Ben Dor and Jagannathan, 2002; Liang 2003).	- Correlation analysis (Fung and Hsieh, 1997; Schneeweis and Spurgin, 1997; Liang, 1999; Agarwal and Naik, 1999).	- Risks (Schneeweis and Spurgin, 1999; Jorion, 2000; Amenc et al., 2002a; Amenc et al., 2002b, Berényi, 2002). - Bias analysis (Liang, 2000; Fung and Hsieh, 2000).
- Comparison with mutual funds (Ackermann et al., 1999 and Liang, 1999).	- Rolling regression (McGuire, Remolona and Tsatsaronis, 2005)	- Diversification power (Amin and Kat, 2001; Amenc and Martellini, 2002).	- Hedge fund indices (Brooks and Kat, 2001; Amenc and Martellini, 2002; Fung and Hsieh, 2002b).
- Persistence in performance (Agarwal and Naik, 2000; Brown et al., 1999; Hübner and Papagergiou, 2006; Liang 2001; Liang, 2000).	- Dynamic model (Swinkels and Van der Sluis, 2001; Posthuma and Van der Sluis)		- CTAs (see for example Edwards and Park, 1996; Fung and Hsieh, 2001; Gregoriou and Rouah, 2003; Liang, 2003; Spurgin and Georgiev, 2001).

Figure 1 reports four global categories of hedge fund academic studies. We group studies on hedge fund performance, hedge fund investment style, correlation analysis, diversification power and finally the other studies.

The vast majority of performance studies on hedge funds have not focused solely on the behaviour under different market conditions. The periods under review do not favour this exercise, as periods of downward trending stock markets were rare and discontinuous between 1994 and March 2000. For the period 1990-1998, Edwards and Caglayan (2000) found that only three types of hedge fund strategies (Market Neutral, Event Driven and Macro) provided protection to investors when stock markets decline. More recently, Ennis and Sebastian (2003) contend that, in general, hedge funds did not provide investor protection after the market downturn of March 2000; rather, their superior performance was mostly due to the good market timing of their managers.

The second global category of hedge fund academic studies includes authors that try to analyse and describe hedge fund investment style and who explain these features with style models (see for example, Fung and Hsieh, 1997; Brown, Goetzmann and Park, 1998; Brealy and Kaplanis, 2001; Brown *et al.*, 2001; Liang 2001; Ben Dor and Jagannathan, 2002 and Liang 2003). In this context, Fung and Hsieh (1997) apply Sharpe's style analysis (see Sharpe, 1992) to a large sample of hedge funds and commodity trading advisors (CTAs). They assume that fund returns are linearly related to the returns through a number of factors and measure those factors through eight mimicking portfolios. They find that the regressions had little explanatory power and consequently suggest that the resulting low adjusted r-square is due to the funds' trading strategy. Ben Dor and Jagannathan (2002) stress the importance of selecting the right style benchmarks and emphasise how the use of inappropriate style benchmarks may lead to the wrong conclusion. A particular aspect that has been taken into account more recently is the style drift in hedge fund returns. This effect comes from the fact that hedge fund managers are opportunity driven and therefore change style over time. Brown, Goetzmann and Park (1998) analyse hedge fund returns during the 1997-98

Asian crisis using rolling regression to take the style drift into account. The methodology consists in realizing a set of linear regressions and moving the estimation period of each of them by one observation. This simple technique enables one to observe style variation of a manager over time. This methodology has one major drawback: the choice of a number of observations used for the estimation. McGuire, Remolona and Tsatsaronis (2005) apply the same methodology. To handle this issue, Posthuma and Van der Sluis (2005) propose to use a dynamic style model in which beta can vary over time developed by Swinkels et Van der Sluis (2001). This technique is adaptive in the sense that changes in the style exposures are priced up automatically from the data. Unlike the ad hoc rolling regression approach, the time variation in the exposures is explicitly modelled. No restrictions are imposed on the betas. As stressed by Posthuma and Van der Sluis, this model is a state-space model and can be estimated by using standard Kalman filter techniques¹. No window size and ad hoc chosen length need to be used. The Kalman filter procedure chooses the optimal weighting scheme directly from the data. The filter is an adaptive system based on the measurement and updating equations.

The third global category of hedge fund academic studies focuses on the correlation of hedge funds with other investment products and analyses the power of the diversification properties of hedge funds. Fung and Hsieh (1997) and Schneeweis and Spurgin (1998) prove that the insertion of hedge funds into a portfolio can significantly improve its risk-return profile, thanks to the weak correlation to the funds with other financial securities. This low correlation is also emphasised by Liang (1999) as well as by Agarwal and Naik (2004). Amin and Kat (2001) find that stand-alone investment hedge funds do not offer a superior risk-return profile, but that a great majority of funds classified as inefficient on a stand-alone basis are able to produce an efficient payoff

¹ See Pollock (1999) for a detailed presentation of the Kalman filtering and space-state models.

profile when mixed with the S&P 500. They obtained the best results when 10-20% of the portfolio value is invested in hedge funds. Kooli (2007) analyzes the power of hedge funds as an efficient frontier enhancer. He finds that hedge funds as an asset class improve the mean-variance frontier of sets of benchmark portfolios but that investors who already hold a diversified portfolio do not improve their statistics using hedge funds. The author finds however that funds of hedge funds do bring diversification for mean-variance investors. Taking all these results into account, hedge funds are seen as good investment tool. Amenc and Martellini (2002) prove on the basis of ex-post estimations that the inclusion of hedge funds in a portfolio can lead to a significant decrease in the volatility of the portfolio without leading to a significant change in the returns. This implies that a stronger risk control does not necessarily correspond to a decrease in return.

In the fourth global category of hedge fund academic studies, "Other studies", other authors have analysed various other aspects of the hedge fund industry. Schneeweis and Spurgin (2000), Jorion (2000), Amenc, Curtis and Martellini (2002), Amenc, Martellini and Vaissi  (2002) and Ber nyi (2002) study the risks involved in hedge fund investment. Schneeweis and Spurgin (1999) as well as Amenc, Martellini and Vaissi  (2002) prove that hedge fund returns are not only exposed to the market risk, but that other risks such as volatility risk, default risk or liquidity risk have to be considered. Liang (2000) analyse the presence of survivorship bias in hedge fund data and Fung and Hsieh (2000) include other biases in their analysis. Ackermann, McEnally and Ravenscraft (1998) emphasise that stricter legal limitations for mutual funds rather than for hedge funds hinder their performance. Some authors also studied hedge fund indices (see Brooks and Kat, 2001; and Amenc and Martellini, 2003). There are many different hedge fund index providers such as EACM, HFR, CSFB/Tremont, Zurich Capital,

Van Hedge, the Hennessee Group, Hedgefund.net, LJH Global Investment, Mar, Altvest and Magnum. Fung and Hsieh (2002b) looked at the natural biases present in hedge fund indices.

Commodity trading advisors (CTAs) are a particular category in the hedge fund world. Unlike hedge funds, which first appeared in an academic journal in 1997, CTAs have been studied for a longer period of time. Many studies were published in the late 80s and in the early 90s (see for example, Elton et al., 1987, 1989, 1990, or Edwards and Ma, 1988). Since 1997, some authors have considered CTAs as part of the hedge fund world (Fung and Hsieh, 1997; Schneeweis and Spurgin, 2000), whereas others have studied them either by separating them from hedge funds (Liang, 2003) or on a stand-alone basis (Fung and Hsieh, 2001; Gregoriou and Rouah, 2003 and Capocci, 2004b). Research on CTAs is very sparse and it is difficult to present a complete literature review. However, Billingsley and Chance (1996) and Edwards and Park (1996) demonstrate that CTAs can add diversification to stocks and bonds in a mean-variance framework. Schneeweis, Savanayana and McCarthy (1991) and Schneeweis (1996) stated that the benefits of CTAs are similar to those of hedge funds, in that they improve upon and can offer a superior risk-adjusted return trade-off to stock and bond indices while acting as diversifiers in investment portfolios.

Fung and Hsieh (1997) prove that a constructed CTA style factor has a persistent positive return when the S&P 500 has a negative return. According to Schneeweis, Spurgin and Georgiev (2001), CTAs are known regularly to short stock markets. Fung and Hsieh (2001) analyse CTAs and conclude that they are similar to a look-back call and a look-back put. Gregoriou and Rouah (2003) examine whether the percentage changes in the NAVs of CTAs follow random walks. They prove that all classifications (except the diversified sub-index) behave in the same way as a random walk. The effectiveness of CTAs in enhancing risk-return characteristics of portfolios could be compromised when pure random walk behaviour is identified. Kat (2002) finds that allocating to managed futures allows investors to achieve a very substantial degree of overall risk reduction at limited cost. Managed futures appear to be more efficient diversifiers than hedge funds.

Regarding performance, the results are mitigated even though Edwards and Caglayan (2001) conclude that, during bear markets, CTAs provide greater downside protection than hedge funds, and have higher returns along with a negative correlation with stock returns in bear markets. Schneeweis and Georgiev (2002) conclude that careful inclusion of CTA managers in an investment portfolio can enhance its return characteristics, especially during severe bear markets. Schneeweis, Spurgin and McCarthy (1996) observe that performance persistence is virtually non-existent between 1987 and 1995. There is little information on the long-term diligence of these funds (Edwards and Ma, 1998, Irwin, Zulauf and Ward, 1994, Kazemi, 1996). In his book *Managed Trading: Myths and Truths*, Jack Schwager reviews the literature on whether CTAs exhibit performance persistence and conducts his own analysis. He concludes that there is little evidence that the top performing funds can be predicted. According to Worthington (2001), between 1990 and 1998, the correlation of managed futures to the S&P 500 during its best 30 months was 0.33 and that it was -0.25 during the worst 30

months. Georgiev (2001) underlines, however, that one of the drawbacks of CTAs is that, during bull markets, their performance is generally inferior to that of hedge funds. Brorsen and Townsend (2002) have shown that a minimal amount of performance persistence is found in CTAs and that some advantages might exist in selecting CTAs based on past performance, when a long time series of data is available and accurate methods are used. Finally, Capocci (2004b) proves that there is persistence in CTA returns for badly performing funds, which tend to continue to significantly underperform their peers.

The Data Issue

The main issue with hedge fund analysis is access to database and the quality of data². There are several hedge fund databases available but only three of them have more than ten years of actual data collection experience: the Centre for International Securities and Derivatives Markets (CISDM) at the University of Massachusetts in Amherst, Hedge Fund Research (HFR) in Chicago, and Lipper TASS (TASS). As of December 2004, TASS had 4,130 funds (2,431 live and 1,699 defunct), HFR had 5,158 funds (2,939 live and 2,219 defunct), and CISDM had 3,246 funds (1,315 live and 1,931 defunct). There are four other entrants to this field – The Barclay Group (Barclays), Morgan Stanley Capital International (MSCI), Eureka Hedge, and Standard and Poors (S&P). Because of their late entry to this field, their data were largely from reconstructed history rather than real-time collection of hedge fund performance.

As stated by Liang (2000) and Fung and Hsieh (2006) many hedge funds report to only a single database. Only few of them report to more than one database. Liang (2000) reports that not only most funds do not report to the two databases he compared but moreover that there are significant differences in returns, inception date, net assets value, incentive fee, management fee, and investment styles across the two databases.

² See for example Fung & Hsieh (2002b).

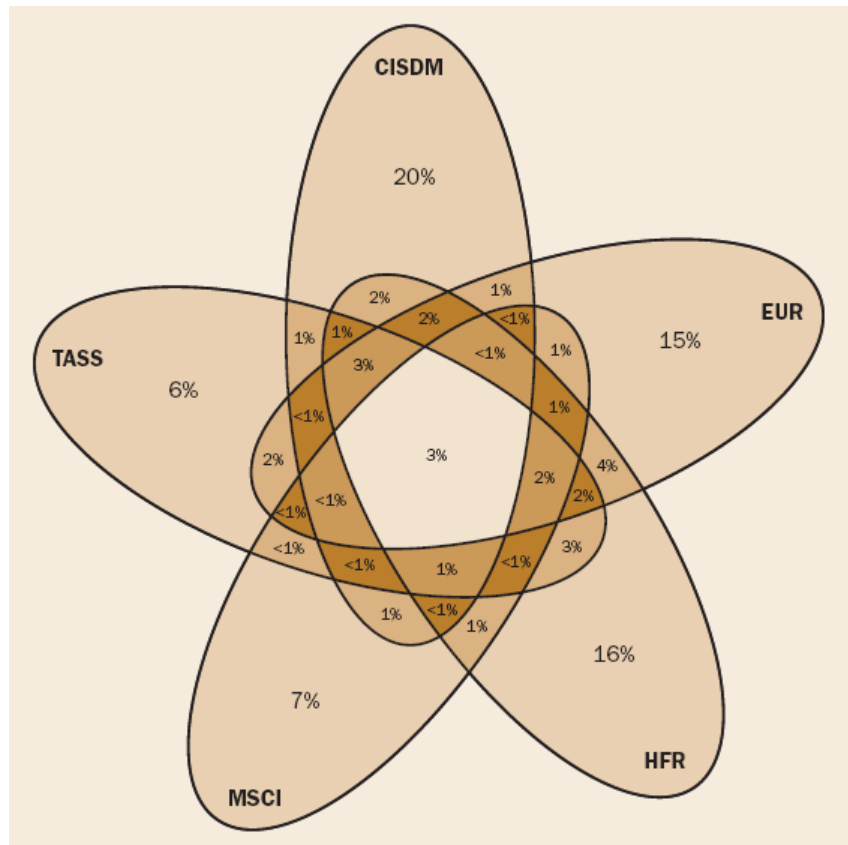
In Figure 2, Fung and Hsieh (2006) compare the HFR, TASS and CISDM databases. The Venn diagram divides the global hedge fund universe composed of five of the main hedge fund databases. As shown in Figure 2, the overlap between the databases is very low. This indicates that results obtained when performing an analysis based on a specific database may be different if another database is used. Moreover, generalization based on a single database may not be true for the entire hedge fund industry since any database only represent part of the industry.

In this Thesis we use HFR, CISDM and Barclays (together and/or individually). Since most funds do not report to all the existing databases it is interesting to apply the same methodology to different databases in order to be sure that the results obtained do not depend on the particular database used. We have done for our extended multi-factor performance decomposition model. We first apply it to a combination of the HFR and CISDM databases. Then, we apply the adapted version to CISDM alone before using a combination of the CISDM and the Barclay databases. Our results remain consistent independently of the database used. The databases used and their characteristics are reported in Table 2.

Table 2 indicates that we use between 634 and 4476 individual funds over the five studies of this Thesis and between 347 and 2011 fund of funds. The period covered goes from 1994/2000 for the shorter one to 1993/2003 for the longest (without considering sub-period analysis).

The second important aspect regarding the quality of hedge fund data is the presence of biases in databases. First, hedge funds report their performance to hedge fund database providers on a voluntary basis and a result in statistical sampling theory is that voluntary participation can lead to sampling biases. Voluntary participation means that only a portion of the universe of hedge funds is observable. This means that funds tend to report to databases only when their performance have been good and may stop reporting once the performance becomes less attractive. This effect leads to a bias in database that is called *instant return history bias* or the *backfill bias*.

Figure 2: Hedge fund database universe repartition



Source: Fung & Hsieh (2006)

Table 2: Database Comparison

	Data provider	Number of strategies	Hedge funds	Percentage dissolved	Funds of funds	Percentage dissolved	Analysis period
An Analysis of Hedge Fund Performance	HFR/ CISDM	28	2449	28%	347	34%	1994/2000
Hedge Fund Performance and Persistence in Bull and Bear Markets	CISDM	16	2247	47%	647	33%	1994/2002
The Sustainability of Hedge Fund Performance	CISDM/ Barclays	16	3060	60%	907	72%	1994/2002
The Neutrality of Market Neutral Funds	CISDM	4	634	37%	n/a	n/a	1993/2002
Diversifying using Hedge Funds	CISDM	16	4476	46%	2011	40%	1993/2003

This Table reports the comparison of the databases used over this PhD Thesis. HFR = Hedge Fund Research, Inc, CISDM = Center for International Securities Derivatives Markets. Nb of strat = number of strategies used, Hedge funds = number of individual hedge funds, Percentage dissolved = percentage of funds in the database that stop reporting to it before the end of the period under review. Funds of funds = funds of hedge funds and analysis period = period under review for the corresponding study.

The *backfill bias* on equity market data is commonly calculated by an indirect approach. As stated by Posthuma and van der Sluis (2003), this indirect approach is eliminating the first two years of reported data; see e.g. Fama & French (1993). Brown, Goetzmann & Park (1998) use the method of Park to estimate an instant history of 15 months for the TASS database. Ackermann et al. (1999), Fung & Hsieh (2000), and Edwards & Caglayan (2001) addressed the backfill bias for hedge funds in different periods for different databases, and all used indirect approaches. Ackermann et al. (1999) eliminate two years and find an average annual bias of 0.5% for MAR and HFR database funds with different sample periods ending in 1995. Fung & Hsieh (2000) calculate the backfill bias for the TASS database over the period 1994 to 1998. They eliminate the first 12 months of returns, because they find a median 343 day incubation period. The lasting mean performance was 1.4% lower over the period 1994–1998, leading to a backfill bias of 1.4% for the TASS database over the period 1994–1998. Edwards & Caglayan (2001) use the same indirect approach of eliminating 12 months of returns from the MAR database and find that the average annual returns of hedge funds in the first year are 1.17% higher than the annual returns in subsequent years. We estimate it by calculating the mean return of a portfolio investing in all funds and then we make the same estimation by leaving the first 12, 24, 36 & 60 first returns of each fund. We then compare the difference in performance.

Another very important bias is the survivorship bias. Funds disappearing from database tend to have poorer performance than existing funds. Not taking these funds into account leads to *survivorship bias*. Survivorship bias is calculated as the performance difference between surviving funds and all funds in the dataset. Survivorship is an issue in hedge fund analysis and this bias is estimated between 1.5%

(Fung & Hsieh, 1998) & 3% (Liang, 2001). We estimate these biases for our databases and the results are reported in Table 3.

Our estimation of backfill bias lies between 1.2% and 1.3% when the 12 first months of existence of each fund is removed to estimations between 2% and 2.2% when more months are removed. The results indicate that funds outperform over their first months of existence. Our estimations are in line with those of other studies even if Posthuma and van der Sluis (2003) recently estimate that the magnitude of the overall backfill bias is about 4% per annum on average. The difference can have several reasons. First, they decide to eliminate the last month of existence of any fund by 50%, this rule will clearly impact estimation. Second, the period they analyse starts in 1996 whereas ours (and many others estimations) is based on data starting in 1993 or 1994. Third, since most hedge funds still report to one database only, there may be differences in statistics of the different databases used. We use together or separately HFR, CISDM and Barclays whereas Posthuma and van der Sluis (2003) has access to TASS. Finally, Posthuma and van der Sluis (2003) use a direct method of examining the backfill bias. Instead of eliminating the same average or median incubation period for all funds, the direct method eliminates the individual incubation period per fund. The information that they use is information from TASS and it is mainly based on qualitative information from TASS employee.

Table 3: Backfill bias and survivorship bias estimation

	Survivorship bias	Backfill bias (12m)	Backfill bias (24m)	Backfill bias (36m)
Analysis of HF Perf.	1.22%	1.2%	1.6%	2.0%
HF Perf. and Pers. in B&B Mkt	1.51%	1.3%	1.8%	2.2%
Sustainability of HF Perf.	1.08%	n/a	n/a	n/a
Neutrality of Mkt Ntl Funds	1.68%	n/a	n/a	n/a

This table reports the estimated survivorship bias and instant return history bias as estimated in four of our studies. Survivorship bias comes from the fact that funds disappearing from database tend to have a worse performance than existing funds. Not taking these funds into account lead to a survivorship bias. Instant return history bias comes from the fact that hedge funds report their performance to hedge fund database providers on a voluntary basis and a result in statistical sampling theory is that voluntary participation can lead to sampling biases.

Without considering what methodology is the best, the differences between Posthuma and van der Sluis (2003) methodology and ours explain the difference in estimations. Throughout this Thesis, we prefer to use the indirect approach with no qualitative influence.

A last element to stress is that a fund can be accessible to investors even if its returns are not reported in any database. There are still good managers building a track record before actively marketing the fund but that will be open to new investors in case of demand. The use of data is to try to represent the hedge fund industry as closely to the reality as possible but the hedge fund industry is not limited to funds reporting to

databases. The fact that many funds still report their performance to one database only comforts us in this idea.

We are convinced that this bias may be quite low. Several authors (see Ackermann et al, 1999; Fung and Hsieh, 2002b) argue that this bias can be counterbalanced by good managers that stop reporting to databases when they close the funds to new investors. Selection bias manifests itself in two basic ways. Hedge funds may enter a database on a voluntary basis. On the one hand, presumably, only those funds that have good performance and are looking to attract new investors want to be included in a database. Therefore, hedge funds in a database tend to have better performance than those that are excluded. On the other hand, hedge funds may not be participating in a database because they are not looking to attract new investors. These self-excluded funds may have better performance than the average hedge fund. Thus, the net effect of selection bias on the returns of hedge funds in a database is ambiguous. Practically, there is no way to mitigate this bias and we have to keep in mind that this bias may be present.

Our estimation of survivorship bias lies between 1.22% and 1.68%. Such values are in the lower end of recent estimation. Brown et al. (1999) report a bias of 3% for offshore hedge funds per year. Fung & Hsieh (2000) use the TASS database and calculate the annual survivorship bias to be 3% with a 15% drop out rate. Liang (2000) examines this survivorship bias in hedge fund returns by comparing the TASS and the HFR database. He finds that the survivorship bias exceeds 2% per year in the TASS database, while the HFR database survivorship bias equals 0.6%, which is consistent with the higher drop out rate in the TASS database. Ackermann, McEnally & Ravenscraft (1999) suggest that two biases, the survivorship bias and the self-selection bias, offset each other. The difference can be explained by several factors. First, most of our studies analyses period ending by the end of 2002. Until recently, only the best managers

managed hedge funds. Since the demand for hedge funds exploded after the internet bubble starting in 2000, more and more players entered the industry. The best managers continue to launch funds, but less experienced individual are also attracted by the high fee levels. As any other these funds get listed in databases but as they do not offer attractive returns, most of them are dissolved after two or three years of data. This element could explain an increase in the percentage of dissolved funds and a higher survivorship bias after 2002 or 2003.

Finally, the three parts of this Thesis are based on individual hedge fund data; several other researchers have used and/or looked at hedge fund indices (see Brooks and Kat, 2001; Amenc and Martellini, 2003). The use of indices to analyse the hedge fund world may also lead to measurement problems. There are many hedge fund indices providers and most of them are reported in Table 4 with their main characteristics.

The literature on the subject report five main potential problems with using hedge fund indices³. First, since the quality of hedge fund data is poor, constructing indices based on hedge fund data will result in biases in the index. As a result the returns of hedge fund indices may not be meaningful. Second, some of the best hedge fund managers do not disclose fund information to the public. If the assets held by these managers make up a large portion of the assets in the hedge fund universe, then hedge fund indices will under-represent the returns of the universe. Third, there is a debate on how indices should be constructed, i.e. equally weighted or asset weighted. Some hedge fund indices use dollars under management as the weighting for the individual components.

³ See Liew (2003) and Amenc and Martellini (2003) for more information on the subject.

Table 4: Hedge Fund Indices Comparison

Providers	Nb of Strategies	Launch	Nb of Funds	Website
EACM	13	1996	100	eacmalternative.com
HFR	15	1994	1,1	hfr.com
CSFB/Tremont	9	1999	340	hedgeindex.com
Zürich Capital	5	2001	60	zcmgroup.com
Van Hedge	12	1995	750	vanhedge.com
Hennessee Group	22	1992	450	hedgefnd.com
Hedgefund.net	33	1979	1,8	hedgefund.net
LJH Global Investments	16	1992	800	ljh.com
MAR	15	1990	1,3	marhedge.com
Altvest	13	2000	1,4	altvest.com
Magnum	8	1994	NA	magnum.com

This Table reports a comparison between the major hedge fund indices available. Nb of strategies = number of strategies as defined by the index provider. Launch = launch date of the indices for the corresponding index provider. Nb of funds = estimated num

In practice this Figure 2 is difficult to determine, since many hedge fund managers have managed accounts and on/off-shore vehicles. Moreover, hedge funds may have different levels of leverage and may vary their leverage employed through time. Standardizing for leverage is problematic in index construction. Fourth, indices, suffer from the problem that they overweight markets that have had strong historical performance. Fifth, as shown by Amenc and Martellini (2003), there are significant differences in return distribution for the same strategies⁴.

⁴ Amenc and Martellini (2003) analysed the largest differences between the same indices of the hedge fund indices providers on a monthly basis and found differences up to 22% for a single month.

All these aspects mentioned above mean that the real hedge fund world can be different from the one analysed in academic papers and that general conclusion cannot always be applied to particular hedge fund strategies or individual managers.

Investing in Hedge Funds

Despite the growing interest in hedge funds, it is difficult for many individual and institutional investors to participate in this area of the market. Several reasons can explain this effect: high minimum wealth levels, sophisticated investor requirements or complexity of the strategy applied. Funds of funds have several advantages in comparison to individual hedge funds. They provide investors with diversification across manager styles and professional oversight of fund operations that can provide the necessary degree of due diligence. In addition, many funds of funds hold shares in hedge funds closed to new investment allowing smaller investors the access to those managers. Because of these, funds of funds constitute the only way of investing in hedge funds for many investors.

There is however, one major drawback: the additional fees. The additional fees has two main impacts. First, the return distribution of fund of funds will be complex because strongly impacted by the level of fees and more importantly by the distribution of these fees. When some underlying funds will offer positive returns, other may be down leading to a complex distribution of returns for the fund of funds. In addition, the fund of funds fee structure over the underlying fund one generally cut the profits by a performance fee once they reach a certain level (LIBOR for example) cutting the upside of the portfolio while on the downside there is no performance fees. The second and

obvious element is that the additional fee will lower the performance of the fund of funds that can only be as attractive as the one of the hedge fund industry as a whole if the fund of funds managers make a good selection of underlying managers. In case of bad choice, the final outcome for investors will be less attractive than stated in academic studies.

Several studies analyse the impact of fees in funds of funds. Brown et al. (2005) concluded that funds of funds offered a relatively poor historical performance relative to the hedge funds in which they invest. They explain the poor performance of funds of funds by the performance fees charges by underlying funds when they offer a positive performance even if the fund of funds as a whole is negative. Gregoriou et al. (2005) compare the performance of funds of funds with the one of portfolio constructed on the basis of alpha, Sharpe ratio and information ratio and find that a portion of the fund of funds available can be beaten through a simple selection strategy based on simple statistics.

These elements stress out that there is a difference between conclusion of academic paper and the reality for final investors. Care has to be given when trying to profit from academic conclusion based on individual hedge funds and these cannot always be applicable for funds of hedge funds.

Abstract Part One: The Persistence in Hedge Fund Performance

As stated in the first part of the introduction, the first objective of this Thesis is to understand hedge fund managers and to explain how they create alpha over time. This involve developing, testing and improving a performance analysis model in order to understand hedge fund performance on the one hand, while on the other developing and adapting a methodology to determine whether there is any persistence in hedge fund returns. We achieved this objective in three complementary studies (*An Analysis of Hedge Fund Performance*, *Hedge Fund Performance and Persistence in Bull and Bear Markets* and *Sustainability in Hedge Fund Performance: New Insights*).

The basis of Part 1 is study 1 that aims at answering to one question: What factors might explain hedge fund returns? We base our multi-factor performance decomposition model on models that are used in the mutual fund literature for years, Fama and French (1993)⁵ and Carhart (1997)⁶ models. Even if hedge funds are different from mutual funds by the strategy they apply, the securities they use and the freedom they have in their management, they remain investment funds. As such, we saw a model coming from the mutual fund literature as a good basis to build a new performance decomposition model specific to hedge funds.

⁵ Fama and French's (1993) model includes the following: a size factor that takes into account the difference in performance between small and large companies; a style factor that takes into account the difference in performance between growth and value players

⁶ Carhart (1997) extension added a momentum factor that takes into account the fact that certain managers favour previously well performing stocks in their portfolio.

Since hedge funds do invest not only in US equities, we add several factors that take into account the fact that hedge funds invest in non-US equities and in bonds (government, corporate, high yield and default), as well as commodities. Our model evolves over time for several reasons. First, some factors didn't help explaining hedge fund performance. Second, in some cases, the correlation between factors increased leading to a risk of multicollinearity. Finally, some factors were added as they seem to help decomposing the performance. The models we developed over the three studies are described in Table 5.

As stated in Table 5, the first model has 11 factors, the second 10 and the one used in the last part of the analysis 10 and 14. From model 1 to model 2, we re-adjust the factor used in the model to integrate a high yield factor and a mortgage backed securities factor to take into account the significant increase in the number of funds exposed to the high yield market and to determine if the exposure of fixed income funds to the mortgage was high or not⁷. The high yield factor finally helps but the mortgage factor does not.

As we will see in the papers, the model with the stronger power of explanation is model 3 that has a relatively limited number of factors but that covers almost all the aspects of hedge fund investing and that enable us to reach very high R^2 .

⁷ There has been a major move in the mortgage market in September 2002 and several hedge funds have faced strong losses.

Table 5: Multi-factor Performance Decomposition Model

	Model 1	Model 2	Model 3	Model 4
	<i>Capocci & Hübner (2004)</i>	<i>Capocci, Corhay & Hübner (2005)</i>	<i>Capocci (2006)-1</i>	<i>Capocci (2006)-2</i>
Alpha	X	X	X	X
US Stock Market	X	X	X	X
Size	X	X	X	X
Style	X	X	X	X
International Style	X	n/a	n/a	n/a
Momentum	X	X	X	X
Non-US Stock Market	X	X	X	X
US Bond	X	n/a	n/a	n/a
Wd Gov Bond	X	X	X	X
EMBI	X	X	X	X
Lehman BAA	X	n/a	n/a	n/a
High Yield	n/a	X	X	X
Mortgage	n/a	X	n/a	n/a
GSCI	X	X	X	X
Currency	n/a	n/a	X	X
Option Factors	n/a	n/a	n/a	X
Number of factors	11	10	10	14

This Table reports a comparison of the multi-factor performance models used in this Thesis. Size = the size market risk premium of Fama and French (1993), style = the style market risk premium of Fama and French (1993), international style = the international style market risk premium of Fama and French (1996), momentum = Carhart's (1997) "momentum" factor, non-US stock market = MSCI World excluding US, US bonds = the Lehman Aggregate US Bond Index, Wd Gov Bond = JPMorgan world government bond index, EMBI = JP Morgan Emerging Market Bond Index, Lehman BAA = the Lehman BAA Corporate Bond Index, High yield = Lehman High Yield Bond Index, Mortgage = Lehman Mortgage-Backed Securities Index, Salomon World Government Bond Index, GSCI = Goldman Sach Commodity Index, Currency = the Federal Reserve Bank Trade Weighted Dollar Index, Option factors = Agarwal and Naik (2004) at-the-money (ATMC), out-of-the money (OTMC) European call option factors, and at-the-money (ATMP) and out-of-the money (OTMP) European put option factors.

Over our three studies on the persistence in hedge fund performance, the objective is to explain long term hedge fund performance in order to determine whether some hedge fund strategies significantly outperform classical markets over time. Our results indicate that most hedge fund strategies *do* offer significant alpha over a long period of time. These results were not due to the lack of power of the model since, in all cases, the adjusted r-squared were very high. The next logical step was to perform the same analysis under various market conditions and we did that in our second study. More precisely, we analyse hedge fund performance and persistence in performance over bull market conditions, bear market conditions and over a full cycle. Our results indicate that hedge funds tend to outperform during bull market conditions but that this out-performance is no longer significant under bear market conditions. The only exception was market neutral strategies, which needed further analysis that is reported later in this Thesis.

Once we discussed that hedge fund strategies do significantly outperform classical markets over time, we analysed the persistence of this performance, that is, we looked at whether there was a repetitive way to isolate it over time. At this level, we reach the second important basic concept also used in the second study: the decile classification of Carhart (1997). As we state in the study:

“Active hedge fund selection strategies could increase the expected return on a portfolio if hedge fund performance is predictable. The hypothesis that hedge funds with a superior average return in this period will also have a superior average return in the next period is called the hypothesis of persistence in performance.”

Carhart's methodology is relatively straightforward to understand. Each year, all funds are ranked in 10 equally weighted portfolios based on their previous year's return. The portfolios are held until the following January and then rebalanced again. The combination of our multi-factor model with this methodology enables us to determine whether there is persistence in hedge fund returns.

Our results indicate that there is some proofs of persistence for low volatility funds that tend neither to be the best performers, nor the worst, but that offer relatively consistent returns over time. This result was the first important conclusion of our thesis. It needs deeper analysis over a shorter period of time, which was done in the second study. Persistence analysis indicates that most of the predictability of superior performance is found in bull market conditions (prior to March 2000). Our results confirm several previous studies that found that persistence, if any, is mostly located among medium performers. In bear market conditions, only negative persistence can be found among the past losers, suggesting that bad performance has probably been the decisive factor for hedge funds mortality.

In both studies, low volatility funds were the ones offering significant alpha. The only issue is that these funds tend to be classified in the middle decile portfolios. This led us to the conclusion that we needed another way of classifying hedge funds in the persistence analysis in order to be able to clearly identify the funds that significantly and consistently outperformed. This is exactly what we did in our third study. We tested several ways of classifying funds on the basis of their past performance: returns, volatility, Sharpe ratio, alpha, beta, skewness and kurtosis. Our results clearly indicates that measures incorporating volatility display a very strong ability to assist investors in creating alpha and in consistently and significantly outperforming classical indices. We checked the robustness of our results by performing the same analysis over sub-periods,

during bull and bear market conditions (defined as the up and down months of the S&P 500 and as consecutive bull and bear market periods) and by changing the month of classification (June instead of January). We found a consistent, systematic way of creating pure alpha using a simple classification methodology based on basic statistics: risk-return trade-off measures (Sharpe score), pure volatility measures (standard deviation) and, to a lesser extent, beta exposure, which appear to be better and more stable ways of classifying hedge funds in order to detect persistency in the returns. Funds offering stable returns, with limited volatility and/or with limited exposure to the equity market consistently and significantly outperformed equity and bond markets.

We report the specificity, objectives and main conclusions of each study of Part 1 in Table 6.

Table 6: Persistence Analysis Studies Specificities, Objectives and Conclusions

	Objective 1	Conclusion 1	Objective 2	Conclusion 2
An Analysis of Hedge Fund Performance	- Determine if hedge fund strategies significantly outperform classical markets	- Most hedge fund strategies do offer significant alpha over the long term despite a high R^2	- Determine if hedge fund strategies significantly and persistently outperform classical markets	- There is no proof of persistence for hedge funds but low volatile funds that tend to neither be the best performers nor the worst
Hedge Fund Performance and Persistence in Bull and Bear Markets	- Determine if hedge fund strategies significantly outperform classical markets in bull and/or bear market conditions	- Hedge funds tend to outperform during bull market conditions (not significantly in bear markets)	- Determine if hedge fund strategies significantly and persistently outperform classical markets in bull and/or bear market conditions	- No significant outperformance in bear market conditions but for market neutral funds
The Sustainability of Hedge Fund Performance	- Determine if hedge fund strategies significantly outperform classical markets using several risk-adjusted measures	- Most hedge fund strategies do offer significant alpha over the long term despite a high R^2	- Find a systematic way of buying hedge funds in order to significantly and persistently outperform classical markets	- Systematic outperformance of hedge fund portfolios invested in previous year' low volatile funds (measured by Sharpe score, standard deviation)

This Table reports the specificities, objectives and conclusion of the studies grouped in Part 1: The Persistence in Hedge Fund Performance. Part 1 contains three studies (An Analysis of Hedge Fund Performance, Hedge Fund Performance and Persistence in Bull and Bear Markets and the Sustainability of Hedge Fund Performance: new insights). For each study we report the main specificities of the study aalong with its first and second objective and conclusions.

Abstract Part Two: The Neutrality of Market Neutral Funds

Self-defined market neutral funds significantly and consistently outperformed the classical market over time. This result requires further analysis. The objective of this second part is clear: to analyse the exposure to the equity market of market neutral funds and to explore how to isolate funds that consistently outperform. The study analyses a complete cycle as well as sub-periods (bull and bear market conditions). Market neutral funds represent a large part of the industry, around 28% of our database used in the second Study of Part 1: *Hedge Fund Performance and Persistence in Bull and Bear Markets*.

Our results confirm that the betas obtained were low in absolute terms even though they were all significantly positive. The decile analysis indicates that the more volatile funds (top and worst performing funds) have the highest market exposure, confirming that low volatility funds emerge over time. At the individual fund level, one third of the funds are significantly positively exposed to the market, while two thirds of the alphas are significantly positive. We perform an analysis at the individual fund level in order to obtain this result because market neutral index analysis lead to controversial results. This result also stresses the importance of considering individual funds when performing an empirical analysis. This can be explained by two reasons. First, the aggregation of funds in indices leads to an increase in exposure to the equity market. Second, the funds that are significantly exposed can bias the results because a) the bulk of the funds are not significantly exposed to the market; only one third of the funds were, and b) only five percent of the funds are significantly negatively exposed to the market.

Table 7: Neutrality of Market Neutral Fund Specificities, Objectives and Conclusions

	Objective 1	Conclusion 1	Objective 2	Conclusion 2
Neutrality of Mkt Ntl Funds	- Determine the market exposure of market neutral funds	- Market neutral funds tend to be significantly exposed to the equity market (low in absolute terms)	- Determine if high/low beta market neutral funds outperform their high/low beta peers	- Real market neutral funds outperform dirty market neutral funds

This Table reports the specificities, objectives and conclusion of the study of Part 2: An Analysis of Hedge Fund's Market Exposure. Part 2 contains one study (The Neutrality of Market Neutral Funds). We report the main specificities of the study and its

The sub-period analysis also reports two interesting results. First, during the bear market, most poor performing market neutral funds out-performed the equity market without being significantly exposed to the market, but the best performing funds significantly out-perform the equity market and offer significantly positive returns. Second, during the bullish period, no index is significantly exposed to the market. However, during the bearish period, all but the best performing deciles are significantly exposed to the market, but they all (except the best performing funds) created significant alpha.

Our analysis leads to the conclusion that most market neutral funds are not significantly exposed to the equity market, but tend to be more exposed during bear markets than during bull markets without being negatively impacted.

We report the specificity, objectives and main conclusions of part 2 in Table 7.

Abstract Part Three: Hedge Funds as Diversification Tools

Hedge fund performance decomposition and strategy analysis were the first two aims of this doctoral thesis. In order to complete these analyses, we analysed in our third and final part the impact of inserting hedge funds into a classical portfolio of stock and bond mutual funds. Hedge funds exhibit abnormal returns. This is the basic reason why traditional tools like the mean-variance efficient frontier analysis should not be used for their analysis. In this paper we develop the idea of an adapted capital market line in an extended risk-return framework that includes not only volatility as a measure of risk but also higher moments.

Our methodology is based on the Taylor's extension of the linex utility function developed by Bell (1988). We decompose this function and take into account the mean return, the volatility, the asymmetry of the return distribution (skewness) and the presence of fat tails (kurtosis). This decomposition enables us to define a new and extended risk measures that we use in a classical risk-return framework. The only difference is that the risk factor is no more only defined by the standard deviation of the returns. This new tool has the same underlying idea as the classical efficient frontier and can be illustrated the same way while taking into account more sophisticated statistics.

Our results indicate that directional hedge funds should be considered separately from undirectional hedge funds and fund of hedge funds. Adding a small allocation to directional hedge funds does not significantly change the risk-return profile offered by the global portfolio. When more than 20% is allocated to directional hedge funds, there is a significant improvement for diversified portfolios (20 to 80% allocated to the risky

asset). Over a allocation of 50% to directional hedge funds offers significantly more attractive returns in every case.

However, adding undirectional hedge funds or fund of funds to a classical portfolio enables investors to reach higher levels of returns for low and medium risk levels for allocation as low as 10% to hedge funds. For high allocation to the risky asset, undirectional strategies do not help diversifying and reaching higher return levels. Our results confirm that undirectional strategies and funds of funds are diversifying low risk profile investments and should be used as such.

The new adapted efficient frontier opens new doors for asset allocators. Based on the clients' objective and the market conditions, it determines if hedge funds must be added to the existing portfolio. Moreover it helps to determine what hedge fund strategy should be favoured.

We report the specificity, objectives and main conclusions of part 3 in Table 8.

Table 8: Hedge Fund as Diversification Tools Specificities, Objectives and Conclusions

	Objective 1	Conclusion 1	Objective 2	Conclusion 2
Diversifying using hedge funds	<ul style="list-style-type: none"> - Develop a methodology to determine if a portfolio can be diversified with securities displaying abnormal return distribution characteristics 	<ul style="list-style-type: none"> - Taylor's expansion of Bell's utility function enables us to take skewness and kurtosis into account - The adapted Capital Market Line and new efficient frontier complete the development 	<ul style="list-style-type: none"> - Determine if bond and/or equity investors should include hedge funds in their portfolio 	<ul style="list-style-type: none"> - High allocation to directional hedge funds do significantly improve the profile - Adding small allocation of undirecitional hedge funds and funds of hedge funds significantly improve the profile

This Table reports the specificities, objectives and conclusion of the study of Part 3: Hedge Fund as Diversification Tools. Part 3 contains one study (Diversifying using Hedge Funds: a utility based approach). We report the main specificities of the study and its first and second objective and conclusions.