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Do Investors Benefit from the Use of Options and Complexity of Derivative Strategy of a Hedge Fund?

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Kieli
Englanti

Julkaisun nimike
Hyötyvätkö hedgerahastosijoittajat rahaston optioiden ja monimutkaisten johdannaisstrategioiden käytöstä?

Tiivistelmä

Tässä tutkimuksessa tarkastellaan optioiden ja monimutkaisten johdannaisstrategioiden käytön vaikutusta hedgerahastojen suorituskykyyn ja riskipiirteisiin. Tutkimuksessa myös huomioidaan mahdollinen hyöty osakeindeksisuureiden käytöstä. Hedgerahastojen lisäksi tämän tutkimuksen analyyseissä huomioidaan myös hedgerahastoihin sijoittavat rahastot. Tutkimusongelmien tutkimiseen käytetään Lipper TASS-hedgerahastotietokantaa, joka mahdollistaa yhteensä 3,403 yksittäisen hedgerahaston ja 763 hedgerahastoihin sijoittavan rahaston käytön tutkimuksessa. Tutkimuksen teoreettiset analyysit keskittyvät hedgerahastojen riskipiirteisiin ja yksittäisen hedgerahaston suorituskyvyn mittaamiseen.

Aragonin ja Martinin (2007) tutkimus implikoi, että hedgerahastot käyttävät optioita informoituun kaupankäyntiin. Tämän tutkimuksen tulokset kuitenkin näyttävät, että suotuisat vaikutukset optioiden käytöstä häviävät, kun markkinaperusteiset riskifaktorit huomioidaan. Lisäksi edellä mainitun kaltainen optioiden käytön havaitaan olevan yhteydessä suurempaan todennäköisyyteen kärsiä suuria tappioita. Frino, Lepone ja Wong (2009) esittävät evidenssiä osakeindeksifutuurien hyödyllisyydestä sijoitusrahastoille. Tämä tutkimus kuitenkin näyttää evidenssiä, että osakeindeksifutuurien käyttö on yhteydessä heikompiin epänormaaleihin tuottoihin hedgerahastojen kohdalla. Tämä tutkimus ehdottaa myös muuttujaa, joka kuvaa hedgerahaston johdannaisstrategian kompleksisuutta. Tutkimuksen tulokset tukevat hypoteesia, jonka mukaan kompleksisuus olisi yhteydessä suurempaan todennäköisyyteen kärsiä suuria tappioita. Kehitetyn muuttujan havaitaan myös olevan negatiivisesti yhteydessä hedgerahaston suorituskykyyn vastoin hypoteesia.

Tutkimustulokset, jotka koskevat hedgerahastoihin sijoittavia rahastoja eroavat, hedgerahastoja koskevista tuloksista. Näiden rahastojen kohdalla johdannaisstrategian kompleksisuuden ei havaita vaikuttavan rahaston suorituskykyyn ja muutaman johdannaisen käyttö saattaa olla jopa yhteydessä parempaan suorituskykyyn. Kompleksisuuden havaitaan myös olevan yhteydessä pienempään riskiin samaisten rahastojen kohdalla. Kompleksisuuden kuitenkin havaitaan olevan yhteydessä lisääntyneeseen todennäköisyyteen kohdata suuria tappioita, joka hedgerahastoihin sijoittavien rahastojen kohdalla on yhteydessä rahastokohtaisen riskiin.

Tutkimustuloksista yhteenvetona voidaan todeta, että monimutkaiset johdannaisstrategiat ovat ennemminkin käytetty riskienpiilottamiseen kuin riskienhallintaan. Täten monimutkaisten johdannaisstrategioiden käyttö voidaan rinnastaa ”piiloriski” strategioiksi, jotka eivät ole sijoittajien etujen mukaisia.

Asiasanat
hedgerahastot, informoitu kaupankäynti, optiot, johdannaisstrategiat

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Do Investors Benefit from the Use of Options and Complexity of Derivative Strategy of a Hedge Fund?

Abstract

This study investigates the possible advantages of the use of options and a more complex derivative strategy of a hedge fund in relation to its performance and risk characteristics. It also considers possible advantages of using equity index futures which may be beneficial for the cash management of a fund. In addition to hedge funds, this study considers funds of hedge funds in its analysis. To investigate these problems this study employs the Lipper TASS hedge fund database, which provides samples of 3,403 individual hedge funds and 763 funds of hedge funds. Theoretical analyses of the study focus on hedge fund risk characteristics and performance measurement of an individual hedge fund.

The study by Aragon and Martin (2007) suggests that hedge funds use options for informed trading. But this study finds that any favorable impact from the use of options for its primary assets (asset specialized use) vanishes after controlling for market-based risk factors. Moreover, the asset specialized use of options is associated with increased probability of suffering large losses. Frino, Lepone, and Wong (2009) present evidence that the use of equity index futures is beneficial for mutual. For hedge funds, the results of this study suggest that the use of equity index futures associated with weaker abnormal performance. This study also proposes a proxy for the complexity of the derivative strategy of a hedge fund. These results are consistent with the hypothesis that the complexity of derivatives use can be related to increased probability of suffering large losses. The impact of the factor on the performance of a hedge fund is also negative and contrary to what is hypothesized.

The results for funds of hedge funds differ from those of hedge funds. The complexity of derivative strategy does not decrease the performance of funds of hedge funds and the use of few numbers may even improve their performance. The complexity is also associated with lower risk in these funds. However, the complexity is still related to increased probability of suffering large losses, which is related to manager-specific risk in these funds.

Overall, the findings suggest that complex derivative strategies are rather used for concealing the risks than for risk management. Accordingly, the use of complex derivative strategies may be related to “hidden risk” strategies not aligned with the benefits of the investors.

Keywords

hedge funds, informed trading, options, derivative strategies

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My drive to pursue PhD studies started as a result of not finding a job while completing a Master's degree in finance. During autumn 2005 I had been searching for a job matching my education but met only with rejections from numerous human resource consultants. Apparently, the only remaining and sensible chance to work in the area of finance was to get back to school and get a PhD degree in finance. Yet, the path to obtaining a PhD in finance appeared to be something much more intellectual and challenging than any of those human resource consultants could have ever have offered me. After trading my chosen way, I owe gratitude to many individuals I met along the way and who came to a lot to me.

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LIST OF ABBREVIATIONS

ABS	Asset-Based Style Analysis
AIC	Akaike Information Criterion
AIMA	Alternative Investment Management Association
APT	Arbitrage Pricing Theory
AR	Autoregressive
CAPM	Capital Asset Pricing Model
CF	Cornish-Fischer
CFA	Certified Financial Analysts
CIDSM	Center for International Securities and Derivatives Markets
CSFB	Credit Suisse First Boston
CTA	Commodity Trading Advisor
EMH	Efficient Market Hypothesis
ES	Expected Shortfall
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
HFR	Hedge Fund Research Inc.
HML	High-Minus-Low
LS	Logistic Regression
LTCM	Long-Term Capital Management
MAR	Managed Account Reports
MBA	Master of Business Administration
MPT	Modern Portfolio Theory
MSCI	Morgan Stanley Capital International
MVaR	Modified Value-at-Risk
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
SAT	Scholastic Aptitude Test
SIC	Schwarz Information Criterion
SMB	Small-Minus-Big
UMD	Carhart's (1997) momentum factor
VaR	Value-at-Risk
VIX	Chicago Board Options Exchange Volatility Index (Ticker Symbol)

1 INTRODUCTION

Hedge funds are loosely regulated investment vehicles that can use options, other complex derivatives, and complex derivative strategies. Derivatives use is indeed popular among hedge funds. Chen (2009) finds that 71 % of hedge funds use derivatives, which is a relatively high ratio in comparison to conventional mutual funds. Considerable motivators for hedge funds to use derivatives could be transaction cost benefits (see Deli and Varma 2002), informed trading (see Aragon and Martin 2007), different derivatives strategies, risk management (see Chen 2009) and cash management (see Frino, Lepone, and Wong 2009). As such, the use of derivatives by hedge funds is a matter of ability rather than disability, and thus derivatives use should offer a wide range of possibilities for hedge funds.

Despite the possibilities inherent in derivatives use and derivatives strategies, many individual cases of hedge funds lead to a rather pessimistic view of the use of derivatives by hedge funds. A well known example of a hedge fund using options and a wide range of different derivative strategies is the Long-Term Capital Management (LTCM). This hedge fund had huge bets with extremely high leverage leading to approximately $4.6 billion losses at the time of the Russian crisis in 1998.

The lesson from the LTCM is that the relation between the use of derivatives and hedge fund performance should be important information. Therefore, the knowledge of the consequences of the actual use of options and complex derivative strategies in hedge funds should deserve more attention. Important questions related to hedge funds and their derivatives use are:

1. How are derivatives used by hedge funds?

2. Do hedge fund investors benefit from the use of derivatives by hedge funds?

3. Are the complex derivative strategies of hedge funds beneficial for investors?

If the investors do not benefit from the use of options and other derivatives by hedge funds, they should possibly perform simple derivative strategies on their own. Further, the questions should be especially relevant for hedge funds as they are not as restricted in their investment strategies as are mutual funds. Therefore, hedge funds can be considered as an important laboratory to investigate the performance and risk arising from the use of derivative strategies and options. As a result, the answers to these questions, in fact, provide a wider perspective for derivatives use rather than hedge fund specific.

1.1 Hedge Funds

Defining the term “hedge fund” is complicated and the term can be defined in multiple ways. McCrary (2005: 1) states that a typical definition of a hedge fund is the following:

> “A hedge fund is a loosely regulated investment company that charges incentive fees and usually seeks to generate returns that are not highly correlated to returns no stocks and bonds.”

Lowenstein (2002: 24) in turn relates the term hedge fund to a limited partnership providing a more juridical meaning for the term. However, this definition may not be sufficient as private equity funds may also be organized as limited partnerships. In some countries, financial regulators aim to regulate and define hedge funds in legal terms. For example, the Finnish regulation recognizes as hedge funds something that is named as special investment funds (in Finnish *erikoisijoitusrahastot*). Such of funds are allowed to use leverage and short sell. Contrary to legal definition of hedge funds, Bookstaber (2003) argues against defining hedge funds based on their regulation as follows:

> “…starting down the regulatory path with hedge funds as the objective is to fail before beginning because you cannot regulate an entity that is not well defined.”

The criticism by Bookstaber (2003) has pith as there are a couple or a few limited liability corporations in Finland which have a hedge fund-like structure. These corporations do not issue shares of the fund but instead issue shares of corporate loans for which the returns depend on the investment performance of the corporation.

In conclusion, it appears that the table is free for various definitions of the term “hedge fund”. As such, defining a hedge fund is rather a subjective matter. However, it is reasonable to take the view that hedge funds share some common characteristics and regulatory issues which merit consideration. Thus, hedge funds can be considered as loosely regulated investment vehicles which aim to produce returns which are not correlated with the markets. Mutual funds in turn are regulated and do not aim to produce absolute returns.

1.2 Measurement of Investors' Benefits from the Use of Derivatives

There are numerous ways to define investors' benefits from the use of derivatives. In this study, the benefits from the use of derivatives are measured in terms of hedge funds from which the investors would also benefit. It is the basic assumption of the modern portfolio theory (MPT) that higher return is desirable while higher return variance is undesirable. Markowitz (1952) expresses the assumption as "….the investor does (or should) consider expected return a desirable thing and variance as undesirable thing." Accordingly, investors would benefit from derivatives use with better return-risk relation for which the risk is measured using the variance of returns. Thus, the better risk-return relation associated with the use of derivatives would also be beneficial for investors. An additional motivator for assuming investors to benefit from the better risk-return relation is the tendency of dead hedge funds to have inferior risk-return relation compared to other funds (see, e.g. Liang 2000; Getmansky, Lo, and Mei 2004). As such, it is reasonable to assume the better risk return-relation to be in the interests of investors as it is the basic characteristic of surviving hedge funds.

Following MPT, the final benefit from the use of derivatives by hedge funds would depend on the investors' ability to improve the risk-return relation of their final portfolio by inclusion of derivatives users in their portfolios. This ability would be difficult to analyse as investors' portfolios may vary considerably and the impact of the inclusion of hedge fund in their portfolios is difficult to analyse. Yet, it is the best considered as controlling for market-based risk factors of hedge fund returns and focusing on the abnormal returns. Other considerable (or potential) investments in investors' portfolios are then controlled for. In this study, *market-based risk factors* used are defined as the factors of hedge fund performance that can be derived from marketable prices to explain time-series returns of hedge funds, and are motivated by the previous academic research.

Admittedly, a limitation of the study is that the actual benefits for each hedge fund investors are difficult to measure. The results are most relevant for those investors who invest significant proportions of their wealth in individual hedge funds as then the risk embedded in an individual hedge fund weights the most.

When measuring the investors' benefits from the use of options, the higher moments of returns are also considered, namely the skewness and the kurtosis of the returns. The previous evidence suggests that investors prefer higher skewness and lower kurtosis for investment returns (see Arditti 1967; Kraus and Litzenberger 1976; Scott and Horvath 1980). Consistently, Baba and Goko (2009) find that hedge funds with lower skewness in returns are more likely to be liquidated. This result implies that also hedge fund investors dislike lower skewness. Therefore, as additional measures, the investors are considered to benefit from the use of derivatives and derivative strategies if they are related to higher skewness and lower kurtosis. Together higher skewness and lower kurtosis would imply that the left tail of the return distribution would be less heavy. For investors, the less heavy left tail of investment returns would mean less "unhappy surprises."

1.3 Research Problems, Hypotheses and Purpose of the Study

The objectives of this study are to investigate advantages and disadvantages of the use of options and the complexity of the derivative strategy of a hedge fund from the investors' viewpoint. Advantages and disadvantages of the complexity are also considered for funds of hedge funds. In this study, the *complexity of the derivative strategy* of a hedge fund is defined as the number of different derivatives used by a hedge fund. This study also investigates hedge fund performance associated with the use of equity index futures. The use of this particular derivative is in the interest of recent academic research due to its potential use for cash management by mutual funds (see Frino et al. 2009). The use of derivatives by financial institutions can also be a relevant aspect for financial stability because the actions of one fund can cause dramatic losses and shake financial markets, which happened in 1998 after the actions of the LTCM. This study investigates three research questions:

1. Does the use of options by a hedge fund for the primary asset class of a fund affect its performance and risk characteristics?

2. Does the use of equity index futures by a hedge fund affect its performance and characteristics?

3. Does the use of a more complex derivative strategy affect the performance and risk characteristics of a hedge fund?

The use of options for the primary asset class of a hedge fund is hereafter defined as *the asset specialized use of options*. Consistently, the use of options for equity when it is the primary asset class of a hedge fund would then be equity specialized use of options. The logic is also applied for primary uses of options for fixed-income, currency and commodity. The advantage of focusing on the asset specialized use of options is its high degree of relevance for the strategy of a hedge fund. For instance, the use of equity options of a hedge fund which focuses on fixed-income does not reasonably matter as much as it matters for a hedge fund which focuses on equity.

The above problems are investigated using 3,403 individual hedge funds and 763 funds of hedge funds obtained from the Lipper TASS hedge fund database. There are also other hedge fund databases available, for example the hedge fund database of Hedge Fund Research Inc. (HFR). But the chosen database provides extensive information concerning derivatives use of hedge funds. Therefore, it can be considered as the best database available to study the above research questions although it does not represent the entire hedge fund industry.

This study posits five main hypotheses. Hypotheses may be directed to both the use of options (denoted by a) and complexity of derivative strategy (denoted by b). The hypotheses are the following:

H_1: The asset specialized use of options enhances hedge fund performance.

H_2: The equity specialized use of equity index futures is related to lower hedge fund performance.

H_3: The use of a more complex derivative strategy of a hedge fund decreases risk.

H_4: The use of a more complex derivative strategy improves hedge fund performance.

H_{5a}: The asset specialized use of options has a negative impact on the skewness and a positive impact on the kurtosis of a hedge fund return distribution.

H_{5b}: The use of a more complex derivative strategy of a hedge fund has a negative impact on the skewness and a positive impact on the kurtosis of its return distribution.

For the first hypothesis, there are also at least three considerable reasons why the use of options may improve hedge fund performance predicted by the hypothesis: first, the ability to trade options can be used for better risk management as the results of Chen (2009) for derivatives use by hedge funds imply. Aragon and Martin (2008) also find that equity options use is associated with higher Sharpe ratio and lower standard deviation. This result implies that the performance statistics of equity options users is specifically higher as a result of risk component of the statistics.

Second, the ability to trade options allows hedge funds to use wider range of trading strategies, which may be profitable. For example, the profitability of the popular covered call strategy, which involves writing call options against underlying equities simultaneously, is suggested by many studies such as Board, Scutliffe and Patrinos (2000), Isakov and Morard (2001), Whaley (2002), McIntyre and Jackson (2007), and Kapadia and Szado (2007).

Third, options especially may be important tools for informed trading in the use of hedge funds. Several scholarly studies indicate that options market can be a channel of informed trading (see, e.g., Easley, O'Hara, and Srinivas 1998; Chakravarty, Gulen, and Mayhew 2004). The study by Aragon et al. (2007) presents evidence that hedge funds use options for informed trading. Hedge funds also seem to have market timing ability in their focus market (see Chen 2006), and therefore asset specialization could be associated with better information. This evidence leads to a need to focus the hypothesis to the asset specialized use of options. Consequently, the asset specialized use of options by a hedge fund should have a positive impact on its measured performance.

For the second hypothesis, it is reasonable to expect that the equity specialized use of equity index futures is associated with lower hedge fund performance. The use of this derivative is related rather to liquidity motivated and uninformed trading by mutual funds (see Edelen 1999; Frino et al. 2009). Accordingly, the use of this derivative can be seen as a substitute for share restrictions which are used to manage illiquid assets by a hedge fund. Thus, equity index futures are also substituted to illiquidity risk premium rewarded from manage illiquid assets efficiently. The hypothesis does not imply that the use of equity index futures would be detrimental for hedge funds but it implies that it is associated with the strategies not profitable on average in the hedge fund industry.

The third hypothesis is based on the evidence presented by Chen (2009) for risk management consistent use of derivatives by hedge funds. Therefore, it is reasonable to assume that the use of a more complex derivative strategy would decrease the aggregate risk of a hedge fund in the terms of standard deviation.

The fifth and also the third hypotheses are based on the evidence presented by John and John (2006) suggesting that the use of complex derivative strategies may lead to better performance statistics but also to higher probability of incurring larger losses. These large losses would appear as lower skewness and higher kurtosis of hedge fund returns distributions. Also, option writing strategies which improve performance statistics are found to exhibit these risk characteristics (see Whaley 2002).

However, the asymmetry of option payoffs may also cause asymmetry in the return distributions of hedge funds. Therefore, possible advantages from hedging risks may vanish after accounting for asymmetry in hedge fund returns. The two arguments may also be related to the use of complex derivative strategies.

The negative impact on skewness and positive impact on kurtosis in the distribution of hedge fund returns as hypothesized (Hypotheses 5a and 5b) implies fatter left tail of the distribution as an effect of derivatives use. The impact on the left tail, which aggregates the skewness and kurtosis, is also measured and tested in accordance with Hypotheses 5a and 5b. Moreover, as funds of hedge funds are closely related to hedge funds, the hypotheses presented above may also be directed at funds of hedge funds.

1.4 Contribution of the Study

By considering the asset specialized use of options, the use of equity index futures and the complexity of the derivative strategy of a hedge fund this study makes a contribution to six different areas of hedge fund research:

- **Complexity of the derivative strategy of a hedge fund as a relevant factor of the performance and risk of a hedge fund:** Well known factors of hedge fund performance prior to this study are, for example, size (see Getmansky 2005), age (see Liang 1999), leverage (see Schneeweis, Martin, Kazemi, and Karavas 2005), management compensation (e.g. Kouwenberg and Ziemba 2007), share restrictions (see Aragon 2007), manager's personal capital invested in the fund (e.g. Kouwenberg et al. 2007), and many other managerial and fund characteristics (see Boyson 2002; Maxam, Nikbakth, Petrova, Spieler 2006). Derivatives use is also considered as a factor of hedge fund performance and risk. Chen (2009) uses a binary variable of derivatives use as a factor of hedge fund performance and risk and finds only little statistically significant difference in the results although some weak evidence when the Sharpe ratio is used. This study extends the debate and presents a proxy for the complexity of a fund's derivative strategy as a factor of hedge fund risk and performance. Thus, while Chen (2009) focuses on analysing how those 71 % of hedge funds using derivatives differ from those not using derivatives, this study also aims to analyse derivatives use in this 71 % subgroup. The factor is hypothesized to have an impact on hedge fund risk characteristics and performance. In relation to these studies, the present study proposes the complexity of the derivative strategy of a hedge fund as a new factor of hedge fund performance. Hedge funds have also been found to exhibit non-normal return distributions by the previous studies (see, e.g., Brooks and Kat 2002; Malkiel and Saha 2004) which make the investigation of this relation especially interesting for hedge funds as it is hypothesized in this study that derivatives use can be the cause of these characteristics.

- **The use of equity index futures and fund performance:** The use equity index futures is of particular interest in the research on derivatives use due to their potential use for cash management. The finding by Koski and Pontiff (1999) implies that derivatives users have lower variation in systematic risk imply the use of index futures for cash management as noted by Frino et al. (2009). The results by Frino et al. (2009) implies that by using equity index futures mutual funds can better adjust exposure to the market when receiving cash inflows. As a result, by using equity index futures funds have an ability to achieve marginally better performance as they can efficiently adjust their portfolio to desired risk level. So far the use of equity index futures by hedge funds has been paid less attention, possibly due to the ability of hedge funds to control their fund flows by imposing share restrictions. Share restrictions in turn are related to higher performance statistics as a result of illiquidity risk premium associated with the restrictions (see Aragon 2007). This study contributes to the literature as it hypothesizes that the use of these derivatives by hedge funds, as an indicator of lower illiquidity risk premium, is associated with lower performance.

- **The asset specialized use of options:** The results by Fong, Gallagher, and Ng (2005) suggest that mutual funds do not use options for informed trading. Aragon et al. (2007) test predictive information of option holdings by hedge funds and stress the use of stock options for informed trading. However, they do not align informed trading and options use directly to hedge fund performance and test how the use of options affects hedge fund risk and performance as does this study. Chen (2008) and Aragon et al. (2008) also test the association between options use and hedge fund performance but do not consider the asset specialized use of options[1]. This study in turn considers the asset specialized use of options. This type of use options relates to the use of options for primary asset class of a hedge

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[1] The results from this study concerning the use of equity options and hedge fund performance were published in the Proceedings of the 46th SWFA Annual Meeting (Houston, March 2008).

fund which can be reasonably assumed as the most relevant asset of the strategy of a hedge fund. Therefore, if options use for informed trading or other profitable strategies on aggregate are important factors of the performance of hedge funds in their primary activities, they are likely to be seen by investigating asset specialized use of options.

- **Complexity of the derivative strategy and the management of a portfolio of hedge funds:** For funds of hedge funds, Chen (2009) uses univariate analysis but to examine the difference between the performance and risk of derivatives users and nonusers. In the multivariate analysis by Chen (2009) funds of funds are analysed in the same sample with the other funds. However, the use of derivatives may differ significantly for hedge funds and funds of hedge funds as the latter ones do not engage in trading similar to hedge funds and their objective is to manage hedge fund portfolios. It may also be reasonable to consider that the use of derivatives by funds of hedge funds is biased towards risk management activity. For instance, Denvir and Hutson (2006) present evidence for funds of hedge funds having diversification advantage over hedge fund indices. Derivatives use may be associated with this diversification advantage. Therefore, it is important to consider the difference between funds of hedge funds and examine their difference from hedge funds as a relevant contribution to Chen (2009). To further investigate the difference, the analyses consider whether the risk and performance characteristics are different for those hedge funds which also invest in other funds. Moreover, the use of derivatives by these special type of funds is not considered in earlier research on hedge funds.

- **Market-based risk of a hedge fund and complexity of derivative strategy:** The relation between the market-based risk, which is the standard deviation of hedge fund returns explained using market-based risk factors, and the complexity of the derivative strategy of a hedge fund is also considered. In the estimation of market-based risk, the option-like risk factors and other reasonable market-based factors motivated by the previous research are used. Option-like and market-based factors have previously been advocated by many studies such as Agarwal and Naik (2004) and Fung and Hsieh (2002a). This study then considers a possible relation between the estimated market-based factors of hedge fund performance and the complexity of derivative strategy of an individual fund. The relation is especially important given the wide use and the credibility of the market-based factors (see, e.g., Fung and Hsieh 2004b). Chen (2009) considers the relation between the exposure of a hedge fund to stock market factor (systematic risk) and derivatives use but does not consider other relevant factors such as the option-like risk factors[2].

- **The relation between the left tail of the return distribution of a hedge fund and fund characteristics:** Several studies such as Eling (2006) and Bali, Gockan, and Liang (2007) apply both the Value-at-Risk (VaR) and Modified Value-at-Risk (MVaR) risk measures in their analyses. These studies, however, do not test which hedge fund characteristics affect the difference between the VaR and MVaR estimates using the Cornish-Fischer expansion. The Cornish-Fischer expansion is useful as it considers both the skewness and excess kurtosis of the return distribution of a hedge fund. Admittedly, some studies, such as Chen (2009), test characteristics affecting the skewness and excess kurtosis separately but they do not aggregate them. This perspective should be extremely interesting as VaR and MVaR are widely used in practice. Unlike the earlier studies, this study considers this issue and tests whether the complexity of the derivative strategy of a hedge fund has an impact on the Cornish-Fischer expansion of its returns. This study also investigates other factors beside the complexity of derivative strategy affecting the Cornish-Fischer expansion.

The construction of the proxy for the complexity of derivative strategy of a fund and the focus on the asset specialized use of options allows one to study the implications of the use of these financial instruments and complex derivative strategies which can contribute to much broader knowledge in finance. The reason is that hedge funds can be considered as a laboratory for the potential consequences of these uses of derivatives due to their free regulation. They are also relatively little restricted in their derivative strategies. The implications relate to the question: do investors and traders benefit from the use of derivatives and complex derivative strategies?

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[2] Specifically, Chen (2009: 10) defines the measure of market risk used in his study as follows: "…market risk is estimated by the time-series regression coefficient of fund returns on the market portfolio." In this study, the focus is on market-based risk, which is important as hedge funds by definition aim to hedge market risk and focus on alternative sources of returns. Chen (2009: 18) reports of the use of alternative benchmarks but he does not indicate that the definition for the market risk is considered differently nor does he explain the use of any additional risk measures in conjunction with the use of the alternative benchmarks.

- **Performance from the use of derivatives and option strategies:** While the previous studies on mutual fund and hedge fund performance such as Koski et al. (1999), Johnson and Yu (2004), Fong et al. (2005), Chen (2009) and Frino et al. (2009) uses binary variables of derivatives use, this study considers the complexity of derivative strategy. This consideration of complexity makes it possible to empirically test the implication of the study by John et al. (2006) that the use of complex derivative strategies may lead to better performance statistics but also to higher probability of incurring larger losses. Earlier studies such as Whaley (2002) suggest that passive option strategies may improve portfolio performance; by focusing on the asset specialized option use this study also attempts to ascertain whether this advantage may really be seen at the fund management level.

- **Derivative strategies and the risk of a managed investment portfolio:** Following John et al. (2006) it can be expected that the use of complex derivatives and options strategies is related to "hidden risk" strategies. The study by Chen (2009) finds that derivatives use is related to lower risk but the concept of complexity of derivative strategy is not considered by the study as it is, none of the previous studies on derivatives use by funds. Following John's et al. (2006) theoretical evidence for derivative strategies and risk, this empirical study aims to assign the use of complex derivative strategies in general to higher moments (the third and the fourth) of investment returns. This investigation of the prediction may also be related to use of derivatives by other institutions and investors which are not strictly regulated.

1.5 Practical Relevance of the Study

Many institutional investors, including pension funds, have invested considerable amounts of wealth in hedge funds. Therefore, the results in this study are important for practitioners. News in the financial press about hedge funds and their strategies may lead investors to subjective thinking if individual cases appearing in financial press are too easily generalized. For example, investors may generalize the failure of the LTCM in its derivative strategies too easily.

The research in this study now aims to provide objective evidence of how derivative strategies and the use of options may actually result in hedge fund performance and risk. Being aware of the risks in hedge funds the institutional investors can avoid "pitfalls" in hedge fund investing. The study also offers objective information to regulators so that they have more objective grounds to regulate the use of derivatives by hedge funds.

1.6 Structure of the Study and Brief Outline of the Results

This study is organized into 8 chapters and three appendices as follows. Chapter 1 presents a relevant introduction to the topic of this study, its research problems and purpose, and presents the contribution of the study. The chapter also defines the investors' benefit which is assigned to the use of derivatives.

Chapter 2 is a review of relevant literature related to the risk and performance of hedge funds, which includes a presentation of this discipline in relation to some other financial theories of applied microeconomics and asset pricing. In this chapter, the performance measurement of hedge funds is also explained and used to define the investors' benefits from the use of derivatives.

Chapter 3 is a review of the research on the use of derivatives by mutual funds and hedge funds. The main purpose of the chapter is to review the studies investigating the impact of the use of derivatives on the performance and risk of a fund. It also presents research on the purposes of derivatives use by investment funds. Chapter 3 is followed by Chapter 4, which is denoted for developing the hypotheses of this study.

Chapter 5 describes the methodology of this study. The chapter also discusses the factors for time-series and cross-sectional analysis which are used in this study. Chapter 6 describes data of this study and reviews relevant biases related to hedge fund return databases.

Chapter 7 reviews the results of this study. The results imply that the options use does not result in better performance by a hedge fund after controlling for market-based risk factors of a hedge fund. The use of equity index futures is associated with lower abnormal performance of a hedge fund. Complexity of the derivative strategy of a hedge fund is related to weaker performance and higher probability of suffering heavier losses than predicted by risk measures, which assume hedge fund returns to be normally distributed. For funds of hedge funds, the use of a more complex derivative strategy is related to lower risk but also to suffering heavier losses than expected similar to hedge funds.Finally, the chapter presents a discussion and additional analysis of the robustness of the results.

Chapter 8 is for the conclusion of this study. The main conclusion of the study is that it is not beneficial for investors to invest in complex derivative strategies. The results will also be discussed in light of financial stability. The results should motivate regulatory authorities to regulate the use of complex derivative strategies as heavy losses of big hedge fund using derivatives which may threat financial stability. An increase in the regulation would still be aligned with the interests of investors as one considers negative association between the complexity of the derivative strategy of a hedge fund and its performance. The chapter moreover presents some possible avenues for future research related to the topic of this study.

Appendix 1 presents the classification of hedge fund strategies which is used in this study. Appendix 2 presents additional analyses for the relation between the use of equity index futures and hedge fund performance.

2 HEDGE FUNDS AND RELATED THEORY

This section presents the background for risk and performance characteristics of hedge funds. Two distinctions are made in the review of the research on hedge funds and their related theory:

- **"Performance and risk measurement:"** For the purposes of this study, the most relevant issue in financial theory is its relation to the often promised abnormal performance by hedge funds, what abnormal performance means and how it can be measured. The theory is followed by a review of empirical studies on hedge funds which presents theories, methods, and empirical risk factors used to measure abnormal performance.

- **"Hedge fund characteristics:"** These hedge fund studies are followed by a review of empirical research and related theory on factors related to the performance of individual hedge funds.

This section concludes with a discussion about relation between these components. General symbols used in this section and thereafter are the following:

R_i = return on the individual *i*th security;

R_p = return on the *p*th fund;

R_m = return on the market portfolio;

R_f = risk-free rate of return;

σ_i = standard deviation of the returns on the individual *i*th security;

σ_p = standard deviation of the returns on the *p*th fund;

σ_m = standard deviation of the returns on the market portfolio;

π = unobservable market factor;

f_n = systematic factor of the returns of a security;

$\overline{\sigma}_m$ = defines the mean standard deviation of market returns.

The following operators are also used: $E(\ )$ defines the expectation of the variable in the brackets; $\sigma(\ )$ defines the standard deviation of the variable in the brackets; $Var(\ )$ defines the variance of the variable in the brackets; $Skew(\ )$ defines the skewness of the variable in the brackets; $Kurt(\ )$ defines the kurtosis of the variable in the brackets, and $Cov(\ )$ defines the covariance of the variables in the brackets.

2.1 Hedge Fund Returns

Hedge fund returns exhibit many statistical properties which are relevant for their analysis. The reliability of the returns may be weak in some cases.

2.1.1 The First Four Moments of Hedge Fund Returns

It makes sensible to start the review of the hedge fund literature related to their "performance and risk measurement" by discussing the returns of hedge funds. In conventional investment analysis, it is common and a standard way to analyse the first and the second moments of hedge funds returns which are the mean and variance of their returns. However, the third and fourth moments of the return distribution, which are the skewness and kurtosis, should also matter to investors, and hedge fund investors in particular. From hedge fund investors' viewpoint, the problem is usually that hedge fund returns exhibit negative skewness and high kurtosis (see, e.g., Brooks et al., 2002; Malkiel et al., 2004). Economic theory generally states that investors prefer higher skewness and lower kurtosis (see, e.g., Arditti 1967; Kraus et al. 1976; Scott et al. 1980). Practically, if a hedge fund exhibits negative skewness and high kurtosis, then it exhibits higher probability of suffering larger losses than predicted if the returns were normally distributed. Thus, even though many hedge fund strategies provide attractive returns against the standard deviation of the returns, negative skewness and high kurtosis make the returns less attractive. In other words, this characteristic is the problem of the fat left tail of the return distribution of a hedge fund. When accounting for skewness and kurtosis, the objective function to construct hedge fund portfolios by Brunel (2004) would be the following:

(1) $$\max\left[E\left(R_p\right) - \sigma\left(R_p\right) + \lambda \times Skew\left(R_p\right) - \gamma \times Kurt\left(R_p\right)\right],$$

where λ defines the scaling constant associated with skewness, and γ defines the scaling constant associated with kurtosis.

Eling (2006) suggests that after accounting for the existence of serial correlation and the higher moments of the return distributions of hedge funds, the attractiveness of hedge fund returns decreases.

To reduce the problem of fat left tails of the return distributions of portfolios that include hedge funds, the study by Kat (2005) suggests that with proper asset allocation it is possible to reduce the adverse characteristics of negative skewness and high kurtosis by portfolio construction. The proposed allocations are the following: purchasing out-of-the-money put options, investing in managed futures funds, overweighting the equity market neutral and global/macro strategies, and avoiding investing in the distressed strategy (Kat 2005).

2.1.2 Hedge Fund Returns: Statistical Properties and Accuracy

The very first problem encountered in the analyses is the accuracy of hedge fund returns. Hedge fund returns are usually self-reported by hedge fund managers to different databases and investors and there is usually no requirement for auditing hedge funds, yet the requirement may depend on the legislation of each country.

Liang's (2003) study on the accuracy of hedge fund returns classifies the factors that affect hedge fund returns into auditing effectiveness, transparency, manager efforts, and ease of calculating returns. Specifically, auditing effectiveness may be measured by non-missing auditing dates while transparency may be measured by exchange listings of a hedge fund and openness to the public. In addition, some hedge fund managers may put or have to put more effort into calculating their returns. The calculation of the returns of some strategies and instruments is more demanding, which may also lead to problems with the accuracy of the data.

By comparing the same funds in different databases and in the different versions of the same databases Liang (2003) finds return discrepancies which are associated with the presentation of auditing dates by hedge funds. Smaller funds, exchange listed funds, funds of funds, funds open to the public, unlevered funds, and funds which invest in only one sector report more accurate returns.

2.1.3 Serial Correlation in Hedge Fund Returns and Return Smoothing

Serial correlation in hedge fund returns is an empirical characteristic which is also associated with the accuracy of hedge fund returns. Asness, Krail, and Liew (2001) open the debate on serial correlation in hedge fund returns. They find positive serial correlation in hedge fund index returns that alters the performance measurement. The estimated exposure of the returns of hedge funds whose returns are serially correlated to asset indices causes the estimated betas to be downward biased. As a result, lagged beta models are proposed to be the most conventional way to account for this bias in the performance measurement. Some empirical studies, more specifically, Amenc, El Bied, and Martellini (2003) and Hamza, Kooli, and Roberge (2006) also offer evidence for predictability in hedge fund returns by using multifactor models.

The cause of serial correlation is an important issue related to the effect itself. Getmansky, Lo, and Makarov (2004) investigate the causes for serial correlation in hedge funds returns. They consider time-varying expected returns, market inefficiencies, time-varying leverage, incentive fees with high watermarks, illiquidity and return smoothing as possible causes for serial correlation in hedge fund returns. They suggest that return smoothing and illiquid assets are the primary reasons for serial correlation in hedge fund returns.

Chandar's and Bricker's (2002) study of earnings management in closed-end mutual funds may shed some light on serially correlated hedge fund returns. They test three objectives of mutual fund managers in managing earnings: maximization of current compensation, maximization of compensation over multiple periods by outperforming passive benchmark, or smooth earnings. The results suggest that fund managers use accounting discretion to manage their earnings in order to manage fund returns around a passive benchmark. Moreover, these results concern both equity security funds and debt security funds. Thus, when a fund has excess performance above the benchmark, the performance would be put away for a rainy day and then on that day the return is shown. Hedge fund managers may compare themselves against some passive benchmarks in the same way, and therefore performance should be a key reason for smoothing returns.

Good performance has indeed been shown to attract investors to invest money in a hedge fund (see Agarwal et al. 2007), and therefore hedge fund managers may be willing to smooth their returns, especially when the current performance is poor. Intuitively, a hedge fund manager also should be more willing to inflate the returns higher when the risk of capital outflow is increased. Bollen and Pool (2008) consider conditionality in return smoothing by hedge funds. They account for the possibility that serial correlation in hedge fund returns depends on whether the performance of a hedge fund is good or bad and they estimate the following model:

$$(2) \qquad R_{p,t}^{0} = a_p + b_1^{+} R_{p,t-1}^{0} + b_1^{-}\left(1 - D_{t-1}\right) R_{p,t-1}^{0} + \eta_{p,t},$$

where $D_{t-1} = 1$ if systematic return component of observed hedge fund return is greater than its mean in month *t*-1, and $\eta_{p,t}$ is the residual error. Conditional return smoothing results in $b_1^- \neq 0$. When $b_1^- > 0$, poor returns are smoothed more than positive returns implying conditional return smoothing. The results of the study relate positive values of b_1^- to the risk of capital outflow and no use of an auditor.

Evidence for return discretion and return smoothing can also be found as seasonality in hedge fund returns. Agarwal et al. (2007) find that hedge fund returns are significantly higher in December. The authors call this phenomenon the December peak and relate it to managers' incentives to improve annual performance at the end of the year due to incentive fees, which are determined at that time. The results show that hedge funds, which have greater incentives and opportunities to manage their returns, exhibit a larger December peak.

Following Agarwal et al. (2007), the December peak may actually be related to both positive and negative return smoothing. Positive return smoothing relates to the use of stored returns and negative smoothing relates to the use of (possible) future returns. Negative return smoothing actually creates negative value for stored returns. Convincing evidence for positive smoothing is seen in the results of Agarwal et al. (2007) suggesting that hedge funds underreport their returns until December, when the remaining reserves are added. Also, these authors find that part of the December spike is created by borrowing from January returns, therefore giving evidence in favour of negative return smoothing.

Discontinuity around zero in hedge fund return distributions may also be a result of misreporting. Pool and Bollen (2007) study this discontinuity in hedge fund returns around zero in the pooled distribution of reported monthly hedge fund returns. Their results show that when the returns cross the zero threshold to negative, the density of hedge fund returns significantly decreases. The result also holds for hedge funds which invest in illiquid assets, and is not found to be related to hedge fund risk factors. The authors' explanation for the result is that hedge fund managers avoid reporting losses to attract and retain investors.

2.2 Common Risk Factors and Performance of Hedge Funds

To understand the performance of hedge funds one must first focus on determining the abnormal performance of a hedge fund and for this purpose theoretical analysis is needed. This theoretical analysis for the determination of the abnormal returns starts from the Capital Asset Pricing Model (CAPM) and is completed with the presentation of Treynor's and Black's (1973) appraisal ratio.

Probably the best established foundation for theoretical asset pricing is the CAPM which is developed by Sharpe (1964), Lintner (1965), and Mossin (1966). The model predicts the following risk-return relation:

(3) $$E(R_i) = R_f + \beta_i\left[E(R_m) - R_f\right].$$

The CAPM implies that under certain assumptions the required rate of return for each stock is determined by its relation with the market returns which is described with beta, β_i. The beta is the covariance between the returns of the stock and the market returns divided by the variance of market returns, formally:

(4) $$\beta_i = Cov(R_i, R_m)/Var(R_m)$$

The CAPM, however, is not suitable for proper analyses of hedge fund returns. Hedge funds, as stated by Fung et al. (2000b), can be considered as "zero-beta like" investments. But the CAPM can be considered as the first essential step to understand the required return for an investment.

In the context of the CAPM, the "zero-beta" nature would mean that the returns of hedge funds would have no significant exposure to the market returns, and they would not carry significant proportion of systematic risk. Fung et al. (2000b) further note that even though hedge funds may carry low systematic risk, they may carry high "absolute" risk, which is related to the "event risk" in their strategy. The market beta is not suitable to analyse this absolute risk. The absolute risk can further be illustrated in the context of Sharpe's (1963) single index model:

(5) $$R_i - R_f = \alpha_i + b_i\left(R_i - R_f\right) + e_i,$$

where α_i is the abnormal return of the security, and e_i is the idiosyncratic risk of the stock. When the above single index model is applied to the context of hedge fund analysis, the above discussion suggests that b_i becomes more irrelevant while e_i becomes more relevant. The assumption for the model is that the variables $\left(R_i - R_f\right)$ and e_i must be independent random variables and $E(e_i) = 0$.

In the analysis of active investment strategies, it is reasonable to focus on the α_i term which is a measure of portfolio performance as first proposed by Jensen (1967). Jensen's (1967) model begins from the CAPM (Equation 2). If investors as an essential assumption are allowed to have heterogeneous horizon periods with continuous trading, the single period CAPM can be extended to a multi-period setup and be rewritten as

$$(6) \qquad E(R_{i,t}) = R_{f,t} + \beta_i\left[E(R_{m,t}) - R_{f,t}\right].$$

Verbally, the difference between Equation (6) and Equation (3) is the interval of time arbitrary with starting and ending time point which is denoted by subscript *t*. As noted by Jensen (1967), the measure of market risk, β_i, can be approximated with the coefficient b_i in the market model (see, e.g., Fama 1968) with the following analogy:

$$(7) \qquad R_{i,t} = E(R_{i,t}) + b_i\pi_t + e_{i,t},$$

and assuming that $E(\pi_t) = 0$, and zero covariance between π_t and $e_{i,t}$ The return on the market portfolio can be approximated with the following formal expression:

$$(8) \qquad R_{m,t} \cong E(R_{m,t}) + \pi_t.$$

The equations (7) and (8) now define the returns for an individual security and the market. The following expression can be formed using Equations (7) and (8) for individual security returns and the market return, and by adding $\beta_i\pi_t + e_{i,t}$ to both sides:

$$(9) \qquad E(R_{i,t}) + \beta_i\pi_t + e_{i,t} = R_{f,t} + \beta_i\left[R_{m,t} - \pi_t - R_{f,t}\right] + \beta_i\pi_t + e_{i,t},$$

In the derivation of the Jensen's (1967) alpha, a marked assumption is that the market model holds for portfolios as well as individual securities. The assumption is evidenced by Blume (1968) and Jensen (1967). Hence, the subscript *i*, which is related to individual stock returns, is hereafter replaced with subscript *p*, which is related to portfolio returns. Equation (9) can be reduced further by using Equation (7) for the left hand side and the model can be presented as:

$$(10) \qquad R_{p,t} = R_{p,t} + \beta_i\left[R_{m,t} - R_{f,t}\right] + e_{p,t}.$$

Following the development of Jensen (1967), it can be shown that the risk premium on the *p*'th portfolio is linearly related to that of the market factor by subtracting risk-free rate from both sides of the equation:

$$(11) \qquad R_{p,t} - R_{f,t} = \beta_i\left[R_{m,t} - R_{f,t}\right] + e_{p,t}.$$

The notion that Jensen (1967) evinced is that an active portfolio manager aims to select securities for which $e_i > 0$. This ability would mean that the manager could earn more than the risk premium for the portfolio would predict. To model the returns of active investment portfolios correctly equation must be not constrained, and the allowance for non-zero constant Equation (11) yields the following expression:

$$R_{p,t} - R_{f,t} = \alpha_{p,t} + \beta_i\left[R_{m,t} - R_{f,t}\right] + e_{p,t}. \tag{12}$$

The α_p term now describes the portfolio performance and measures portfolio manager's predictive ability, which is defined by Jensen (1967) as

"…ability to earn returns through successful prediction of security prices which are higher than those which we could expect given the level of riskiness of his portfolio."

The analogy of the alpha as a performance measure is that if $\alpha_p > 0$ and α_p is statistically significant, the manager is doing better than the random selection of securities. And, if $\alpha_p < 0$ and α_p is statistically significant the manager is doing worse than the random selection of securities.

However, the alpha as a performance measure has its weaknesses. It does not consider the active part of the risk. Therefore, it is reasonable that the fund analyst also need to focus to evaluate relation between α_p and e_p. Jensen's (1967) alpha (hereafter alpha) does not consider additional risk taken by portfolio managers related to individual securities. In this case, the market risk would not alone be a satisfactory variable to capture all relevant risk of the portfolio. Hence, the residual term e_p is often considered in the analysis. Treynor et al. (1973) propose the use of the residual term in the performance analysis:

$$Appraisal = \frac{\alpha_p}{\sigma(e_p)} \tag{13}$$

The appraisal ratio considers an active part of the portfolio's risk which is the denominator in Equation (13). The active part depends on the manager's ability to balance his active portfolio. The major difference from the alpha is that the ratio does not depend on security selection but also on the efficiency of the balance of the manager's portfolio. Hereafter, the analysis of this chapter focuses mainly on the alpha of a hedge fund to undermine the underlying market-based risk factors of hedge fund performance.

2.2.1 From Sharpe's Style Analysis to Hedge Fund Analysis

The foundation of hedge fund analysis depends very much on the style analysis of mutual funds which is based on Ross's (1976) Arbitrage Pricing Theory (APT). This innovation leads motivates one to use more than one factor when evaluating the alpha and appraisal ratio of a fund. The APT assumes that stock returns are dependent on a set of factors which can be formally presented as:

$$R_i = E(R_i) + b_{i1}f_1 + b_{i2}f_2 ....b_{in}f_n + e_i \tag{14}$$

where $E(R_i)$ is the expected return of security i and e_i defines the residual return of the security. The factors $f_1...f_n$ have zero expected values as they measure surprises. The model also involves assumptions that $E(e_i) = 0$ and $E(e_i, e_j) = 0$. Verbally, this means that the expected residual has zero value and that the residuals for different securities are uncorrelated. If the conditions cannot be fulfilled, the APT does not fully work as the error term cannot be fully ignored through diversification and the analyst must not just merely focus on the systematic factors.

In relevance for the analyses of active investment strategies, the APT is followed by the early foundation of mutual fund evaluation based on the following Sharpe's (1992) asset allocation model:

$$R_p = b_{p1}f_1 + b_{p2}f_2 ....b_{pn}f_n + e_p, \tag{15}$$

where f_n defines a factor but can now be considered as an asset class return; b_{pn} defines the exposure of the portfolio of a fund manager to asset classes; e_p defines the residual term, and R_p defines the returns of the overall portfolio of a fund manager. In Equation (15), the major difference from the previous equation is that the focus is the portfolio of stocks instead of an individual stock.

Sharpe (1992) developed the asset class factor model presented to evaluate style of a mutual fund. This model assumes that the returns of a mutual fund are proportional to the returns of standard asset classes or investment styles. It captures the fund's exposure to the variation in the returns of the asset classes and different investment styles. Sharpe's model describes the asset mix allocation style (strategy) of the overall portfolio; a manager can choose asset classes and his/her portfolios' exposure to asset classes and investment styles.

Style analysis is an important procedure when investing in hedge funds. Indeed, the style analysis can be a helpful tool when capturing important aspects of hedge funds, more specifically their underlying risk factors. However, the problem is that there are no standard procedures for performing style analysis and the risk factors for the model must be chosen by the analyst.

In their pioneering study of hedge fund risk characteristics, Fung and Hsieh (1997) applied Sharpe's model to analyse hedge funds. Fung et al. (1997) analyse the returns of 409 hedge funds and 3,327 mutual funds with the following application of Sharpe's (1992) model:

(16) $$R_p = \alpha_p + \sum b_{pn} f_n + u_p \,,$$

where α_p defines the constant term which describes abnormal returns of the portfolio of hedge funds or an individual hedge fund. Fung et al. (1997) referred $\sum b_{pn} f_n$, as "style," and $\alpha_p + u_p$ as "skill." Thus, it can be noticed that the concept of skill is closely related to the appraisal ratio (see Jensen 1967). Further, the authors argue that the "style" can be decomposed into two dimensions: location and trading strategy. Location of the "style" is the set of assets, f_n, chosen by a hedge fund. The trading strategy of the "style" is the way the assets are applied by hedge funds. Fung et al. (1997) relate the trading strategy to the quantity and direction of the application.

Following Fung et al. (1997), manager's "skill" can also be decomposed into two parts: "selectivity", which is related to a manger's ability to pick securities, and "market timing" which is related to a manager's ability to predict the market. In their research context, Fung et al. assume that the selectivity may be assumed to consist of idiosyncratic risks while market timing consists of non-diversifiable and nonlinear payouts of asset returns contingent upon the trading strategy of a hedge fund.

Fung et al. (1997) find that the returns of hedge funds and mutual funds are dramatically different. Specifically, the authors find the returns of hedge fund strategies to be more dynamic than those of mutual funds and have low correlation to the standard asset indices. The regression analyses estimated using the application of Sharpe's style analysis suggest that mutual fund returns are primarily generated from static asset mix decisions while hedge fund returns are primarily generated from managers' skill. Therefore, the model has poor explanatory power for hedge funds versus mutual funds when static factors are used. For hedge funds, the authors find five dominant styles estimated using Principal Component Analysis (PCA). The factors can be used in the analysis of hedge funds when the Sharpe's model is applied.

Fung's et al. (1997) application of the style analysis can provide a dynamic benchmark for the performance measurement of hedge fund returns. In conclusion, the major contribution of Fung et al. (1997) is that they found how the traditional Sharpe's style analysis does not work well with hedge funds and that the benchmark factors in the style analysis should be different and more dynamic than the factors of mutual fund returns.

Following the APT by Ross (1976), it is important to note that the abnormal returns measured as the constant term in Equation (16) can only be arbitrage if investors can fully diversify the idiosyncratic risk of a hedge fund, which is described by the residual term in Equation (16). Thus, whenever a hedge fund manager is performing actual arbitrage in its strict definition the variance of the error term should be diversifiable; arbitrage should truly be return with no risk. Thus, with more replication of hedge fund returns (i.e. explaining systematic risk), there is relatively less idiosyncratic risk whose relevance must be determined.

The relevance of systematic risk in relation to idiosyncratic risk is also relevant in hedge fund research. Empirically, Tiu (2005) using a combined database of Altvest, HFR and the TASS over the period 1994-2003 finds that hedge funds with lower systematic risk exposure perform better in relation to funds with higher systematic risk exposure.

2.2.2 Market Neutrality of Hedge Funds

An important issue related to hedge fund risk factors is their market neutrality. Some hedge funds are marketed as market neutral hedge funds, or they aim to follow the market neutral strategy. When a hedge fund claims that its returns are market neutral, the returns should not be exposed to the market returns.

Capocci (2006) focuses on investigating the neutrality of market neutral hedge funds using both hedge fund indices and a sample of 634 individual hedge funds obtained from the Center for International Securities and Derivatives Markets (CIDSM) database over the period 1993–2002. His results suggest that most of the market neutral hedge funds are not significantly exposed to market returns. More specifically, those market neutral hedge funds which do not belong either to the deciles of the best and the worst performers are rather market neutral. Moreover, the results show evidence that market neutral hedge funds seem to be less market neutral during bear market than bull market.

Patton (2007) proposes that the completeness of the market neutrality of a hedge fund can be decomposed into four different concepts: "mean neutrality", "variance neutrality", "tail neutrality", and "complete neutrality". Here complete neutrality is that which corresponds to the strict market neutrality so that hedge fund returns are totally independent of market returns. Mean neutrality relates to the zero correlation between the returns of a hedge fund and the market returns. Variance and tail neutrality predicts that the risk of a hedge fund is neutral to market risks.

Patton (2007) performs empirical tests for the neutrality of hedge funds which follow different strategies using a sample of 1,423 hedge funds obtained from the HFR and TASS databases from April 1993 to April 2003. His results indicate that one quarter of market neutral hedge funds exhibit non-neutrality while for those funds which are not declared as market neutral funds this ratio is 85 %. For the funds of hedge funds, approximately half of them show non-neutrality.

In conclusion, even many market neutral hedge funds may be exposed to market returns. A further issue on the neutrality of hedge fund returns is to examine whether hedge fund returns are contagious to the market returns, in other words, extremely poor hedge fund returns incidences with extremely poor market returns. The evidence for the contagion is mixed as Boyson, Stahel, and Stulz (2007) present evidence against contagion while Brown and Spitzer (2006) present evidence for such contagion.

2.2.3 *Market Timing Ability and Conditional Performance of Hedge Funds*

The skill of a hedge fund may be a result of a manager's market timing ability. Two popular and widely accepted market timing models are used in the performance measurement literature. The first model is that proposed by Treynor and Mazuy (1966) which can be presented as a simple quadratic model and can be applied formally for an individual hedge fund as follows:

$$R_p - R_f = \alpha_p + \beta\left(R_m - R_f\right) + \gamma\left(R_m - R_f\right)^2 + e_p \,. \tag{17}$$

If the estimated regression slope is increasing against higher excess market return, specifically, $\gamma > 0$, the results would imply that a hedge fund manager has market-timing ability.

The second popular market-timing model is that proposed by Henriksson and Merton (1981) which uses a piecewise linear relation but the basic idea is the same; test whether the regression slope is increasing. Yet the model imposes a threshold when estimating market timing ability, assuming that a skilled fund manager can on average weight more risk on his portfolio during a bull market.

The model of Henriksson et al. (1981) as applied to hedge funds can be presented formally as follows:

$$R_p - R_f = \alpha_p + \beta\left(R_m - R_f\right) + \gamma\left(R_m - R_f\right)D + e_p, \tag{18}$$

where D defines a dummy which takes a value of 1 if the excess market return is positive, $R_m - R_f > 0$, and otherwise zero. Analogously to the model by Treynor (1966), the results of the model suggest that a hedge fund manager has market-timing ability when $\gamma > 0$. The remaining α_p now refers to stock the selection ability of the manager.

In spite of the popularity of the models of Treynor et al. (1966) and Henriksson et al. (1981) the measurement of the market timing ability of hedge fund managers can be problematic and the results of the analyses should be interpreted with some caution. The study by Jagannathan and Korajczyk (1986) casts doubts on the ability to measure market timing ability when performing dynamic trading strategies. The authors show both empirically and theoretically that fund managers can show spurious market timing ability when investing in options or levered securities. Further, the authors argue that the spurious market timing ability is caused by negative correlation between these securities and measured selectivity and market timing ability of the other fund managers.

The ability to time the market volatility by fund managers can also be tested in addition to testing the market timing. The fundamental model for testing market volatility timing is the model by Busse (1999). The volatility timing model can be presented as follows when applied for hedge funds[3]:

$$R_p - R_f = \alpha_p + \beta\left(R_m - R_f\right) + \gamma\left(R_m - R_f\right)\left(\sigma_m - \overline{\sigma}_m\right) + e_p. \tag{19}$$

Verbally, the model captures returns which are conditional on the deviations of the market volatility from its mean and exposure to these returns is defined by the coefficient γ. A reformulation of this model yields the following expression:

$$R_p - R_f = \alpha_p + \left(\beta + \gamma\left(\sigma_m - \overline{\sigma}_m\right)\right)\left(R_m - R_f\right) + e_p, \tag{20}$$

where $\left(\beta + \gamma\left(\sigma_m - \overline{\sigma}_m\right)\right)$ is the time-varying market beta when the timing of market volatility is considered. Verbally, the market beta is expressed in Busse's

[3] In his original model, Busse (1999) also uses lagged return to control for non-synchronous trading.

(1999) model as a linear function of the difference between market volatility and its mean.

The exposures of hedge funds may also be conditional on the economic information. Following the conditional asset pricing framework by Shanken (1990) and assuming a single risk factor (the market factor), a simple conditional performance measurement model applied for hedge funds can be presented formally as follows:

$$(21) \qquad R_{p,t} - R_{f,t} = \alpha_p + \beta_0\left(R_{m,t} - R_{f,t}\right) + \beta_1\left(R_{m,t} - R_{f,t}\right)Z_{t-1} + e_{p,t}$$

where $R_{p,t}$ defines the return of a hedge fund at time *t*; $R_{f,t}$ defines the risk-free rate at time *t*; $R_{m,t}$ defines the market return at time *t*; Z_{t-1} defines the variable that describes conditioning information at time *t*, and e_{pt} defines the residual return at time *t*. Equation (10) can be reformulated to the following form:

$$(22) \qquad R_{p,t} - R_{f,t} = \alpha + \left(\beta_0 + \beta_1 Z_{t-1}\right)\left(R_{m,t} - R_{f,t}\right) + e_{pt},$$

where $\left(\beta_0 + \beta_1 Z_{t-1}\right)$ denotes the time-varying market risk exposure of a hedge fund at time *t*.

A well known conditional performance measurement model for mutual fund management is tested by Ferson and Schadt (1996). Their results suggest that conditioning on public information is important in the performance measurement of funds and can make the performance of mutual funds look better than what it actually is.

In their empirical models, several studies on hedge funds account for time-varying exposure of hedge funds conditional on economic information (see, e.g., Chen 2006; Chen and Liang 2007). Gregoriou's (2004) study in turn suggests that the use of conditioning information is also important when analysing the funds of hedge funds.

For the market-timing ability of hedge funds, Gregoriou, Rouah, and Sedzro (2002) argue that hedge funds generally do not aim at market timing ability because of their drive to produce absolute returns. The authors examine the market-timing ability of hedge funds using a sample of 1,494 live and dead offshore hedge funds (from the U.S. investors' viewpoint) over the period 1990-2000. The results suggest that hedge fund managers have rather poor market-timing skills. Instead, the managers seem to have good security selection skills.

Fung, Xu and Yau (2002) investigate the market timing ability of a hedge fund and focus on hedge funds which follow the Global/Macro strategy and focus on equity. Their sample includes 115 hedge funds over the period 1994-2000. The results are analogous to those of Gregoriou et al. (2002) and suggest that hedge fund managers have security selection skills rather than market-timing ability.

Gregoriou (2004) investigates the market timing ability of funds of hedge funds using unconditional and conditional models. In his study, Gregoriou uses data of 437 live and dead funds of hedge funds from January 1993 to December 2001 obtained from the Zurich database. He finds that the fund of hedge fund managers do not show market timing ability after the use of conditional models accounting for time-varying exposure on economic information.

Do, Faff and Wickramanayake (2005) focus on investigating Australian hedge fund managers. Their sample includes monthly returns for 71 hedge funds over the period 2000-2003. The empirical evidence suggests that the Australian hedge fund managers do not show any significant market timing ability.

Chen et al. (2007) examine the market timing ability of hedge funds which proclaim themselves to be market-timing hedge funds. The sample of the study includes 221 market timing hedge funds obtained from the CIDSM, HFR, and TASS databases from January 1994 to June 2005. In contrast to the studies by Fung et al. (2002) and Gregoriou et al. (2002), the authors find evidence for market timing-ability of hedge funds for portfolios of hedge funds and individual funds. The results also show that the timing ability is more pronounced during high market volatility and bear markets. The results are controlled for options use, conditioning information, and illiquid holdings.

Chen et al. (2007) also propose a new model for the joint evaluation of timing market returns and market volatility. In the model by Chen et al. (2007), volatility and market return timing of a hedge fund are measured using the relation of its returns to the squared Sharpe ratio of the market portfolio. The model can be presented for a market model formally as follows:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_0\left(R_{m,t} - R_{f,t}\right) + \gamma\left(\frac{R_{m,t} - R_{f,t}}{\sigma_{m,t|S_t-1}}\right)^2 + e_{p,t} \tag{23}$$

where $\sigma_{m,t|S_{t-1}}$ defines the conditional standard deviation. Positive γ would imply joint ability of a hedge fund to time market volatility and market return.

Chen (2006) investigates the market timing ability of hedge funds in their focus market by the applying the conditional multiple market framework of Treynor et al. (1966) and Henriksson-Merton (1981). Specifically, the timing ability of different hedge fund strategies is examined against the corresponding focus market. In this study, Chen uses the TASS database which includes 1,471 hedge funds from January 1994 to June 2005. The results suggest that hedge funds show better market timing ability than mutual funds. As an explanation for the nonlinear hedge fund characteristics found by Fung et al. (1997), Chen also argues that the market timing ability of a hedge fund is an important source of these characteristics.

2.2.4 Asset-Based Style Analysis and Trend-Following Strategies

Since the study by Fund et al. (1997) many studies have proven nonlinear features in hedge fund returns. Fung et al. (2001) study dynamic trading strategies of hedge funds which follow trend-following strategies. Specifically, the returns of the trend-following strategies are modelled using lookback straddles. A long position on lookback straddles provides right to purchase the underlying asset at the lowest price or to sell the underlying asset at the highest price. Accordingly, the theoretical framework of the return factors for trend-followers assumes that trend-followers buy breakouts and sell breakdowns of the market. Thus, an optimal payout of the primitive trend-following strategy (PTFS), R_{PTFS}, which is the return of the perfect market timing strategy (PMTS), R_{PMTS}, can be characterized formally using the following equation:

$$R_{PMTS} = S_{\max} - S_{\min}, \tag{24}$$

where $S_{\max}$ defines the maximum return over the given time interval, and $S_{\min}$ defines the minimum return over a given time interval. R_{PMTS} is analogous to return of a perfect market timer, for which Merton (1981) shows that the market timer's return, R_{MT}, in the absence of short sales constraints is the following:

$$R_{MT} = R(t) + Max\{0, Z(t) - R(t)\} + Max\{0, R(t) - Z(t)\}, \tag{25}$$

where $R(t)$ defines the return of a portfolio of T-bills, and $Z(t)$ defines the return of a portfolio of stocks.

Fung et al. (2001) estimate R_{PTFS} using the returns on options. Following Goldman et al. (1979), the price of a lookback straddle is replicated dynamically by rolling standard straddles over the life of the option. The rolling process resembles buying the breakouts and selling the breakdowns, which corresponds to the assumption of Fung et al. (2001) of the risk characteristics of trend-followers. Thus, by rolling R_{PTFS} the return series can be calculated by rolling option prices. As a practical matter, Fung et al. use three-month options given their high liquidity.

The empirical evidence of Fung et al. (2001) suggests that the return factors modelled using lookback straddles explain the returns of trend-following hedge funds better than standard asset indices. The results also suggest that characteristics of the returns of the trend-following hedge funds resemble the returns of the constructed factors.

2.2.5 Asset-Based Style Analysis for the Risk Arbitrage and Event-Driven Strategies

While the trend-following strategy seems to be related to a long position in options, some other hedge fund strategies, in contrast, resemble rather short positions in options. Mitchell and Pulvino (2001) investigate the risk in risk arbitrage using both the returns of hedge funds which follow risk arbitrage strategy and the returns of the portfolio constructed by the authors of merger deals resembling the returns of risk arbitrage. In their analyses, Mitchell et al. (2001) use data on 4,750 mergers and the returns from 1963 until 1998 and the HFR merger arbitrage index from 1990 until 1998.

The results of Mitchell et al. (2001) characterize the returns of risk arbitrage with a piecewise linear regression for which the results indicate that risk arbitrage returns are positively related to the market returns during bear markets but that the relation is flat during bull markets. Accordingly, the authors relate risk arbitrage returns to those of the short put option for the market index. Interestingly, while hedge funds may be considered as "zero-beta like" investments (see Fung et al. 2000b), the study by Mitchell et al. (2001) actually shows evidence that the "zero-beta" characteristic holds rather during bull market conditions.

Anson and Ho (2003) refer to the event-driven and merger arbitrage strategies as short volatility strategies. The authors also consider merger arbitrage hedge funds as merger insurance agents as they take the risk that a merger will fail. The merger arbitrage funds collect the spread between the bid price and market price after the merger announcement which should converge to one price once the merger is completed. However, the underlying risk persists that the merger will fail and the merger arbitrage fund is exposed to a "volatility event" causing mergers likely to fail.

Anson et al. (2003) also relate the event-driven funds to the same risk characteristics as merger arbitrage funds as they invest in the same type of special corporate situations as merger arbitrage funds. The returns of both these strategies resemble short put options for the market index. The empirical evidence of Anson et al. confirms these expectations.

2.2.6 Asset-Based Style Analysis and the Fixed-Income Strategies

For fixed-income hedge fund strategies, Fung and Hsieh (2002c) propose the use of credit spread as a risk factor which relates the risk in fixed-income hedge funds to the risk of convergence trading using fixed-income instruments. Similar to the risk characteristics of the risk arbitrage, a fixed-income hedge fund may take a position for two closely related fixed-income instruments which they expect to converge sooner or later.

In their empirical analysis, Fung et al. (2002c) use the HFR indices. The different fixed-income indices which they examine are the style indices for convertible bonds, high yield bonds, mortgage backed securities, arbitrage, and diversified styles. The authors argue that most fixed-income funds are especially vulnerable to large jumps in credit spreads. All in all, the study suggests that fixed-income hedge funds are exposed to convertible/Treasury spread, high yield/Treasury spread, mortgage/Treasury spread, and emerging market bond/Treasury spread. Moreover, the results of the study suggest that fixed-income hedge funds are not likely to engage convergence trading.

2.2.7 Asset-Based Style Analysis and the Equity Long/Short Strategy

For the equity long/short strategy, Fung and Hsieh (2004a) identify two main sources of the alpha of the strategy: conventional and hedge fund-like risk factors. Fung et al. also argue that the primary risk factor of this strategy, which is a hedge fund-like risk factor, is the return difference between small and large capitalized stocks. This risk characteristic is similar to the study by Mitchel et al. (2001) which also suggests that the returns on risk arbitrage are positively exposed to this risk factor (specifically Fama's and French's 1993 SMB factor). However, Fung et al. (2004a) do not find evidence for the market timing ability of the equity long/short strategy.

The primary conventional factor for the equity long/short strategy according to Fung et al. (2004b) is the market return factor. The evidence also suggests that fat tailed returns of the equity long/short strategy are associated with the exposure of this strategy to the return difference between small and large capitalized stocks. In their study, Fung et al. (2004b) consider the generalized autoregressive heteroskedasticity (GARCH) model to account for conditional heteroskedasticity in hedge fund returns. Specifically, they use successfully the AR(1)-GARCH(1,1) model to capture serial correlated and fat-tailed returns of the strategy.

Kuenzi and Shi (2007) advocate the use of volatility factors in the ABS analyses of hedge funds not previously stressed in the ABS analysis by Fung et al. (2004b). Admittedly, the study of Agarwal et al. (2004) considers volatility risk as they explain hedge fund returns using option prices which include a volatility component. But Kuenzi et al. use four different approaches to capture the volatility risk exposure of equity-based hedge funds:

- At-the-money call and put options on the S&P 500 index.
- The straddle, which is the combination of at-the-money call and put options on the S&P 500 index.
- Variance swaps.
- VIX futures and gamma derivatives.

In their empirical analyses Kuenzi et al. (2007) use data of hedge funds which follow the equity hedge, equity market neutral, and equity non-hedge strategies. The data is obtained from the HFR database from June 2002 to December 2005. The results by Kuenzi et al. suggest that volatility factors are important in explaining the returns of equity-based hedge fund strategies. The authors state that the choice of volatility factors does not actually matter in explaining the returns but for risk management purposes exchange traded instruments may be preferable.

2.2.8 Asset-Based Style Factors and Diversified Portfolios of Hedge Funds

The risk factors for hedge funds proposed in the studies by Fung et al. (2001), Mitchel et al. (2001), Fung et al. (2002c), Anson et al. (2003), and Fung et al. (2004a) are referred to as the ABS factors of hedge fund returns (see, e.g., Fung et al. 2002b). Following Fung et al. (2002a) the ABS factors are important because they provide a reasonable link between the observed market prices and the returns of hedge fund strategies. Hence, as Fung et al. (1997) distinguish different factors (principal components) from raw hedge fund returns, the ABS factors can be used to analyse the source of hedge fund returns.

Fung et al. (2004b) use the seven factor ABS model to explain hedge fund index returns. Specifically, the model examined includes the factors for the returns of the S&P 500 index, return difference between small (the Wilshire Small Cap 1750 Index) and large capitalized stocks (the Wilshire Large Cap 750 index), change in credit spread (Moody's Investor Service Baa bonds – the yield on constant-maturity T-bond), end of the month difference of the yield on constant-maturity T-bond, and the PTFS factors for bonds, currency and commodities.

Fung et al. (2004b) show evidence that the ABS factors can explain up to 80 percent of monthly return volatility of well diversified hedge fund portfolios. Thus, the examined factor model can be considered as well performing and sound benchmark for the returns of the broad hedge fund universe. However, Fung et al. (2004b) still list the following limitations for their ABS model:

1. *Uniqueness of the ABS factors*: other, theoretically sounder, factors could also be considered.

2. *Capability to explain the returns of niche hedge fund strategies*: the ABS factors which explain well the returns of broad asset indices may not perform well with all hedge fund portfolios when approaching the individual fund level.

The ABS model proposed by Fung et al. (2004b) is related to the APT theory of Ross (1976) as the returns of the portfolio of a hedge fund are replicated using other assets with dynamic risk factor coefficients. Thus, when assuming only one factor (for simplicity), the return of a hedge fund using the ABS based modeling can be presented formally using the following expression:

(26) $$R_p = E(R_i) + \beta_p f_{ABS} + e_i,$$

where R_p defines the return of a hedge fund; f_{ABS} defines the deviation of an ABS factor from its expected value, and e_p is the idiosyncratic component of the return on a hedge fund. Thus, it can be seen in Equation (26) that the return of a hedge fund consists of three different components: the expected return on a hedge fund, deviation of an ABS factor from its expected value, and an idiosyncratic component which is related to either the assets possessed by the hedge fund or the strategy of the hedge fund.

The return variance of a hedge fund can be explained by idiosyncratic risk and systematic risk as follows:

(27) $$Var(R_p) = \beta_p^2 Var(f_{ABS}) + Var(e_p),$$

where $Var(f_{ABS})$ defines the variance of the ABS factor, and $Var(e_p)$ defines the idiosyncratic variance of the returns of a hedge fund.

2.2.9 Option-Like Factors of Hedge Fund Returns

Agarwal and Naik (2004), following the studies of Fung et al. (2001), Mitchel et al. (2001), and Anson et al. (2003) advocate the consideration of option-like features of hedge funds. Agarwal et al. propose the use of buy-and-hold and option-based strategies to explain the returns of hedge funds. The option-based risk factors which they use are the S&P 500 at-the-money and out-of-the-money call, S&P 500 at-the-money and out-of-the-money put options.

In their empirical analysis, Agarwal et al. (2004) use the HFR return indices from January 1990 to June 2000 but also ensure the robustness of their findings using the Credit Suisse First Boston/Tremont (CSFB) hedge fund indices from January 1994 to June 2000. The study follows the theoretical framework of the contingent claim-based specification by Glosten and Jagannathan (1994) which is the following:

$$(28) \qquad R_p = \alpha + b_1 R_m + b_2 \max(R_m - k_1, 0) + b_3 \max(R_m - k_2, 0) + b_4 \max(R_m - k_3, 0) + \varepsilon,$$

where k_n defines the delivery price of an option. Agarwal et al. (2004) modify the framework of Glosten et al. (1994) and construct a piecewise linear model which empirically employs both put and call options. Their model is formally the following:

$$(29) \qquad R_p = \alpha + b_1 R_m + b_2 \max(R_m - k_1, 0) + b_3 \max(R_m - k_2, 0) + b_4 \max(k_1 - R_m, 0) + b_5 \max(k_3 - R_m) + \varepsilon,$$

where the coefficients b_1 and b_2 capture the exposure of hedge fund returns on call options and b_3 b_4 capture the exposure of hedge fund returns to put options.

While the ABS analysis is based on the APT, the model of Agarwal et al. (2004) relates their asymmetric model for hedge fund analysis to the use of higher moments in the asset pricing. What their model, in fact, does is that to account for co-skewness of the returns of the security with the market returns which can be motivated by the asset pricing model of Harvey and Siddique (2000). Thus, approach of Agarwal et al. (2004) to hedge fund analysis is slightly different than that of the ABS analysis (see, e.g., Fung et al. 2004b) from theoretical perspective.

The intuitive idea of the model of Harvey et al. (2000) is that if asset returns have systematic skewness, it should result in higher expected return as a compensation for this additional risk. In theory, utility maximizing investors should dislike lower skewness and higher kurtosis of the return distribution of asset returns (see Arditti 1967; Kraus et al. 1976; Scott et al. 1980). Formally, Harvey's et al. (2000) asset pricing model, which assumes that the stochastic discount factor is quadratic in the market return, is the following:

(30) $$m_{t+1} = a_t + b_t R_{m,t+1} + c_t R_{m,t+1}^2,$$

where m_{t+1} defines the stochastic discount factor (SDF) which prices all assets, and $R_{m,t+1}$ defines the market return. The expression for the risk premium is the following when the existence of a conditional risk-free asset is assumed:

(31) $$E\left[R_{i,t+1}\right] = \lambda_{1,t} Cov_t\left[R_{i,t+1}, R_{m,t+1}\right] + \lambda_{2,t} Cov_t\left[R_{i,t+1}, R_{m,t+1}^2\right].$$

In this model, $\lambda_{1,t}$ and $\lambda_{2,t}$ should be the same for all assets. They can also be further defined as:

(32) $$\lambda_{1,t} = \frac{Var_t\left[R_{m,t+1}^2\right]E_t\left[R_{m,t+1}\right] - Skew_t\left[R_{m,t+1}\right]E_t\left[R_{m,t+1}^2\right]}{Var_t\left[R_{m,t+1}\right]Var_t\left[R_{m,t+1}^2\right] - \left(Skew_t\left[R_{m,t+1}\right]\right)^2} \text{ and}$$

(33) $$\lambda_{2,t} = \frac{Var_t\left[R_{m,t+1}\right]E_t\left[R_{m,t+1}^2\right] - Skew_t\left[R_{m,t+1}\right]E_t\left[R_{m,t+1}\right]}{Var_t\left[R_{m,t+1}\right]Var_t\left[R_{m,t+1}^2\right] - \left(Skew_t\left[R_{m,t+1}\right]\right)^2}.$$

Finally, Equation (31) can be rewritten as follows:

(34) $$E\left[R_{i,t+1}\right] = A_t E_t\left[R_{m,t+1}\right] + B_t E_t\left[R_{m,t+1}^2\right],$$

where A_t and B_t define the functions of variance, skewness, co-variance, and co-skewness. This characterization implies that the expected returns on hedge funds can be explained as a function of market return and squared market return.

Following the logic of the priced co-skewness in asset returns, the results of the study by Agarwal et al. (2004) suggest that the option-like risk factors are important in explaining the returns of equity-based hedge fund strategies. These strategies are found to be associated with simple strategies for writing options.

The study by Agarwal et al. (2004) also replicates hedge fund returns for the time period 1927–1989 using their systematic risk exposure and find that the time period for which hedge fund return indices are available may not be representative of their long-run performance. In conclusion, the study casts doubts that the hedge fund industry has grown during exceptionally convenient economic and financial market conditions.

2.2.10 Alternative Benchmarks for the Evaluation of Hedge Funds

One solution for the analysis of individual hedge funds would be to use hedge fund strategy indices as their benchmarks. However, these benchmarks are subject to numerous biases. Consequently, Fung and Hsieh (2002b) advocate the use of fund of hedge fund returns as hedge fund benchmarks to overcome these limitations of hedge fund strategy indices. The results of the study show that the survivorship and backfill biases are smaller among funds of hedge funds than individual hedge funds. Further, the use of funds of hedge funds as performance benchmarks can extract the backfill bias among individual funds. This advantage occurs simply because funds of hedge funds include only the return history of a hedge fund for their investment period. Fung et al. (2002b) relate the use of fund of hedge fund benchmarks to investor experience of hedge fund investors. Accordingly, they should serve as a better benchmark for the market portfolio of hedge funds.

Fung et al. (2004b) state that the ABS factors are free of all biases related to hedge fund databases, unlike hedge fund indices, as they are observable from market prices. Hence, these biases still limit the use of fund of hedge funds and hedge fund strategy indices as benchmarks for the evaluation of hedge funds. In conclusion, this advantage of market-based hedge fund risk factors may be generalized to other possible risk factors observed in market prices.

Fama's and French's (1993) factors for high minus low book-to-value (HML) firms and small minus big firms (SMB), and Carhart's (1997) momentum return factors (UMD) are also applied to the analysis of hedge funds. For instance, Capocci et al. (2004) use these factors in their analysis of hedge fund performance. The authors also examine the ability of the international model which includes an international factor for book-to-market equity ratio.

The sample of the study by Capocci et al. (2004) includes 2,796 hedge funds obtained from the MAR and HFR databases. The data history for the funds starts in January 1986 and ends in June 2000. However, the authors build their conclusions only for the post 1993 period as survivorship and backfill biases may decrease the statistical reliability of the results. The results of the study suggest that the SMB, HML, and UMD factors explain hedge fund returns well. The study also finds that a significant proportion of hedge funds are exposed to the returns of emerging market bonds. Specifically, these factor exposures found by Capocci's et al. (2004) reveal that the best performing hedge funds follow momentum strategies and prefer to invest in low book-to-market value companies. Also, the best performing funds do not invest significantly in the emerging market bonds. The worst performing funds, in turn, invest significantly in emerging market bonds, prefer low book-to-market value firms, and are momentum contrarians.

One solution to capture the nonlinear characteristics of hedge funds (see, e.g., Fung et al. 1997) is to use higher moment market models. In their study, Ranaldo and Favre (2005) advocate the use of these models to capture co-skewness and co-kurtosis between hedge fund returns and the market returns. The authors estimate both the three moment CAPM and four moment CAPM, which involve estimating the exposure of hedge fund returns to market returns using quadratic and cubic market models. The estimated quadratic market model is the following:

(35) $$R_{p,t} - R_{f,t} = \alpha + b_1\left(R_{m,t} - R_{f,t}\right) + b_2\left(R_{m,t} - \overline{R}_{m,t}\right)^2 + e_t$$

where $\overline{R}_{m,t}$ defines the average of market returns. In this model, b_2 accounts for co-skewness between hedge fund returns and market returns. The idea of this model is similar to that of Agarwal et al. (2004). But the key difference is that Agarwal et al. (2004) use option data to capture nonlinear characteristics of hedge funds while Ranaldo et al. (2005) use an estimation approach which can account for the nonlinearities.

The quadratic model does not yet account for co-kurtosis of hedge fund returns and market returns, and therefore a cubic market model must be used for that purpose. The estimated cubic market model by Ranaldo et al. (2005) is the following:

(36) $$R_{p,t} - R_{f,t} =$$

$$\alpha + b_1\left(R_{m,t} - R_{f,t}\right) + b_2\left(R_{m,t} - \overline{R}_{m,t}\right)^2 + b_3\left(R_{m,t} - \overline{R}_{m,t}\right)^3 + e_t.$$

In this quadratic model, b_3 now accounts for co-kurtosis between hedge fund returns and market returns. Ranaldo et al. (2005) use hedge fund strategy indices obtained from the HFR database over the period January 1990 – August 2002. Their results for the quadratic and cubic market models estimated suggest that different hedge fund strategies show different risk characteristics. The results also show evidence that co-skewness and co-kurtosis are important drivers of hedge fund returns. Thus, the quadratic and cubic market models examined by Ranaldo et al. can be considered suitable tools for hedge fund analysis.

2.3 Factors Related to Individual Funds

After the literature analyses of performance and risk measurement it is reasonable to continue to review the literature on individual hedge fund characteristics which can be important factors of performance and risk of a hedge fund. These factors, which are also named "microeconomic" determinants of hedge fund performance by Schneeweis et al. (2005), may also indicate information of the underlying market-based risk factors, trading strategies, and quality of hedge funds. In practice, the information of hedge fund characteristics and their relation to the performance can be important information for hedge fund investors as the time-series data for hedge funds may be limited. Accordingly, individual fund characteristics can be important indicators of hedge fund risk.

2.3.1 Hedge Fund Size

The size of a hedge fund may be considered as an indicator of its evolution and sophistication. The results of related studies, however, are somewhat contradictive. Liang (1999), Edwards and Gaglayan (2001) reported that the size of a hedge fund is positively related to its performance. They also find that the relation is rather concave such that an increase in the size of a large hedge fund does not increase the performance as much as for the smaller hedge funds. Amenc and Martellini (2003) investigate the performance of hedge funds and their size using the Center for International Securities and Derivatives Markets (CISDM) database. Their sample of hedge funds consists of 581 hedge funds. By dividing hedge funds into large and small sub-groups, Amenc et al. (2003) find that larger hedge funds outperform the smaller ones in terms of the abnormal returns estimated using different factor models.

Herzberg and Mozes (2003) show evidence contradictory to that of Liang (1999), Edwards et al. (2001), and Amenc et al. (2003). That is, smaller hedge funds outperform larger ones. Gregoriou and Rouah (2003), instead, do not find evidence for a size-performance-relation for hedge funds but their sample includes only 276 hedge funds and funds of hedge funds. Hedges (2004) reports that mid-sized hedge funds are the poorest performers, and smaller hedge funds outperform larger ones.

Ammann and Moerth (2005) investigate the impact of hedge fund sizes in relation to fund returns, standard deviations, Sharpe ratios and alphas extracted form an empirical factor model. The authors use the TASS database and include both live and dead databases of both hedge funds and Commodity Trading Advisors (CTA) which all together include 5,707 hedge funds. The authors find a negative size-return relation. Larger hedge funds have lower volatilities, but Sharpe ratios similar to those of smaller ones since smaller hedge funds are able to produce better returns. Smaller hedge funds are also able to produce higher alphas on average. Further, very small funds produce weaker returns, seemingly, due to their higher expense ratios.

Getmansky (2005) investigates the life cycle, size and age of a hedge fund. She also uses the TASS database and a sample of 3,928 hedge funds from both live and dead databases. She finds a concave relation between current returns of a hedge fund and its past size. The relation between the volatility of the return of a hedge fund and its size, instead, is found to be convex. But her results also suggest that for different hedge fund strategies the size-asset relation assumes different functional forms. Specifically, the relation is concave for the emerging market and convertible arbitrage strategies.

The results of Getmansky (2005) also suggest that it is possible to find an optimal asset size for hedge funds by optimizing returns, especially for hedge funds which follow the emerging market and convertible arbitrage strategies. As a result, hedge fund investors should focus on the optimal size of a hedge fund in these strategy categories.

In her recent study, Jones (2007) classifies hedge funds into three different size groups: small, medium and large. She uses a single combined database of Hedge Fund Research, HedgeFund.net, Altvest from InvestorForce and Barclays Global Hedge Source databases. The results suggest that, in order to maximize returns, investors should rather invest in smaller hedge funds to achieve better performance.

Gupta and Liang (2005) investigate the capital adequacy of hedge funds and consider fund size and age. These authors also use the TASS database. By using risk measures such as VaR and Expected Shortfall (ES), they show that nearly all under-capitalized hedge funds are small sized. This implies that small hedge funds take risks more actively and with higher leverage.

2.3.2 Hedge Fund Age

Beside the size of a hedge fund, its age can be another important factor to describe the evolution and sophistication. Liang (1999) finds evidence that the age of a hedge fund is negatively related to its performance. Gupta et al. (2005) find that the age of a hedge fund is negatively related to the capitalization of a fund. Thus, older hedge funds are more likely to be undercapitalized. In addition to the analysis of the relation of the size of a hedge fund and its performance, Jones (2007) classifies hedge funds into three different age groups: young, middle-aged, and older funds. The results suggest that, in order to maximize returns, investors should invest in younger hedge funds in addition to smaller funds. Aggarwal and Jorion (2008) report similar evidence to Jones (2007). The authors find that emerging hedge fund managers defined as having a maximum life of two years outperform mature ones. The abnormal return for emerging hedge fund managers is found to be 2.3 %.

As the age of a hedge fund may be an important factor of hedge fund performance, similarly, there may be factors which affect the age of a hedge fund, more specifically, its survival time. One considerable factor of fund survival is naturally its size; small hedge funds may not have adequate capital resources and may be more sensitive than big hedge funds to quit their action (see Gupta et al. 2005). Consequently, hedge fund age is endogenous in explaining hedge fund performance, as many other factors have an impact on it, which, indeed, can be very much the problem with hedge fund size. Therefore, one should always treat results related to hedge fund age with caution.

The research offers many other factors than size which influence hedge fund age. Liang (2000) finds that poor performance is the main reason for a hedge fund being dissolved from the database, and thus poor performance should be an important factor of fund survival. In his analysis, Liang (2000) uses a sample combined from HFR and the TASS databases.

Amin and Kat (2002) study hedge fund attrition and survival using the TASS database consisting of 2,183 live and dead hedge funds over the period 1994-2001. The analyses of the authors suggest that lack of size, and lack of performance associated with shorter survival of a hedge fund. For these factors, size and performance seem to be the most important in explaining shorter survival of a hedge fund.

Boyson (2002) shows even further evidence that size has a marked effect on survival so that smaller hedge funds die younger than larger ones. To conclude, in order that a hedge fund can survive longer, the manager should perform well enough to be able to increase its capital to a required level. Indeed, the empirical evidence of Baquero and Verbeek (2005) suggests that investors promptly withdraw their money from low quality funds.

Baquero, der Horst and Verbeek (2005) suggest that hedge fund attrition is driven by poor past performance in line with Liang (2000). Getmansky (2005) also suggests that stiff competition among hedge funds in the same category increases the liquidation probability of a hedge fund. Thus, according to Getmansky (2005), competition among hedge funds in the same category may decrease their survival time when investors chase returns from the hedge funds and weakly performing funds are liquidated. Moreover, as the size of a hedge fund has a positive impact on the performance of a hedge fund in the study, the size also affects the survival time of a hedge fund through its impact on the returns.

2.3.3 Leverage Use

In fund management, leverage may be used to increase the risk of a fund. Rubin, Greenspan, Levitt and Born (1999:4) propose two possible ways to define leverage: first, if leverage is defined in balance-sheet terms, the leverage is the ratio of that to the net worth. Second, if leverage is defined in terms of risk, it is the economic risk of a fund related to its capital. There are various ways to obtain economic value, for example: repurchase agreements, short positions, and derivative contracts.

Leverage, however, is not exactly the same as risk. Breuer (2002) provides an illustration for the distinction between leverage and risk. Following Breuer (2002), the risk for equity has two components: the market risk on the invested assets, and the leverage ratio which transforms the market risk to the equity position. These components could be interpreted as the risk of the positions of hedge funds (by the present author): the risk of the underlying assets of a hedge fund, and the leverage ratio which transforms this risk of the assets to the position of a hedge fund manager. Following the analogy of Bauer (2002), the conventional presentation of leverage, L, when applied to hedge funds, is the elasticity of the value of assets, E, to the value of the assets, A, which can be presented formally as:

(37) $$L = \frac{dE}{E}\frac{A}{dA} = \frac{A}{E} \text{ for } E \succ 0.$$

Leverage can also be defined in multiple ways. Schneeweis et al. (2005) present three different ways in which the leverage can be presented:

1. Gross Leverage = (Longs + Shorts)/Net Asset Value.

2. Net Leverage = (Longs – Shorts)/Net Asset Value.

3. Gross Longs = (Longs)/Net Asset Value.

The use of leverage is important when focusing on hedge funds as they tend to take leveraged and risky positions, which may lead to determination in extreme market conditions. Specifically, some empirical studies suggest that heavy use of leverage leads to a shorter life-cycle (Liang 2000; Baquero et al. 2002). However, an interesting contradiction arises from the results of Schneeweis et al. (2005), who suggest that those hedge fund strategies which have low risk use higher leverage. By using data from the CIDSM and TASS databases over the period January 2000 – March 2003, the authors also find no statistically significant relation between the amount of leverage used by a hedge fund and its performance.

Leverage may also be seen as a sign of quality. In corporate finance theory, Ross (1977) advocates the use of debt as a sign of the quality of the manager of a firm. The idea of the Ross's model is that entering financial distress is costly for managers but better firms are less likely to enter financial distress than other firms. Thus, the better firms can take more leverage. For example, for the costs of the financial distress of a hedge fund, a fund manager in the hedge fund industry may experience a loss of reputation if his hedge fund fails. Social reputation may be important for hedge funds as they are rather marketed for a smaller group of investors when compared to traditional mutual funds. Indeed, Isa and Ameer (2007) present evidence that social networks are important to attract wealthy investors for their funds.

In conclusion, the predictions of Ross's (1977) model can be applied to hedge fund managers at least to some extent and they may give some explanations why Schneeweis et al. (2005) find a negative relation between the leverage of a hedge fund and its risk. Yet, extremely high leverage may not be advantageous, as Gregoriou (2005) reports evidence that those event-driven hedge funds which take lower leverage tend to survive longer than highly leveraged event-driven funds.

2.3.4 Management Fees and Performance Compensation

In the investment management industry, incentive fees should in theory align the interests of fund managers to those of the investors according to the theoretical framework by Ross (1973) and Holmström (1979). Intuitively, option-like (long call) incentive contracts pays more for managers when the returns of the underlying assets are high and fund managers would have reason to make major efforts to reach high payoff.

Instead of safeguarding investors' interests, the option-like incentive fee may also lead to higher risk taking as the manager is not penalized for extremely low incomes due to long position in an option. Carpenter (2000) particularly shows that under an option-like incentive fee structure and manager's optimal policy, the compensation options ends up either deep in-the-money or deep out-of-the-money. And consistently, the volatility of the underlying asset goes to infinity when the value of the underlying asset goes to zero.

The empirical study by Ackermann, McEnally and Ravenscraft (1999) investigates the impact of incentive fees on hedge fund performance. The authors use data on 923 hedge funds obtained from the Managed Accounts Reports (MAR) and HFR databases over the period 1988-1995. The results of the study suggest that incentive fee is the most significant determinant of risk adjusted returns of hedge funds. Thus, incentive fee seem to be an important motivator for a hedge fund to be aligned to the interests of the investors. However, the study does not find strong evidence for the relation between the incentive fees of a hedge fund and its risk in contrast to the implications of Carpenter (2000). Ackermann et al. (1999) even find that the relation between the risk and incentive fees is negative, which is the opposite to the expected but not statistically significant.

The results of Liang (1999) continue to advocate the importance of incentive fees of a hedge fund for its performance. He uses data on 385 hedge funds obtained from the HFR database over the period 1992-1996. Liang finds that incentive fees are positively related to the average returns of a hedge fund. However, in a recent study, Agarwal, Daniel and Naik (2009) do not find evidence that the incentive fee percentage itself explains a hedge fund performance. They rather emphasize managerial incentives including delta of option-like incentive contracts, managerial ownership, and high watermark provision.

For the management fees, the results of Kouwenberg et al. (2007) suggest that the management fees charged by a hedge fund are negatively related to its net-of-fees average returns and positively related to its risk. Thus, the results of the study also show evidence that higher management fees result in lower performance. However, the results of Agarwal et al. (2009) do not support the evidence of Kouwenberg et al. (2007) regarding the importance of management fees in explaining hedge fund performance.

2.3.5 Risk Gaming Behaviour and Option-Like Performance Compensation

Individual managerial behaviour in hedge funds may also make the risk in hedge funds time-varying as an effect of behaviour caused by the pursuit of target incentive fees by a hedge fund manager. This fund managers' behaviour to shift risk depending upon their performances is named as risk gaming (see Chen 2009). The lack of transparency in hedge funds and their loose regulation leaves ample scope for risk gaming, which can be considered speculative risk shifting decisions. Managerial compensation may also be a considerable component of risk gaming behaviour.

Risk gaming in the mutual fund industry is traditionally linked to both incentive fees and competition among mutual fund managers. For incentive based risk gaming, Grinblatt and Titman (1989) suggest that a fund manager prefers to leverage his positions to maximize compensation if his incentive fee can be hedged. For competition between mutual fund managers, Brown, Harlow, and Starks (1996) suggest that when compensation of fund managers is linked to their relative performance, underperformers tend to increase their risk.

However, a fund manager may not be able to hedge his incentive fee over short horizons. Carpenter (2000) aims to solve the portfolio optimization problem of a fund manager when manager's incentive fee cannot be hedged and assuming the manager to be risk averse. As already stated, the study suggests that under the fund manager's optimal policy, the fund manager's option should end up either deep in or deep out-of-the money, which relates to speculation.

Brown, Goetzmann and Park (2001) investigate the risk of hedge funds and commodity trading advisors (CTA), and focus on managerial career concerns, and survival of hedge funds. In their study, they use the TASS database over the period 1989-1998. The role of managerial career concerns in the mutual fund industry is advocated by Chevalier and Ellison (1997). The results by Brown et al. (2001) showed evidence that poor performance in the first half of the year drives managers to increase the volatility of their portfolios. Conversely, good performance drives them to reduce volatility. The study of Brown et al. (2001) suggests that hedge fund managers' risk choice is rather dependent on their relative performance than the moneyness of their option-like incentive contracts. The authors relate this finding to managerial career concerns.

Many hedge funds also use high watermarks. High watermarks are based on a hurdle rate of return which must be exceeded in order to collect performance fees. If the watermark is not exceeded, the returns below a certain requirement will be accounted and they reduce the future performance fees until the cumulative performance loss is exceeded. Goetzmann, Ingersoll, and Ross (2003) show that incentive fees are important for hedge funds but the high watermark contracts limit the value of incentive fees. Also, as high watermark contracts together with incentive fee compensation form an option-like performance compensation structure, the manager has an incentive to increase risk when the returns fall below the watermark. Thus, the characteristics of the incentive contract and high watermark of a hedge fund, in theory, can lead to risk gaming behaviour of a hedge fund.

Chen (2009) finds evidence that hedge funds with poor relative performance during the first half of the year tend to increase their risk during the second half of the year. In contrast to Brown et al. (2001), hedge fund managers' risk choice is also found to be altered by the moneyness of their option-like incentive contracts. Moreover, the results of Chen (2009) suggest that past fund inflows are associated with lower future volatility, and that hedge fund managers who use derivatives engage less in risk gaming.

Hodder and Jackwerth (2007) show further evidence on the relationship between managers' behaviour and hedge fund risk. They paid attention to the fact that managers' compensation may potentially include both a proportional management fee and an incentive fee based on the return exceeding the high watermark. Their results suggest that the closer the value of a hedge fund is to its liquidation barrier, the more likely is the manager to be willing to take risk. This result is also consistent with Goetzmann et al. (2003).

Following Hodder et al. (2007), if a high watermark has been achieved, a manager lowers risk taking and adopts a lock-in strategy to ensure his/her earnings. Thus, incentive fee contracts and high watermarks can also become a burden for investors. Admittedly, the analyses by Liang (2001) gives some evidence that hedge funds may also change their fees as an effect of bad performance, and not only their risk exposures.

Kouwenberg et al. (2007) further examine the link between incentive fees and risk taking among hedge funds and consider the option-like fee structure. They use the Zurich Hedge Fund Universe Database which offers a sample of 2,078 hedge funds and a sample of 536 funds of hedge funds. The estimation period is from January 1995 to November 2000. The results of the study suggests that the use of incentive fees decreases net-of-fee returns of hedge funds but no significant relation between incentive fees and the standard deviation of the returns of a hedge fund. Interestingly, the evidence also suggests that the first downside moment of the returns of a hedge fund has a positive relation to incentive fees, which indicates that incentive fees are likely to increase downside risk.

For funds of hedge funds, Kouwenberg et al. (2007) find a positive relation between the incentive fees and net-of-fee returns of a fund. Moreover, the relation between standard deviation and incentive fee seem to be positive for these funds. All in all, the results by Kouwenberg et al. (2007) suggest that the risk adjusted performance of both hedge funds and funds of hedge funds is not found to be altered by the use of incentive fees. Further, Agarwal et al. (2009) find that it is more specifically the delta of the option value of the compensation structure for the hedge fund manager which affects the performance of a hedge fund and not its incentive fee. Consequently, the latest research on the performance compensation for hedge fund management proposes that the performance compensation should be analysed as a whole option-like contract.

2.3.6 Share restrictions

Hedge funds often impose restrictions on investors' ability to withdraw money from the fund. Considerable share restrictions include a redemption notice period, payout period, and lockup period. The TASS definitions for these characteristics are as follows[4]:

- **Redemption notice period:** "how much notice has to be given to the fund before shares can be redeemed";
- **Payout period:** "Time period before an investor will receive cash back";
- **Lockup period:** "minimum period one has to be invested in the fund".

These characteristics can be considered as share restrictions limiting the liquidity of hedge fund investors as considered by Aragon (2007).

Liang (1999) finds that the lockup period of a hedge fund is positively related to its returns. Agarwal et al. (2009) investigate the impact of return discretion of a hedge fund on its performance. The authors use lockup period and restriction period as proxies for the return discretion. Restriction period used by Agarwal et al. (2009) is the sum of a redemption notice period and a lockup period. The authors use a comprehensive database which consists of four large hedge fund databases: CIDSM, HFR, Morgan Stanley Capital International (MSCI), and TASS over the period 1994-2002. The combined database includes information on 7,535 hedge

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[4] These definitions are given in the Lipper TASS questionnaire: http://tass.lipperweb.com/LipperTASSQuestionnaire.xls

funds. The results suggest that longer lockup and restriction periods which are proxies for managerial discretion are associated with higher returns. Following Agarwal et al. (2009), the profitability of using share restrictions by hedge funds arises from their ability to be protected against noise trader risk. Thus, hedge funds may take on profitable arbitrage opportunities while its assets are protected.

Aragon (2007) also analyses the relation between the imposed restriction of a hedge fund and its performance. He uses a dataset of 3,354 hedge funds obtained from the TASS database over the period 1994-2001. The results of the study show that compared to hedge funds which do not impose lockup periods, the abnormal returns of hedge funds which impose lockup period restrictions are much higher.

Aragon (2007) also finds a negative relation between the liquidity of the portfolio of a hedge fund and the share restriction that it imposes. Thus, the returns generated by hedge funds which impose share restrictions may be substituted for higher illiquidity risk premium. Indeed, when the share restrictions are controlled in the performance analysis of hedge funds, hedge fund performance is much less attractive as the average alpha of the examined funds becomes negative. Consequently, the study by Aragon (2007) casts serious doubts on the skills and ability to perform arbitrage of hedge funds.

It is also notable that the study by Agarwal et al. (2009) takes a different perspective from the study by Aragon (2007). The first mentioned study relates share restrictions to managerial discretion and emphasizes noise trader risk while the second mentioned study relates share restrictions to illiquidity risk.

Gibson and Wang (2008) further investigate whether the hedge fund alphas of various hedge fund portfolio strategies reflect compensation for illiquidity risk. The authors find evidence using time-series analysis that the alphas are closely related to compensation for bearing illiquidity risk.

2.3.7 Personal Capital of a Hedge Fund Manager

A considerable indication of better quality of a firm which is closely related to the use of leverage by a manager is risk bearing, as shown by Leland and Pyle (1977). Analogous to the theory of leverage by Ross (1977), the larger stake of equity the manager holds, the more costly it is to him as the idiosyncratic risk arising from holding the stock. As such, the reward-to-risk ratio of the investment portfolio of the manager becomes less attractive. Thus, if the manager knows his type as a better manager, he will be willing to bear a larger stake of equity of the firm that he runs at the aggregate level. The prediction of the model of Leland et al. (1977) could also be applied to hedge fund managers; the more a hedge fund manager is willing to invest in his own fund the more likely it is that the hedge fund is a good hedge fund which will show good performance in future.

Personal capital invested in the own fund of a hedge fund manager, indeed, can be an important driver of investor aligned hedge fund management. Hodder et al. (2007) show that, when an option-like incentive structure is assumed, the manager of a hedge fund tends to gamble more if his share holding in the fund is lower. Kouwenberg et al. (2007) also study how the personal capital invested by the manager of a hedge fund affects its risk. Their results show that the risk taking of the manager is significantly lower if the manager invests a significant amount of money in his own fund.

For the link between performance and managerial ownership, Agarwal et al. (2009) find evidence that personal capital of the manager invested in his fund is associated with superior performance. In conclusion, personal capital of the fund manager invested in his hedge fund is a good indicator of hedge fund quality in theory (see Leland et al. 1977) as well as empirically (see Hodder et al. 2007; Kouwenberg et al. 2007; Agarwal et al. 2009).

2.3.8 Other Managerial and Fund Characteristics and Hedge Fund Performance

Boyson (2002) investigates the impact of managerial characteristics on hedge fund performance, volatility and survival. The data for the study is obtained from the TASS database over the period 1994-2000. The final sample used for the empirical analysis includes 288 funds. The variables for manager's skill, experience, and training are manager's age, educational indicators, for example, Certified Financial Analyst (CFA), Master of Business Administration (MBA), professional experience, and Scholastic Aptitude Test (SAT) score.

Boyson's (2002) results suggest that managers with longer professional experience, lower level of education, and managers with MBAs have lower returns but once the returns are adjusted for risk the effect disappears. The results also suggest that managers with more professional experience tend to take less risk and survive longer.

Maxam et al. (2006) is the next study after Boyson (2002) to investigate managerial characteristics and hedge fund performance. These authors use a unique sample of 147 hedge funds provided by a well known investment management firm over the period 1994-2004. Their results suggest that managers with degrees from top universities are able to outperform other managers, while the managers with lower degrees in economics are underperformers. In addition, the impact of longer work experience on the performance of a hedge fund is not evident. Thus, the education of a hedge fund manager seems to remain the most important factor of managerial characteristics for hedge fund performance.

2.3.9 Persistence of Hedge Fund Performance

In order to find hedge fund managers with actual extraordinary performance, the performance of a manager must be sustained. The reason is that "beating" the market or the underlying indices for some time is possible even if the financial markets work perfectly according to the efficient market hypothesis (EMH) (see Fama 1970).

To illustrate further the above prediction consider that a hedge fund manager may be lucky and guess the direction of the market. And when many hedge fund managers, for example, 1,000 managers bet whether the market is either going down or up each with 50% probability, it is expected that 500 of them would guess the direction of the market correctly. Following this logic, some lucky hedge fund managers would be able to produce significant abnormal returns for a while. Besides, this luckiness does not require that the assumptions of the EMH would be violated. Instead, it means that "beating" the market is spurious. As such, the major point here for hedge fund investors is that they would not benefit from momentary abnormal returns of the lucky asset manager as his performance may not persist.

The problem in which a hedge fund manager may show false performance as a result of manipulation is known as the "piggy-bag" problem after Foster and Young (2008). These authors show that a manager who actually is not able to show any abnormal performance can "game" to produce spurious performance if there is no penalty for underperformance.

Following Foster et al. (2008), a hedge fund manager could be able to earn incentive fees to which he is not entitled by gaming. As a result, many of the academic studies on hedge funds investigate the performance persistent of hedge fund managers. As an alternative to the "piggy-bag" problem to generate fake abnormal performance by a hedge fund manager, Foster et al. also mention options strategies such as taking short positions on put-options which are deep out-of-the-money.

Agarwal and Naik (2000) study the multi-period performance persistence of hedge funds. They use a sample of 746 hedge funds obtained from the HFR database over the period 1982–1998. The authors find evidence for short-term performance persistence of hedge funds at the quarterly horizon. Thus, the performance persistence among hedge funds does not last long while hedge funds may simultaneously require long lockup periods. Moreover, the study also suggests that the performance persistence is weaker in multiple-period framework than in the two-period framework. Thus, when the number of monitoring periods is increased, the performance persistence is likely to disappear.

Malkiel et al. (2005) construct a sample of 2,065 hedge funds obtained from the TASS database over the period 1996–2003 which they conclude to be as least sensitive to common hedge fund database biases. The authors find no evidence for the performance persistence of hedge funds at yearly horizons.

Baquero et al. (2005) study performance persistence of hedge fund managers and also take multi-period sampling bias, which they call look-ahead bias, into account. Specifically, multi-period sampling bias relates to the dependence of the survival of a hedge fund on its past performance. The characteristics of performance persistence would be spuriously dependent on the survival of a hedge fund and the characteristics of the survival. This bias is a problem especially in hedge fund studies as the attrition rate (the ratio of funds that become dead) of hedge funds is high. For example, Getmansky et al. (2004) finds 8.8 % attrition rate for hedge funds. Baquero et al. (2005) aim to handle this bias in their study; they first model the liquidation by considering its dependence on the historical performance of a hedge fund and then use the dependence to eliminate and weight the bias in the analysis of performance persistence analysis.

Baquero et al. (2005) use the TASS database which includes 1,797 hedge funds over the period 1994–2000. They also adjust their analysis for different investment styles of hedge funds. The analyses provide evidence for positive performance persistence in the hedge fund industry even though they account for the multi-period sampling bias.

Kosowski, Naik, and Teo (2006) use a Bayesian and bootstrap analysis to study hedge fund performance. In their study, the authors use a dataset of hedge funds constructed from the TASS, HFR, CIDSM, and MSCI databases which together provide data for 5,533 hedge funds over the period 1994–2002. The results of the study suggest that top hedge funds are able to produce consistently good performance at yearly horizons which are not attributed to the luck of a hedge fund manager. The results are also relatively robust to backfill bias and serial correlation in hedge funds returns.

As already noted by Foster et al. (2008), option strategies, and thus option-like return characteristics may result as a false alpha. In their study, Jagannathan, Malakhov, and Novikov (2007) control for option-like payoffs of hedge funds using the data obtained from the HFR hedge fund database from May 1996 to April 2005. Despite accounting for the option-like features, the authors still find evidence for significant performance persistence among superior hedge funds.

To sum it up, the performance persistence studies on hedge funds show mixed evidence for the persistence. Many studies do not find performance persistence at yearly time horizon (see, e.g., Brown and Goetzmann 2003; Capocci et al. 2004; Capocci et al. 2005), while many other studies show evidence for the performance persistence at three-month time horizon (see, e.g. Boyson and Cooper 2004; Barès, Gibson, and Gyger 2003). A recent study by Kosowski et al. (2006) on a large sample of hedge funds also shows evidence for longer performance persistence. Also, Kouwenberg (2003) shows evidence even for the performance persistence at three-year time horizon.

In conclusion of the performance persistence in hedge fund industry, the performance persistence for short-term time horizons is robust but the evidence for the longer persistence is not so robust. Indeed, Eling (2007) examines the performance persistence of hedge funds using different methodologies and concludes that performance persistence is related to the methodology adopted as well as the hedge fund strategy.

2.4 Conclusion and Discussion

Hedge funds are considered as alternative investments since their returns are different from those of the traditional investments as standard asset classes weakly explain the returns of hedge funds strategies (see Fung et al. 1997). The ultimate question is whether hedge funds really add value when added to the portfolios of investors. To address this question there are two considerations from the investor viewpoint:

1. *Can hedge funds produce abnormal returns for investors which are truly arbitrage?*
2. *Do alternative risk characteristics improve the performance of investors' investment portfolios?*

The second consideration does not necessarily mean that arbitrage opportunities exist in the market. In turn, hedge funds may "market" some risks and assets which would not be available for investors otherwise. In other words, hedge funds may expand the investment opportunity set. Consequently, by following Markowitz's (1952) MPT, one can conclude that investors are able to improve their risk-return profiles due to better diversification arising from holding a more complete market portfolio which includes some hedge funds. For instance, hedge funds may provide illiquidity risk to be better marketed for investors as their abnormal returns are closely related to illiquidity risk (see Aragon 2007; Gibson et al. 2008).

The first step to address the above questions is to test whether returns relate to marketable securities and trading strategies: The factors of ABS analysis (see Fung et al. 2000d; Fung et al. 2004b), option-like risk factors (see Agarwal et al. 2004), and other market-based models (see, e.g., Capocci's et al. 2004; Ranaldo et al. 2005) are extremely important in the studies of abnormal performance of hedge funds. These factors and models can explain a significant proportion of hedge fund returns, and therefore provide a more reliable basis for the analysis of hedge fund performance and sources of hedge fund returns. However, abnormal and positive returns do not yet imply that a hedge fund is capable of performing arbitrage but their absence would strongly suggest that hedge funds cannot perform either arbitrage or offer significant diversification benefits.

The second step to address the above questions is to test the performance persistence of a hedge fund: If performance persistence does not exist, it is likely that the abnormal returns may be attributed to chance and definitely not arbitrage. The studies on the performance persistence of hedge funds provide mixed evidence for longer time-horizons as contrasted between the studies by Brown et al. (2003), Capocci et al. (2004) and Capocci et al. (2005) against the performance persistence and the studies for performance persistence by Kouwenberg (2003) and Kosowski et al. (2006). Possibly, it is a small group of hedge fund managers who are able to produce superior performance consistently (see Kosowski et al. 2006).

The third step to address the above questions is the examination of the "microeconomic factors" of hedge fund returns: Here, the link between *performance and risk measurement* and *hedge fund characteristics* becomes important. The research on share restrictions and hedge funds by Aragon (2007) implies that the abnormal returns of hedge funds are rather subject to alternative risks, particularly illiquidity risk, which are marketed by hedge funds, than pure arbitrage. Yet, this statement does not imply that hedge funds would be useless from investor viewpoint as they may provide diversification benefits and market alternative risks. If one cannot explain abnormal hedge fund returns with marketable prices, but they may be otherwise related to risk, then hedge funds are likely to offer investors a more complete market portfolio. As a result, their diversification would increase and the reward-to-risk relation would improve, but not as a result of arbitrage. In this case, hedge funds, indeed, could be interpreted as very important market participants.

Admittedly, this possibility to improve the risk-return profile seems to be challenging; mean-variance characteristics can be improved but the higher moments and nonlinear characteristics of hedge fund returns makes the inclusion of hedge funds in investors' portfolios less attractive (see Agarwal et al. 2004; Kat 2005). Therefore, the higher moments must also be considered in hedge fund analysis.

3 DERIVATIVES USE AND FUND PERFORMANCE

The earlier research offers little relevant theoretical evidence on derivatives use, fund management, and its performance. Nevertheless, the study by Grossman and Zhou (1996) on the equilibrium analysis of portfolio insurance provides the starting point. The study allows one to analyse the use of derivatives and fund performance as the study distinguishes between portfolio insurers and non-insurers. Here, it is interesting that the use of options and other derivatives is originally much motivated by their use for risk management. However, the intention of hedge funds is often to hedge risk, and thus the analysis by Grossman et al. (1996), indeed, may have some practical relevance.

Grossmann et al. (1996) show that risk in option markets is reallocated between two groups, insurers and non-insurers. The reallocation which is the trading between these groups depends on the size of insurers' losses. When news are positive, the insurers prefer less insurance and pay lower premiums for non-insurers. When news are rather negative, the insurers are willing to pay more for insurance. The most relevant implications by Grossmann et al. (1996) for this study is that when the state of the economy is bad insurers' activity offers a chance of a higher Sharpe ratio for non-insurers. Due to insurers, the non-insurers can receive a higher risk premium, which may also be a component of hedge fund returns as interpreted.

The relevance of the study by Grossmann et al. (1996) is considerable for hedge funds as their returns resemble short put options on stock indices (see Agarwal et al. 2004) meaning that hedge funds behave like non-insurers. Admittedly, this feature does not exclude the possibility for options to be used for hedging or portfolio insurance as in Grossmann et al. (1996), yet the insurance strategy using options is very likely not the dominant one for hedge funds.

3.1 Derivatives and Mutual Funds

The pioneering empirical evidence of Koski et al. (1999) for derivatives use and fund performance employed data conducted using telephone interviews with mutual fund managers. The sample period for fund returns in the study is from January 1992 to December 1994. The results of the study suggest that equity mutual funds using derivatives show similar risk exposures than equity mutual funds not using derivatives. In addition, the performance between these groups is found to be similar. However, the results also suggest that mutual funds can alleviate negative impact of past performance on fund risk. Particularly, when investors invest new capital in a mutual fund as a result of good past performance, the fund faces a problem to fully achieve its objective market exposure. Thus, mutual fund managers seem to use derivatives to efficiently employ new fund capital attracted by fund's performance.

Besides investigating the impact of the use of derivatives on fund performance and risk of a fund, many studies on derivatives use of funds also study the causes of the use of derivatives. Deli et al. (2002) report such information as they investigate funds' incentives to use derivatives. The key finding is that derivatives offer transaction costs benefits. Moreover, their empirical results support the hypothesis of the study that the choice of a fund to permit derivative investments is driven by transaction cost benefits weighted against the potential agency costs.

Johnson et al. (2004) study the use of derivatives of 988 mutual funds in Canada on information of funds' derivatives use as of September 30 1998. In general, their results show that the use of derivatives by Canadian mutual funds does not have an adverse effect on fund return and risk. The results are also heterogeneous for different kinds of funds. Fixed-income funds using derivatives show higher return and risk than derivative non users. Domestic equity funds that use derivatives seem to have higher returns and bear higher risks than derivative non users. However, the exclusion of warrants from the derivative definition causes the risk-return differential of domestic equity funds to disappear[5].

Pinnuck (2004) examines both the characteristics of stocks preferred by 35 Australian equity investment managers and their use of derivatives over the period 1990-1997. The results show that the use of derivatives by fund managers is more popular among large than small fund managers. Moreover, the study suggests that fund managers use derivatives to both increase and decrease their exposure to stock market risk.

Fong et al. (2005) study the role and benefits of derivative securities in active equity portfolio management. The study also employs Australian data of 48 equity funds obtained from the Portfolio Analytics Database over the period 1993-2003. In light of their results the authors conclude that the use of derivatives has a negligible impact on fund returns. The results for their sample also suggest that options are not used for informed trading. In addition, the study presents evidence

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5 The authors relate the effect of excluding equity warrants to natural resource bias in the Canadian stock market

that options trading patterns of investment managers are related to the execution of momentum trading strategies.

Marín and Rangel (2006) study the use of derivatives in the Spanish mutual fund industry of 1,707 funds from March 1995 to March 2005. The results of the study relate derivatives use to larger fees, large funds, funds with low dividend yield, and members of fund families in which other funds also use derivatives. The authors also argue that derivatives are used for speculative purposes instead of hedging purposes and that management of cash inflows and outflows more efficiently.

Marin et al. (2006) in line with Koski et al. (1999), Johnson et al. (2004), and Fong et al. (2005) find that the use of derivatives on average does not improve fund performance and in most of their fund categories derivatives users underperform nonusers. However, for fixed-income funds, the authors find weak evidence supporting outperformance which arises from derivatives use.

Frino et al. (2009) investigate the impact of derivatives use on fund performance using a survey of derivatives use for 274 Australian fund managers. They separate funds that use derivatives for cash equitisation from other derivatives users[6]. The survey enquired particularly whether funds trade SPI 200 index futures for cash-equisation. The findings of the study differ from those of Koski et al. (1999), Johnson et al. (2004), and Fong et al. (2005). In particular, the results of the study suggest that derivatives use can reduce the burden of increased fund flow and improve managed fund performance when derivatives are used for cash equitisation.

3.2 Derivatives and Hedge Funds

As the evidence discussed above concerns conventional mutual funds, five recent studies by Chen (2006), Chen and Liang (2007), Aragon et al. (2007), Aragon et al. (2008), and Chen (2009) report evidence of derivatives use of hedge funds. Specifically, Chen (2006) compares market timing characteristics between portfolios of hedge funds that use options and do not use options. The author concludes that the results are not different between the option users and nonusers. Chen et al. (2007) also find that the results for the market timing ability of hedge funds are

6 Cash equitisation refers to the use of derivatives for converting assets such as equities into cash more easily and with lower transaction prices.

not altered by the use of options but they focus only on market timing hedge funds and examine only a sample of 100 funds reporting their use of options.

Aragon et al. (2007) investigates the quarterly holdings of 250 hedge fund advisors over the 1999-2005 period. These advisors offer asset management for individual hedge funds. The authors find that stock holdings have some predictive power but the predictive power of asset holding is found to be more pronounced for options. Moreover, in the sample of Aragon et al. (2007) deep out-of-the-money options and puts exhibit the highest predictive power for future stock returns.

In following study after Aragon et al. (2007), Aragon et al. (2008) focus more on hedging and options use by hedge funds. The authors find that option positions by hedge funds are associated with higher than normal subsequent realized volatility on the underlying security. The evidence also suggests that option holdings are significantly used in hedging strategies. In the sub-sample of 179 hedge fund advisors, higher Sharpe ratio and lower standard deviation are also found to be associated with the use of equity options which adds up to the evidence. However, the study by Aragon et al. (2008) does not show evidence for statistically significant association between equity options use by a hedge fund advosor and abnormal returns.

Chen (2009) investigates derivatives use and risk taking in the hedge fund industry using the Lipper TASS hedge fund database with a sample period from January 1994 to December 2006 and an initial sample of 6,241 hedge funds. Chen (2009) also investigates extensively the determinants of the use of derivatives by hedge funds. His results suggest that higher minimum investment requirement, higher incentive fees, the absence of lockup provision, and effective auditing are associated with greater likelihood of a hedge fund using derivatives. The results of Chen (2009) also suggest that some hedge fund categories affect the probability of hedge funds using derivatives. The probability of using derivatives is highest for the global/macro strategy (the managed futures strategy is not included in the analysis).

Chen (2009) does not find a significant difference in risk-adjusted performance between derivatives users and nonusers. For the association between risk and derivatives use, he finds that the use of derivatives is associated with lower risk of a hedge fund. Chen (2009) also considers the third and fourth co-moments of the distribution of hedge fund returns in addition to the conventional third and fourth moments. The results suggest that using derivatives has a positive and statistically significant impact on the kurtosis of a hedge fund. Moreover, derivatives use is found to be associated with lower co-kurtosis and co-skewness. Thus, Chen's

(2009) evidence for the higher moments and higher co-moments may imply that derivatives use is associated with less market-wide risk.

Derivatives may also be used to manipulate performance. Chen (2009) acknowledges this potential use of derivatives and uses a manipulation proof performance measure by Goetzmann, Ingersoll, Spiegel and Welch (2007). Chen's (2009) results do not evince any statistically significant association between the measure and derivatives use by hedge funds. Accordingly, the results suggest that hedge funds do not manipulate their performance using derivatives.

The study by Chen (2009) finds further evidence for responsible use of derivatives by hedge funds. The study evinces that derivatives users engage less in risk gaming. The results also do not show statistically significant evidence for the relation between fund failure likelihood and derivatives use. This result implies that single cases of hedge fund failures closely associated with derivatives use such as the collapse of the LTCM may not be generalized.

4 HYPOTHESES DEVELOPMENT

This study presents five different hypotheses regarding the derivatives use of hedge funds. Given the free regulation of mutual funds the hypotheses for the complexity of the derivative strategy of a hedge fund also concern funds of hedge funds, which are likewise loosely regulated.

4.1 Informed Trading, Options Use, and Hedge Fund Performance

As related research on hedge funds and informed trading, Wermers (2000) shows evidence that those mutual funds which have high turnover beat the Vanguard Index 500 fund on a net return basis in favour of abnormal returns generated by informed trading. The remaining question for the interests of the present study is whether funds use options for informed trading.

A potential reason for the use of derivatives by hedge funds, and especially options, is informed trading. The information on how derivatives are used by hedge funds should be important information from the perspective of informed trading. Black (1975) suggests that the higher leverage available in options markets may attract speculators to prefer options to their underlying assets. Several studies followed by Black (1975), for example, Easley et al. (1998), Chakravarty et al. (2004), suggest that informed traders invest in option markets. Chakravarty et al. (2004) also suggest that the price discovery across option strike price is associated with leverage supporting Black's (1975) viewpoint.

For mutual funds, Fong et al. (2005) present evidence that there is no abnormal price movement in the underlying stocks after fund managers' purchases of options. Therefore, the results of the study suggest that the managers do not engage in informed trading. However, Fong et al. (2005) construct their data on an invitation basis to the largest Australian investment managers. Hedge funds which are natural arbitrageurs, instead, aim to mask their investment strategies not giving detailed information, making the results of Fong et al. (2005) less applicable.

Fong's et al. (2005) results may also be biased towards uninformed fund managers. Indeed, if fund managers have private information, it should be much more convenient to run a hedge fund rather than a mutual fund due to less transparency so that the private information would not be revealed to other market participants. And, considering the evidence by Wermers (2000) for an association between high fund turnover and outperformance, it is plausible to expect that hedge funds which may have very high turnover engage in informed trading. Indeed, Aragon et al. (2007) find that the option holdings of hedge funds include more predictive power than their stock holdings, implying that hedge funds use options for informed trading.

Informed trading by a hedge fund should follow the asset specialization of a hedge fund and cause willingness to use higher leverage to enhance its returns from informed trading. This assumption should be credible, as Eichhold, Veld, and Schweitzer (2000) show evidence for REIT investment trusts that their property specialization leads to outperformance. Chen (2006) also finds that hedge funds show market timing ability in their focus market implying that the asset specialization of a hedge fund is beneficial. In a close relation to the assumed performance-specialization relation, the results of Teo (2008) suggest that the physical presence of a hedge fund close to their market leads to information advantage. The asset focus of a hedge fund would likewise lead to information advantage.

The above evidence supports the view that asset specialization results in greater likelihood of information advantage. Positive impact from the use of options on hedge fund performance should be seen most of all when the performance associated the use of options for each asset class is examined which respect to the asset specialization of a fund.

Beside the possibility of using options for informed trading, options and other derivatives can be used in various profitable investment and hedging strategies such as volatility trading. The study by Liu and Pan (2003) suggests that derivative securities are important for investors as they expand the dimension of risk-return tradeoffs. Some studies suggest that derivative strategies can improve portfolio performance. Board et al. (2001), Isakov et al. (2001), Whaley (2002), McIntyre et al. (2007), and Kapadia et al. (2007) suggest that the covered call strategy is profitable. Hill, Balasubramariam, Gregory, and Tierens (2006) suggest that short-term index option strategies can enhance investment risk profiles. For a sample of hedge funds, Aragon et al. (2008) find that higher Sharpe ratio and lower standard deviation of hedge fund returns are associated with equity options use. For currencies too, Guo (2000) presents empirical evidence that dynamic volatility trading strategies on currency option markets may improve risk-return profiles. These studies, together with the possibility of using options for informed trading, leads to the following hypothesis:

H_1: The asset specialized use of option enhances hedge fund performance.

4.2 Equity Index Futures and Hedge Fund Performance

Considering the use of other derivatives, the use of equity index futures for cash management becomes relevant. The first study implying the use of this derivative type for cash management is the study by Koski et al. (1999) which shows evidence for mutual fund managers using derivatives to alleviate the impact of new fund inflows on fund risk. This result may also have relevance for hedge fund performance, as the study by Edelen (1999) relates fund flows negatively to its alpha upon a rationale that new cash force mutual fund managers to engage in liquidity motivated trading instead of informed trading. As a result of uninformed trading, the alpha suffers from trading costs. Equity index futures in turn are highly liquid and can be used to adjust the exposure of the fund to the desired risk under new cash flows. Frino et al. (2009) follow this rationale investigating the use of stock index futures for the management of cash flows. They find that derivative-based management can prevent the negative impact of new cash on the alpha of a hedge fund.

Hedge funds are different from mutual funds as they can restrict more their fund flows. Therefore, the use of equity index futures may not be as essential for them as it is for mutual funds. In the hedge fund industry, the use of equity index futures may be a substitute for share restrictions, which can be used to manage liquidity efficiently. For instance, some less promising hedge funds may lack bargaining power to impose sufficiently restrictive redemption policy to attract investors. These funds can then use inferior financial instruments (regarding their strategy) to manage liquidity. Share restrictions are seen as proxies for illiquidity risk premium (see Aragon 2007), and the use of equity index futures would imply lower illiquidity risk premium as the instrument itself is highly liquid. Thus, the use of equity index futures is related to lower illiquidity risk premium. This argument leads to the following hypothesis which is sensible to direct at hedge funds which focus on equity:

H_2: The equity specialized use of equity index futures is related to lower hedge fund performance.

The second hypothesis does not imply that the use of equity index futures has a detrimental impact on hedge fund performance or that equity index futures is not be used for informed trading. Instead, it implies that the use of the derivative is associated with activity not profitable enough for an average hedge fund.

4.3 Performance and Risk Characteristics of Hedge Funds and Derivatives Use

The use of more complex derivative strategies by a hedge fund should lead to better performance statistics. Especially when considering the implications of the study by John et al. (2006) that when commonly used incentive characteristics are assumed, managers use complex derivative strategies which result in an improvement of performance statistics. Thus, the following hypotheses are formed:

H_3: The use of a more complex derivative strategy of a hedge fund decreases risk.

H_4: The use of a more complex derivative strategy improves hedge fund performance.

Hypothesis 3 can also be seen as a considerable component of Hypothesis 4 as risk is also a component of performance. As such, these hypotheses together predict that the better performance associated with the complexity of the derivative strategy of a hedge fund is particularly related to risk.

The third hypothesis especially concerns the risk measured using standard deviation. However, it is already known that the return distributions of hedge funds have fat left tails (see, e.g., Brooks et al. 2002). There are at least three weighty reasons why derivatives use by hedge funds may be associated with fatter left tails of their return distributions: first and foremost, John et al. (2006) show that when commonly used incentive characteristics are assumed, managers indeed use complex derivative strategies which also lead to larger probability of large losses in addition to improved performance statistics. In relation to Liu and Pan (2003) who suggest that derivatives use may expand the risk-return dimension, the implications of John et al. (2006) would mean that the expanded risk-return dimensions from derivative strategies would be rather miss-used.

Second, the use of options may be one cause of these hedge fund return characteristics because options have asymmetric payoffs and hedge fund managers may employ derivative strategies which produce high kurtosis and negative skewness. Indeed, hedge fund payoffs resemble synthetic options, which may be due to the use of options (see, e.g., Fung et al. 1997, 2001; Mitchell et al. 2001; Agarwal et al. 2004).

Third, the return distributions of popular derivative strategies such as the covered call strategy are empirically found to exhibit negative asymmetry and fat tails (see Whaley 2002). These strategies may also be popular among hedge funds given their profitability (Isakov et al. 2001; Whaley 2002; McIntyre et al. 2007; Kapadia et al. 2007).

Given the above mentioned arguments, it is important to account for the asymmetry and fat tails of the return distributions of hedge funds. The arguments also lead to the following hypotheses:

H_{5a}: The asset specialized use of options has a negative impact on the skewness and a positive impact on the kurtosis of a hedge fund return distribution.

H_{5b}: The use of a more complex derivative strategy of a hedge fund has a negative impact on the skewness and a positive impact on the kurtosis of its return distribution.

5 DATA

The analysis in this study uses monthly data from January 1994 to December 2006. Data for hedge funds is obtained from the Lipper TASS database[7]. This data includes 8,515 hedge funds consisting of both live hedge funds (4,577 funds) and dead hedge funds (3,938 funds) to mitigate survivorship bias in the sample. Data before January 1994 is not included in the sample as before this month TASS had not recorded data for defunct funds and the use of earlier data would increase survivorship bias in the sample. Data in the Lipper TASS hedge fund database is self-reported and updated by hedge fund managers on daily basis. Thus, the information may change.

All hedge fund returns obtained are *net-of-fees* in percentages, reported *monthly* in *U.S. dollars*. Hedge funds that do not report their returns in this way are excluded from the sample. Data is downloaded in November 2007 but hedge fund returns between January-October 2007 are excluded from the sample to reduce late reporting bias (see Tiu 2005). This bias means that some hedge funds delay reporting their returns while some hedge funds do not, and the bias is subject to the return difference between these funds. Indeed, this bias may slightly alter the results as Schneeweis, Spurgin and Waksman (2006) find that hedge funds which delay reporting their returns often report poorer performance than hedge funds which report early. For better accuracy of performance statistics, reducing the last ten months of the data should eliminate the late reporting bias and offer a sample of hedge funds which is annually complete.

Hedge fund databases also exhibit backfill bias, which is caused by the possibility for funds to include their past return history in the database when they list. However, the downloaded sample likewise does not provide clear information on which of the returns are backfilled. One can attempt to alleviate the bias by excluding return data prior to the inception date of a fund which is defined as “the date the fund became fully operational and commenced trading.” However, this action does not considerably exclude the bias of the database as it does not exclude return data prior listing of a fund in the database[8]. Moreover, there are only

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7 Chen (2008) also reports that he uses hedge fund data 1994-2006 but in the data section he announces that “… as of June 2006, TASS contains information about 6,241 individual hedge funds…” Chen (2008) downloaded his data over one year before that this study.

8 The Lipper TASS database used by the present study does not contain information needed to fully exclude backfill bias. Malkiel et al. (2004: 81) states that “Fortunately, TASS indicates when a hedge fund began reporting, so we were able to examine the backfilled returns and compare them with those returns that were contemporaneously reported to TASS.” However,

24 funds in the TASS database which report earlier performance start day other than the inception day. Chen (2009) deletes return data prior the inception date.

All hedge funds that do not report information on asset focus and derivatives use are excluded from the sample. It is also feasible to separate funds of hedge funds (2006 funds) from the sample of hedge funds as they are different investment vehicles from conventional hedge funds as their primary investment focus is to invest in other funds. This study also includes managed futures funds in the analysis, which is not done by Chen (2009). The exclusion of funds of funds and the inclusion of managed futures funds causes a significant difference from a closely related study by Chen (2009). The sample selection choices related to hedge fund strategies should be reasonable to validate the results for all assets and broader knowledge in finance. Also, the exclusion of managed futures funds from the sample may be reasonable when using a binary variable of derivatives use because the use of derivatives is nearly essential for these funds. However, as this study uses the complexity of derivative strategy as a variable, the inclusion of the strategy is reasonable for this study. As such, it is one of the benefits of using the complexity variable to also include strategies in the sample for which derivative trading is almost essential, but the extent and complexity of derivatives use may vary.

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a later database used by this study does not include such information. The database used reports only a "performance start date" and a "inception date." Also, Tremont Capital Management acquired the database in 1999 which may also have resulted in major changes in the database.

Table 1. Variables of Cross-Sectional Analysis

This table defines the variables used in the cross-sectional analysis of this study. Panel A presents the statistics for variables which are not related to hedge fund returns. Panel B presents the statistics for variables which are related to hedge fund returns.

Panel A.

Variable	Definitions
AUDIT	If a fund is audited, then 1, otherwise 0.
AVGLEVERAGE	Average leverage of a fund in percentages.
LNSIZE	Natural logarithm of average fund size.
LNAGE	Natural logarithm of fund age.
MFEE	Management fee of a fund as percentages
IFEE	Incentive fee of a fund as percentages.
HMARK	If a fund has a high watermark, then 1, otherwise 0.
IMILLS	Inverse Mills ratio
LEVERAGED	If a fund is leveraged, then 1, otherwise 0.
PERCAPITAL	If a fund manager invests personal capital, then 1, otherwise 0.
LOCKUP	Lockup period of a fund denoted in months.
RESTRICTION	The sum of payout and redemption periods of a fund denoted in days.
MIN	Minimum investment in a fund in U.S. dollars.
OPEN	If a fund is open to public, then 1, otherwise 0.
OPENENDED	If a fund is open-end fund, then 1, otherwise 0.
COMPLEXITY	Complexity of the derivative strategy of a fund.
OF	If a fund invests in other funds, then 1, otherwise 0.
E_OPTION	If a fund uses equity options, then 1, otherwise 0.
F_OPTION	If a fund uses fixed-income options, then 1, otherwise 0.
C_OPTION	If a fund uses commodity options, then 1, otherwise 0.
CUR_OPTION	If a fund uses currency options, then 1, otherwise 0.
E_WARRANT	If a fund uses warrants issued with equity securities, then 1, otherwise 0.
F_WARRANT	If a fund uses warrants issued with fixed-income securities, then 1, otherwise 0.
E_OTHER	If a fund uses other equity derivatives than options or warrants, then 1, otherwise 0.
F_OTHER	If a fund uses other fixed-income derivatives than options, then 1 otherwise 0.
C_OTHER	If a fund uses other commodity derivatives than options, then 1 otherwise 0.
CUR_OTHER	If a fund uses other currency derivatives than options, then 1 otherwise 0.
S_CA	If a fund follows Convertible Arbitrage strategy, then 1 otherwise 0.
S_DS	If a fund follows Dedicated Short Bias strategy, then 1 otherwise 0.
S_ED	If a fund follows Event-Driven strategy, then 1 otherwise 0.
S_ELS	If a fund follows Equity Long/Short strategy, then 1 otherwise 0.
S_EM	If a fund follows Emerging Market strategy, then 1 otherwise 0.
S_EMN	If a fund follows Equity Market Neutral strategy, then 1 otherwise 0.
S_FI	If a fund follows Fixed-Income Arbitrage strategy, then 1 otherwise 0.
S_GM	If a fund follows Global/Macro strategy, then 1 otherwise 0.
S_MF	If a fund follows Managed Futures strategy, then 1 otherwise 0.
S_MS	If a fund is a multi-strategy fund, then 1 otherwise 0.

Table 1. Continued

Panel B.

Variable	Definition
SHARPE	Sharpe ratio of a hedge fund.
SHARPED	Sharpe ratio with downside volatility of a hedge fund.
ALPHA	Alpha of a hedge fund.
APPRAISAL	Appraisal ratio of a hedge fund.
VAR	Value-at-Risk- of a hedge fund
MVAR	Modified Value-at-Risk of a hedge fund.
MEAN	Mean return of a hedge fund.
STDEV	Sample standard deviation of the returns of a hedge fund.
D	Downside volatility of the returns of a hedge fund.
SKEW	Skewness of the returns of a hedge fund.
EXKURT	Excess kurtosis of the returns of a hedge fund.
CF	Cornish-Fischer expansion on the returns of a hedge fund.
SCF	Cornish-Fischer expansion on the market-based returns of a hedge fund.
ICF	Cornish-Fischer expansion on the residual returns of a hedge fund.
RSTDEV	Sample standard deviation of the residual returns of a hedge fund.
SSTDEV	Sample standard deviation of the market-based returns of a hedge fund.
RSKEW	Skewness of the residual returns of a hedge fund
SSKEW	Skewness of the market-based returns of a hedge fund
RXKURT	Excess kurtosis of the residual returns of a hedge fund.
SKURT	Excess kurtosis of market-based returns of a hedge fund.

All hedge funds that have a return history shorter than 24 months are excluded from the sample. This data reduction is similar to that of Bali et al. (2007), who also use MVaR estimates. This reduction provides a reasonable return history for the use of risk and performance measures. It especially ensures better robustness for the estimates of skewness and kurtosis, but it may also reduce backfill bias because funds with a short return history are weighted less. Also, all funds that do not report their size are excluded from the sample which then consists of 3,403 hedge funds. Some of the funds, however, have missing data for explanatory variables, and the exclusion of these funds reduces the investigated sample in multivariate analysis to 3,382 funds. In addition to the entire sample, hedge funds are classified into four subsamples according to the hedge fund's primary asset focus. The subsamples are for equity (1,841 funds), fixed-income (838 funds), commodity (245 funds), and currency (363 funds)[9].

[9] The subsamples may be overlapping as some funds have more than one asset focus.

Table 2. Descriptive Statistics for Hedge Funds

This table presents descriptive statistics and the Jarque-Bera (JB) test statistics of the variables used in the cross-sectional analysis of this study. The sample includes 3,382 hedge funds used in multivariate analysis for hedge funds of this study. Panel A. presents the descriptive statistics. Panel B presents mean values for the dichotomous variables used for hedge funds. See Table 1 for definitions of the variables.

Panel A.

	LNSIZE	LNAGE	IFEE	MFEE	MIN	RESTRICTION
Mean	17.17	7.62	18.85	1.47	782321.30	46.71
Median	17.24	7.60	20.00	1.50	500000.00	41.50
Maximum	22.49	10.58	50.00	8.00	25000000.00	700.00
Minimum	3.40	6.55	0.00	0.00	0.00	0.00
Std. Dev.	1.73	0.57	5.08	0.72	1303007.00	37.93
Skewness	-0.48	0.26	-1.57	2.49	7.96	2.69
Kurtosis	5.22	2.47	13.01	15.76	117.33	33.99
JB	824.81***	77.19***	15517.47***	26440.23***	1877679.00***	139423.30***

	LOCKUP	STDEV	MEAN	VAR	MVAR	CF
Mean	3.60	4.13	0.92	-8.68	-8.77	-2.46
Median	0.00	3.19	0.85	-6.53	-6.46	-2.42
Maximum	48.00	73.69	7.81	0.90	150.09	9.96
Minimum	0.00	0.05	-6.68	-164.93	-86.96	-7.60
Std. Dev.	6.22	3.64	0.89	8.25	10.06	1.07
Skewness	1.88	4.36	0.58	-4.33	0.02	1.75
Kurtosis	7.43	55.55	11.79	54.22	34.29	21.61
JB	4741.82***	399816.80***	11080.25***	380327.10***	137931.50***	50531.29***

	DD	SKEW	EXKURT	SHARPE	SHARPED
Mean	3.96	0.07	3.38	0.24	0.27
Median	3.04	0.08	1.46	0.20	0.21
Maximum	42.81	7.65	109.03	7.88	8.18
Minimum	0.04	-10.11	-1.33	-0.80	-0.79
Std. Dev.	3.31	1.27	7.20	0.36	0.44
Skewness	2.64	-1.15	6.93	6.82	7.40
Kurtosis	16.90	13.94	70.53	106.84	103.23
JB	31134.83***	17617.53***	669586.60***	1545854.00***	1446437.00***

	APPRAISAL	ALPHA	SCF	ICF
Mean	0.26	0.50	-2.62	-2.57
Median	0.21	0.43	-2.34	-2.30
Maximum	12.35	26.96	-1.49	-1.52
Minimum	-5.23	-11.57	-13.23	-27.95
Std. Dev.	0.62	1.36	1.03	1.49
Skewness	4.29	2.97	-3.93	-10.16
Kurtosis	70.36	62.04	26.79	137.17
JB	649711.30***	496171.00***	2595005.00***	88484.36***

	SSKEW	SSTDEV	RSTDEV	RSKEW	RKURT	SKURT
Mean	-0.09	2.82	2.88	0.1	1.92	1.53
Median	-0.04	2.14	2.17	0.08	0.77	0.71
Maximum	4.43	53.64	50.51	6.21	82.86	31.4
Minimum	-5.02	0.03	0.03	-8.69	-1.4	-1.5
Std. Dev.	0.78	2.67	2.62	0.9	5.13	2.85
Skewness	-0.82	4.29	4.54	-1.52	8.7	4.15
Kurtosis	7.77	52.25	54.42	22.21	104.32	28.8
JB	3592.35***	352125.10***	384188.30***	53300.29***	1489203.00***	103559.00***

Table 2. Continued

Panel B.

	HMARK	AUDIT	PERCAPITAL	OPEN	OPENENDED	LEVERAGED
Mean	0.63	0.77	0.42	0.17	0.62	0.68

	S_MF	S_GM	S_FI	S_EMN	S_EM	S_ELS	S_ED	S_DS	S_CA
Mean	0.12	0.06	0.06	0.07	0.08	0.40	0.12	0.01	0.04

Mean	AE_OPTION	AE_WARRANT	AF_OPTION	AF_WARRANT	AC_OPTION	ACUR_OPTION
	0.45	0.24	0.18	0.08	0.07	0.12

Mean	AE_OTHER	AF_OTHER	AC_OTHER	ACUR_OTHER
	0.30	0.27	0.15	0.31

Mean	AE_PRIMARY	AF_PRIMARY	AC_PRIMARY	ACUR_PRIMARY
	0.54	0.25	0.07	0.11

In the cross-sectional analysis, excess returns when used in this study are calculated over 1-month U.S. T-bill rate of return from Ibbotson Associates, Inc. Table 1 presents definitions for the variables used in the analyses of this study. The use of options for different assets (equity, fixed-income, commodity, and currency) form variables while warrants issued with equity and fixed-income securities also form variables on their own due to their nonlinear characteristic. The use of other derivatives including forwards, futures, and swaps for the same assets are classified as other derivatives[10]. For example, whether a hedge fund uses fixed-income swaps, futures and/or forwards the variable F_OTHER.

Table 2 presents the summary statistics for the variables of the cross-sectional analysis. The performance and risk measures do not seem to be normally distributed. The problems, at least to some extent, may cause bias for the estimates. This may be difficult to control with log-transformation since many normally distributed variables have negative values. As a result, the variables are not transformed, but one should also consider this problem with the dataset. Also, the Cornish-Fischer expansion measure can have large positive values and the source may be the sensitivity of the estimates to heavy outliers which may occur in individual hedge fund returns.

The performance measures (the Sharpe ratio, the Sharpe ratio with downside volatility, alpha, and appraisal ratio) are heavily skewed towards the right tail of the distribution. This means that there are more extremely good performers than extremely bad performers. This characteristic, however, may be related to the fact that extremely bad performers soon discontinue their activities, which causes a survivorship bias.

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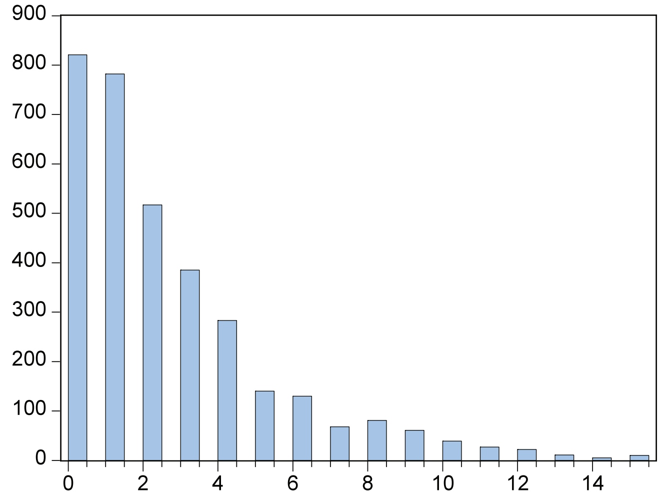
[10] Interest rate swaps are considered as swaps for fixed-income and cross-currency swaps are considered as swaps for currency.

This figure presents the number of different types of derivatives used by a hedge fund for the sample of this study. This figure also presents descriptive statistics for the variable COMPLEXITY which describes the number of different type of derivatives used by a hedge fund.



Series: COMPLEXITY
Observations 3382

Mean	2.534
Median	2.000
Maximum	15.000
Minimum	0.000
Std. Dev.	2.783
Skewness	1.630
Kurtosis	5.750
Jarque-Bera	2562.270
Probability	0.000

Figure 1. Number of Different Type of Derivatives Used by a Hedge Fund

Figure 1 presents an illustration and the summary statistics for the number of different derivatives used by a hedge fund, which is a proxy for the complexity of derivative strategies. The figure shows that the distribution of the complexity variable is positively skewed and has a high kurtosis. These characteristics are related to the concentration of hedge funds using different derivatives from 0 to 3. Also, the average of 2.534 is low, meaning that hedge funds on average do not use even 3 different derivatives. Thus, the density of hedge funds using multiple derivatives in their investment strategies is relatively small.

Table 3 presents the correlation statistics for fund characteristics. The statistics indicate that the complexity of derivative strategy of a hedge fund correlates with many other fund characteristics. Specifically, the variable has a statistically significant and positive correlation at least at the 10 % level with minimum investment, the use of auditing services, management fee, whether a fund is open to the public, whether a fund is open-ended, whether personal capital of the manager is invested in the fund, the use of leverage, size, and age. The variable also has a negative and statistically significant correlation at the 10 % level with high watermark, lockup period and restriction period. The magnitude of the correlation is between the complexity of derivative strategy and the other variables is generally moderate but with the use of leverage it is relatively high (0.25). These statistics together imply that

1. Complex derivative strategies possibly do not attract and are not performed by skilled managers due to the absence of a statistically significant and positive correlation between complexity and incentive fees.

2. Complex derivative strategies are related to higher liquidity due to its negative correlation with restriction period following the logic that funds which have more illiquid assets restrict asset flow more (see Aragon 2007).

3. Complexity is associated with higher management fees and larger size of a hedge fund, suggesting that the use of complex derivative strategies is costly and requires resources which can be acquired via economies of scale. The results are similar to the comparisons between derivatives users and nonusers in the hedge fund industry (see Chen 2008, 2009).

Table 3. Correlation Statistics for Hedge Fund Characteristics

This table presents a list of correlation statistics for fund characteristics. The probability statistics on the right hand side of the correlation statistics indicate significance of correlation based on the *t*-statistics.

		Cor.	Prob.			Cor.	Prob.
COMPLEXITY	AUDIT	0.03	0.093	RESTRICTION	AUDIT	0.03	0.110
IFEE	AUDIT	0.02	0.162	RESTRICTION	COMPLEXITY	-0.13	0.000
IFEE	COMPLEXITY	0.00	0.989	RESTRICTION	IFEE	0.09	0.000
MIN	AUDIT	0.05	0.008	RESTRICTION	MIN	0.23	0.000
MIN	COMPLEXITY	0.10	0.000	RESTRICTION	LOCKUP	0.41	0.000
MIN	IFEE	0.10	0.000	RESTRICTION	MFEE	-0.13	0.000
LOCKUP	AUDIT	0.04	0.042	RESTRICTION	OPEN	-0.03	0.116
LOCKUP	COMPLEXITY	-0.13	0.000	RESTRICTION	OPENENDED	-0.26	0.000
LOCKUP	IFEE	0.07	0.000	RESTRICTION	HMARK	0.41	0.000
LOCKUP	MIN	0.23	0.000	RESTRICTION	PERCAPITAL	-0.10	0.000
MFEE	AUDIT	-0.04	0.027	LEVERAGED	AUDIT	0.02	0.238
MFEE	COMPLEXITY	0.20	0.000	LEVERAGED	COMPLEXITY	0.25	0.000
MFEE	IFEE	0.04	0.016	LEVERAGED	IFEE	0.15	0.000
MFEE	MIN	-0.03	0.068	LEVERAGED	MIN	-0.01	0.431
MFEE	LOCKUP	-0.10	0.000	LEVERAGED	LOCKUP	-0.08	0.000
OPEN	AUDIT	-0.03	0.082	LEVERAGED	MFEE	0.07	0.000
OPEN	COMPLEXITY	0.04	0.020	LEVERAGED	OPEN	0.01	0.544
OPEN	IFEE	-0.03	0.104	LEVERAGED	OPENENDED	0.11	0.000
OPEN	MIN	-0.04	0.031	LEVERAGED	HMARK	-0.04	0.011
OPEN	LOCKUP	-0.02	0.382	LEVERAGED	PERCAPITAL	0.12	0.000
OPEN	MFEE	0.09	0.000	LEVERAGED	RESTRICTION	-0.11	0.000
OPENENDED	AUDIT	0.02	0.344	LNSIZE	AUDIT	0.24	0.000
OPENENDED	COMPLEXITY	0.14	0.000	LNSIZE	COMPLEXITY	0.10	0.000
OPENENDED	IFEE	-0.05	0.005	LNSIZE	IFEE	0.03	0.111
OPENENDED	MIN	-0.09	0.000	LNSIZE	MIN	0.29	0.000
OPENENDED	LOCKUP	-0.26	0.000	LNSIZE	LOCKUP	0.11	0.000
OPENENDED	MFEE	0.05	0.009	LNSIZE	MFEE	-0.06	0.000
OPENENDED	OPEN	0.06	0.000	LNSIZE	OPEN	-0.02	0.349
HMARK	AUDIT	0.02	0.298	LNSIZE	OPENENDED	-0.02	0.162
HMARK	COMPLEXITY	-0.12	0.000	LNSIZE	HMARK	0.18	0.000
HMARK	IFEE	0.21	0.000	LNSIZE	PERCAPITAL	-0.05	0.002
HMARK	MIN	0.16	0.000	LNSIZE	RESTRICTION	0.22	0.000
HMARK	LOCKUP	0.31	0.000	LNSIZE	LEVERAGED	-0.05	0.002
HMARK	MFEE	-0.07	0.000	LNAGE	AUDIT	0.34	0.000
HMARK	OPEN	0.04	0.013	LNAGE	COMPLEXITY	0.08	0.000
HMARK	OPENENDED	-0.35	0.000	LNAGE	IFEE	-0.08	0.000
PERCAPITAL	AUDIT	0.04	0.031	LNAGE	MIN	0.03	0.081
PERCAPITAL	COMPLEXITY	0.09	0.000	LNAGE	LOCKUP	-0.02	0.294
PERCAPITAL	IFEE	0.01	0.424	LNAGE	MFEE	-0.02	0.182
PERCAPITAL	MIN	-0.02	0.295	LNAGE	OPEN	-0.03	0.049
PERCAPITAL	LOCKUP	-0.04	0.028	LNAGE	OPENENDED	0.10	0.000
PERCAPITAL	MFEE	-0.06	0.000	LNAGE	HMARK	-0.14	0.000
PERCAPITAL	OPEN	0.05	0.001	LNAGE	PERCAPITAL	0.14	0.000
PERCAPITAL	OPENENDED	0.25	0.000	LNAGE	RESTRICTION	-0.05	0.002
PERCAPITAL	HWMARK	-0.23	0.000	LNAGE	LEVERAGED	0.00	0.905
				LNAGE	LNSIZE	0.27	0.000

Table 4. Correlation Statistics for the Complexity of Derivative Strategy, and Hedge Fund Risk and Performance

This table presents a list of correlation statistics for the characteristics of hedge funds. The probability statistics to the right of the correlation statistics indicate the significance of the correlation based on the *t*-statistics.

		Cor.	Prob.
CF	COMPLEXITY	-0.03	0.044
RCF	COMPLEXITY	-0.02	0.188
SCF	COMPLEXITY	-0.02	0.197
STDEV	COMPLEXITY	0.02	0.284
SKEW	COMPLEXITY	-0.04	0.016
VAR	COMPLEXITY	-0.03	0.115
MVAR	COMPLEXITY	-0.02	0.166
EXKURT	COMPLEXITY	0.04	0.019
SSTDEV	COMPLEXITY	-0.02	0.293
SSKEW	COMPLEXITY	0.04	0.028
SKURT	COMPLEXITY	0.07	0.000
RSKEW	COMPLEXITY	-0.04	0.028
RKURT	COMPLEXITY	0.01	0.671
RSTDEV	COMPLEXITY	0.05	0.002
APPRAISAL	COMPLEXITY	-0.04	0.022
ALPHA	COMPLEXITY	0.00	0.921
SHARPE	COMPLEXITY	-0.08	0.000
SHARPED	COMPLEXITY	-0.09	0.000

The statistics in Table 4 suggest that the complexity of derivative strategy is strongly correlated with all other performance measures except alpha. The correlation is statistically significant at the 5 % level for appraisal ratio. For the Sharpe ratio and the Sharpe ratio with downside volatility, the correlation is statistically significant at the 1 % level. Admittedly, the correlations are relatively small but they imply that there is a seemingly negative association between the performance of a hedge fund and the complexity of its derivative strategy. The complexity, however, is weakly correlated with traditional risk measures.

The complexity of derivative strategy also has a negative and statistically significant correlation with the Cornish-Fischer expansion at the 5 % level, suggesting that complexity of derivative strategy is associated with the fatter left tail of the hedge fund return distribution. Consequently, the complexity is also positively correlated with the excess kurtosis of the return distribution and negatively correlated with the skewness of the return distribution, which supports the result for the Cornish-Fischer expansion. But, the complexity does not show a statistically significant correlation between the Cornish-Fischer expansion of market-based and idiosyncratic risks. The correlation with the skewness of idiosyncratic risk is also different from that of the market-based risk. For the former the correlation is negative and for the latter the correlation is positive. These statistics imply that more weight may be given to results concerning both the market-based and idiosyncratic risks of a hedge fund. However, market-based risks may be different for different strategies, and thus the use of market-based factors is more relevant for some strategies. Therefore, the controls for the strategies are important in this case.

In the sample of this study, which includes 3,403 hedge funds, 168 of these funds invest in other funds. Table 5 presents the characteristics of hedge funds investing in other funds for which the correlation statistics is not presented in Table 3 given that a separate description of the variable is more informative. The statistics in Table 5 suggest that hedge funds which invest in other funds use more complex derivative strategies. They also have higher management fees and lower incentive fees. They also impose less restrictive redemption policy as they have lower lock-up and restriction periods.

Table 5. Characteristics of Hedge Funds Investing in Other funds

This table presents the mean values of fund characteristics for hedge funds which invest and do not invest in other funds.

	Invests in other funds	
	Yes	No
COMPLEXITY	4.33	2.44
LNSIZE	17.03	17.17
LNAGE	7.78	7.61
MFEE	1.56	1.47
RESTRICTION	37.49	46.95
IFEE	13.30	19.10
LEVERAGED	0.64	0.69
HMARK	0.40	0.64
MIN	522782.40	795760.10
LOCKUP	2.49	3.64
OPEN	0.25	0.16
OPENENDED	0.70	0.61

5.1 Funds of Hedge Funds

This study also uses data on funds of hedge funds in its analysis. The use of this sample is important to highlight the differences between this study and the study by Chen (2009). Chen (2009) particularly includes funds of hedge funds in the sample with other hedge funds in the multivariate analysis of his study. Applying the same criteria as for hedge funds to select funds of hedge funds from the TASS database provides a sample of 763 funds of hedge funds of which 2 funds do not report minimum investment. Thus, 761 funds of hedge funds are used in the cross-sectional analysis of risk and performance of funds of hedge funds.

Table 6 presents the descriptive statistics for funds of hedge funds. The statistics are very similar to that of hedge funds presented in Table 2. For instance, the average management fee 1.47 % for funds of hedge funds is approximately the same as for hedge funds. However, the incentive fee is 9.76 % (18.85 % - 9.09 % = 9.76 %) lower for funds of hedge funds. The risk is significantly lower for funds of hedge funds when measured using the standard deviation, downside volatility, MVaR, and VaR. This is likely the result of diversification in different hedge funds. However, the average Cornish-Fischer estimate is more negative for funds of hedge funds implying a fatter left tail of the return distribution of a fund of hedge funds. It is also interesting that this estimate is lower for idiosyncratic returns than for market-based returns, which is the opposite for hedge funds. The interesting question remains as to the cause of this distinguishing characteristic of funds of hedge funds.

The statistics in Tables 2 and 6 also suggest that the performance statistics are weaker for funds of hedge funds than for hedge funds. This result, however, can be related to fewer biases in the funds of hedge funds data (see Fung et al. 2002b), therefore it is obvious that funds of hedge funds cannot be judged to perform better without further evidence.

Table 7 presents the correlation statistics between the variables of the characteristics of funds of hedge funds. The correlation statistics for the complexity of the derivative strategy of funds of hedge funds is fairly similar to that of hedge funds. However, the complexity does not have statistically significant correlation with management fees and the correlation with the natural logarithm of the size of a hedge fund is also weaker. These statistics imply that the complexity would not be as costly for funds of hedge funds.

Table 6. Descriptive Statistics for Funds of Hedge Funds

This table presents descriptive statistics and the Jarque-Bera (JB) test statistics of the variables used in the cross-sectional analysis for funds of hedge funds of this study. The sample includes 761 funds of hedge funds used in multivariate analysis of this study. See Table 1 for definitions of the variables.

	LNSIZE	LNAGE	IFEE	MFEE	MIN	RESTRICTION
Mean	17.22	7.70	9.09	1.47	552451.40	57.75
Median	17.23	7.65	10.00	1.50	250000.00	60.00
Maximum	21.74	9.29	30.00	6.00	25000000.00	180.00
Minimum	11.63	6.55	0.00	0.00	0.00	0.00
Std. Dev.	1.63	0.57	7.29	0.62	1379536.00	39.84
Skewness	-0.18	0.20	0.31	1.67	9.76	0.48
Kurtosis	2.90	2.26	2.20	10.56	143.91	2.70
JB	4.52***	22.11***	32.60***	2165.36***	641623.40***	32.39***

	LOCKUP	STDEV	MEAN	VAR	MVAR
Mean	2.14	2.41	0.65	-4.96	-5.64
Median	0.00	1.78	0.65	-3.38	-4.00
Maximum	60.00	28.45	5.08	-0.05	85.94
Minimum	0.00	0.22	-3.29	-63.37	-90.88
Std. Dev.	5.34	2.13	0.49	4.99	7.25
Skewness	3.69	4.34	-0.23	-4.21	-0.84
Kurtosis	26.30	38.92	19.89	35.44	64.26
JB	18931.48***	43307.63***	9051.67***	35611.90***	119070.10***

	CF	DD	SKEW	EXKURT	SHARPE
Mean	-2.70	2.41	-0.19	3.28	0.24
Median	-2.55	1.82	-0.18	1.26	0.25
Maximum	11.32	25.73	7.60	74.23	1.59
Minimum	-10.26	0.22	-8.00	-1.05	-0.66
Std. Dev.	1.06	2.05	1.18	6.92	0.23
Skewness	1.78	4.29	-0.85	5.11	0.41
Kurtosis	48.04	36.88	11.61	37.48	5.83
JB	64720.79***	38716.41***	2444.30***	41017.28***	274.77***

	SHARPED	APPRAISAL	ALPHA	SCF	ICF
Mean	0.24	0.26	0.25	-2.53	-2.80
Median	0.23	0.24	0.26	-2.36	-2.40
Maximum	1.84	2.43	6.45	-1.57	-1.64
Minimum	-0.64	-2.01	-5.76	-10.66	-20.30
Std. Dev.	0.24	0.42	0.71	0.75	1.54
Skewness	1.05	0.32	-0.56	-3.74	-5.29
Kurtosis	8.66	7.30	23.46	27.36	43.13
JB	1154.95***	599.82***	13318.02***	20599.17***	54616.29***

	SSKEW	SSTDEV	RSTDEV	RSKEW	RKURT	SKURT
Mean	-0.09	1.72	1.62	-0.12	2.19	1.13
Median	-0.05	1.32	1.16	-0.06	0.83	0.60
Maximum	2.52	22.57	17.33	5.97	56.81	22.54
Minimum	-4.34	0.10	0.06	-6.56	-1.22	-1.09
Std. Dev.	0.61	1.56	1.52	0.92	5.10	2.04
Skewness	-0.97	4.79	3.88	-0.90	5.48	3.93
Kurtosis	8.51	49.38	27.72	12.71	42.99	29.28
JB	1082.56***	71113.55***	21281.24***	3090.48***	54518.96***	23853.10***

	HMARK	AUDIT	PERCAPITAL	OPEN	OPENENDED	LEVERAGED
Mean	0.48	0.66	0.35	0.24	0.72	0.50

Table 7. Correlation Statistics for Fund of Hedge Funds Characteristics

This table presents a list of correlation statistics for the characteristics of funds of hedge funds. The probability statistics on the right hand side of the correlation statistics indicate significance of correlation based on the *t*-statistics.

		Cor.	Prob.			Cor.	Prob.
LNAGE	LNSIZE	0.27	0.000	PERCAPITAL	LNSIZE	-0.14	0.000
HMARK	LNSIZE	0.15	0.000	PERCAPITAL	LNAGE	0.21	0.000
HMARK	LNAGE	-0.20	0.000	PERCAPITAL	HMARK	-0.18	0.000
IFEE	LNSIZE	-0.05	0.143	PERCAPITAL	IFEE	-0.06	0.081
IFEE	LNAGE	-0.08	0.025	PERCAPITAL	MFEE	-0.02	0.498
IFEE	HMARK	0.31	0.000	PERCAPITAL	LEVERAGED	0.14	0.000
MFEE	LNSIZE	-0.08	0.021	PERCAPITAL	MIN	0.05	0.197
MFEE	LNAGE	0.10	0.007	PERCAPITAL	LOCKUP	-0.04	0.225
MFEE	HMARK	-0.24	0.000	PERCAPITAL	RESTRICTION	-0.09	0.011
MFEE	IFEE	0.21	0.000	PERCAPITAL	AUDIT	0.14	0.000
LEVERAGED	LNSIZE	-0.11	0.004	OPEN	LNSIZE	0.10	0.006
LEVERAGED	LNAGE	0.13	0.000	OPEN	LNAGE	0.03	0.350
LEVERAGED	HMARK	-0.20	0.000	OPEN	HMARK	-0.05	0.180
LEVERAGED	IFEE	0.03	0.478	OPEN	IFEE	-0.21	0.000
LEVERAGED	MFEE	0.08	0.022	OPEN	MFEE	0.03	0.459
MIN	LNSIZE	0.19	0.000	OPEN	LEVERAGED	-0.06	0.109
MIN	LNAGE	0.01	0.731	OPEN	MIN	-0.04	0.236
MIN	HMARK	0.10	0.004	OPEN	LOCKUP	-0.04	0.297
MIN	IFEE	-0.03	0.430	OPEN	RESTRICTION	0.01	0.773
MIN	MFEE	-0.14	0.000	OPEN	AUDIT	0.01	0.835
MIN	LEVERAGED	-0.05	0.135	OPEN	PERCAPITAL	0.00	0.986
LOCKUPP	LNSIZE	-0.01	0.703	OPENENDED	LNSIZE	-0.04	0.308
LOCKUPP	LNAGE	-0.07	0.043	OPENENDED	LNAGE	0.11	0.002
LOCKUPP	HMARK	0.22	0.000	OPENENDED	HMARK	-0.25	0.000
LOCKUPP	IFEE	-0.02	0.640	OPENENDED	IFEE	-0.06	0.094
LOCKUPP	MFEE	-0.16	0.000	OPENENDED	MFEE	0.07	0.053
LOCKUPP	LEVERAGED	-0.10	0.006	OPENENDED	LEVERAGED	0.12	0.001
LOCKUPP	MIN	0.12	0.001	OPENENDED	MIN	-0.10	0.006
RESTRICTION	LNSIZE	0.23	0.000	OPENENDED	LOCKUP	-0.29	0.000
RESTRICTION	LNAGE	-0.06	0.096	OPENENDED	RESTRICTION	-0.26	0.000
RESTRICTION	HMARK	0.38	0.000	OPENENDED	AUDIT	0.02	0.510
RESTRICTION	IFEE	-0.13	0.000	OPENENDED	PERCAPITAL	0.09	0.016
RESTRICTION	MFEE	-0.25	0.000	OPENENDED	OPEN	0.11	0.002
RESTRICTION	LEVERAGED	-0.11	0.003	COMPLEXITY	LNSIZE	0.07	0.067
RESTRICTION	MIN	0.19	0.000	COMPLEXITY	LNAGE	0.09	0.012
RESTRICTION	LOCKUP	0.30	0.000	COMPLEXITY	HMARK	-0.12	0.001
AUDIT	LNSIZE	0.16	0.000	COMPLEXITY	IFEE	-0.06	0.103
AUDIT	LNAGE	0.35	0.000	COMPLEXITY	MFEE	0.04	0.279
AUDIT	HMARK	-0.10	0.005	COMPLEXITY	LEVERAGED	0.22	0.000
AUDIT	IFEE	-0.02	0.555	COMPLEXITY	MIN	0.01	0.853
AUDIT	MFEE	0.00	0.940	COMPLEXITY	LOCKUP	-0.15	0.000
AUDIT	LEVERAGED	0.08	0.023	COMPLEXITY	RESTRICTION	-0.08	0.023
AUDIT	MIN	0.07	0.047	COMPLEXITY	AUDIT	0.09	0.014
AUDIT	LOCKUP	0.02	0.591	COMPLEXITY	PERCAPITAL	0.10	0.007
AUDIT	RESTRICTION	-0.05	0.144	COMPLEXITY	OPEN	0.16	0.000
				COMPLEXITY	OPENENDED	0.11	0.002

Table 8 presents the correlation statistics for the complexity of the derivative strategy of funds of hedge funds and their performance and risk measures. The statistics suggest that the complexity is negatively correlated with the Cornish-Fischer expansion of residual returns. Thus, the complexity seems to be associated with the fatter left tail of the residual return distribution of a fund of hedge funds. The statistics for VaR and the standard deviation suggest that the complexity is associated with less risk. The complexity is also negatively associated with the standard deviation of residual returns. The performance ratios instead do not seem to be correlated with the complexity. All in all, the statistics support Hypotheses 3 and 5b and the support for Hypothesis 5b is related to idiosyncratic returns of funds of hedge funds. Hypothesis 4 is not supported.

Table 8. Correlation Statistics for the Complexity of Derivative Strategy, and Fund of Hedge Funds Risk and Performance

This table presents a list of correlation statistics for the characteristics of hedge funds. The probability statistics to the right of the correlation statistics indicate the significance of the correlation based on the *t*-statistics.

		Cor.	Prob.
CF	COMPLEXITY	-0.06	0.105
RCF	COMPLEXITY	-0.07	0.043
SCF	COMPLEXITY	0.00	0.963
STDEV	COMPLEXITY	-0.07	0.049
SKEW	COMPLEXITY	-0.08	0.029
VAR	COMPLEXITY	0.07	0.050
MVAR	COMPLEXITY	0.03	0.385
EXKURT	COMPLEXITY	0.05	0.204
SSTDEV	COMPLEXITY	-0.09	0.011
SSKEW	COMPLEXITY	0.01	0.724
MEAN	COMPLEXITY	0.00	0.953
D	COMPLEXITY	-0.06	0.114
SKURT	COMPLEXITY	0.01	0.797
RSKEW	COMPLEXITY	-0.10	0.006
RKURT	COMPLEXITY	0.04	0.291
RSTDEV	COMPLEXITY	-0.04	0.241
APPRAISAL	COMPLEXITY	-0.03	0.393
ALPHA	COMPLEXITY	0.00	0.891
SHARPE	COMPLEXITY	-0.02	0.583
SHARPED	COMPLEXITY	-0.03	0.473

Figure 2 presents an illustration and the summary statistics for the complexity of the derivative strategies of funds of hedge funds. The distribution of the complexity is clearly different from that of hedge funds as illustrated in Figure 1. The complexity peaks at the high and low values of the variable meaning that there are relatively many funds of hedge funds using either a highly complex derivative strategy or not using derivatives at all.

The mean value for the complexity variable is also 109 % higher for funds of hedge funds than hedge funds. This statistic is also consistent with those presented in Table 5 for hedge funds which invest in other funds. Thus, funds of funds use more complex derivative strategies than hedge funds and have a different profile of the use of derivatives which motivates one to investigate these funds separately.

This figure presents the number of different types of derivatives used by a fund of hedge funds for the sample of funds of funds. This figure also presents descriptive statistics for the variable COMPLEXITY.

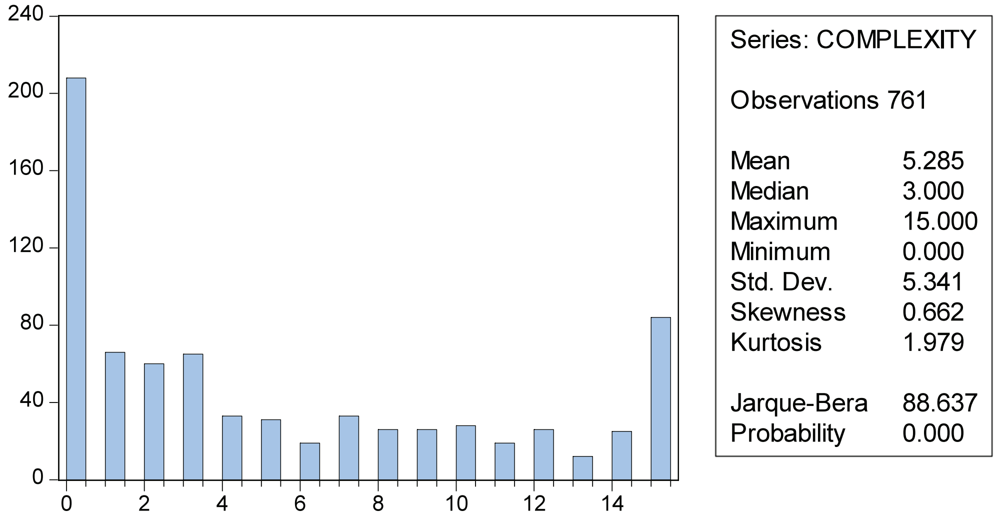


Figure 2. Number of Different Type of Derivatives Used by Funds of Hedge Funds

5.2 Database Biases Related to Hedge Fund Research

The databases of hedge fund returns also exhibit many biases which are relevant to empirical research. Fund and Hsieh (2002b) call biases that arising from the way data vendors collect hedge fund information "spurious biases." They further present and discuss survivorship bias, selection bias, and instant history bias:

Survivorship Bias: Fung et al. (2002b) explain survivorship bias as follows: "Survivorship bias arises when a sample of hedge funds includes only funds that are operating at the end of the sample period and excludes funds that have ceased operations during the period." However, it is important to consider that the bias also may work in the opposite direction. For example, best performing funds close their funds to new investors and stop reporting their returns to the database vendor. Indeed, Ackermann et al. (1999) using monthly returns for the period 1988-1995 find evidence that positive and negative survival-related biases offset each other.

Malkiel and Saha (2005) using a sample of the TASS database from 1994 to 2003 find that the survivorship bias causes hedge fund returns to be upward biased. Using the same database as Malkiel et al. (2005), Amin and Kat (2002) also find that ignoring survivorship bias leads to overestimation of the standard deviation and kurtosis and underestimation of the skewness of the returns of hedge funds.

Selection Bias: The sample of hedge funds provided by a database vendor is just a sample and not the explicit "truth" of the hedge fund industry. Thus, not all hedge funds are collected in the sample of the database leaving a possibility of selection bias. Fung et al. (2002b) define selection bias as follows: "The combination of the voluntary nature of information databases and the different inclusion processes of database vendors can lead to differences between the performance of funds in a database and that of funds in the universe of hedge funds…" For instance, some best performing hedge funds which do not need additional capital do not need to advertise their performance to investors, and therefore they do not need to report their returns to the database either. Like survivorship bias, the impact of selection bias on the performance may also be the opposite so that poorly performing funds do not want to report their returns in the database. This possibility, however, may be less credible.

Instant History Bias (Backfill Bias): This bias exists in a sample of hedge funds when hedge funds are included in the database and the database vendor allows a hedge fund to report its instant or longer history prior to inclusion. The problem arising is that this data may not be fully relevant for a hedge fund after the inclusion as, for example, the strategy may have changed or the size of a fund has increased. Also, funds may provide backfilled returns only for good performance. Indeed, Fung et al. (2000) and Malkiel et al. (2005) find that the backfilled returns in the TASS hedge fund database are much higher than the contemporaneously reported returns.

Late Reporting Bias: This bias, which is not discussed by Fung et al. (2002b) and is first documented by Tiu (2005), arises when hedge funds report their return up to 8 months late to the database vendors and these funds may appear as defunct funds even though they may still be running, yet not reporting returns instantly. When using data which suffers from the late reporting bias, the return difference between funds that report their returns on time and funds that delay reporting their returns is subject to this bias. According to the results of Schneeweis, Spurgin and Waksman (2006), hedge funds which delay reporting their returns often report lower performance than hedge funds which report early. This bias should have an impact on the performance measurement, at least to some extent.

6 METHODS

The empirical analysis of this study begins as a multivariate analysis of the determinants of derivatives use of a hedge fund. The method for this analysis is logistic regression (LR) analysis. The empirical analysis continues as a univariate method for asset specialized options use and hedge fund risk and performance. This analysis compares the average difference in the risk and performance statistics between asset specialized options users and nonusers. The method of univariate analysis is the conventional *t*-test. Similar analysis is applied on the asset specialized use of equity index futures and hedge fund performance to test Hypothesis 2. The analysis continues with a multivariate analysis of the performance and risk characteristics of hedge funds. The methods for this analysis are Ordinary Least Squares (OLS) and quantile regression analyses. The selection of control variables in the multivariate analyses is first motivated before the presentation of the analysis models. After the presentation of the control variables used this study presents the selected risk and performance measures. Lastly, the analysis methods are presented.

6.1 Selection of Other Fund Characteristics in the Cross-Sectional Analysis

Chen's (2008) results suggest that the use of derivatives by a hedge fund is associated with higher minimum investments, higher incentive fees, less restrictive redemption policy, managerial ownership, the absence of lockup periods, the absence of high watermarks, and the use of auditing services[11]. Therefore, management fee, incentive fee, restriction period time, lockup period, a dummy variable if the manager invests personal capital in the fund, and a dummy variable indicating that a hedge fund is audited if its value is one are included as control variables to account for these characteristics. Other relevant hedge fund characteristics included in the model are minimum investment in a hedge fund, natural logarithms of size and age, a dummy variable indicating that a hedge fund is open to the public if its value is one, a dummy variable indicating that a hedge fund is a closed-end fund if its value is one, a dummy variable indicating that a hedge fund uses a high watermark if its value is one, hedge fund strategy dummies excluding the

[11] In an earlier version of the study by Chen (2009), Chen (2008) uses a more extensive set of explanatory variables to explain derivative use by hedge funds.

multi-strategy[12], dummy variables of fund's reported asset classes, and dummy variables for fund's reported asset focuses other than examined. The difference between closed-end fund and open-end fund is that closed- end fund has a limited number of shares while open-end funds can redeem existing shares and issue new shares. The use of asset class dummies is justified by the fact that the definitions for hedge fund strategies may differ and be overlapping as can be seen in Appendix 1. Therefore, other classification approaches than the strategy classifications may also be beneficial. Chen (2009) does not include size and age variables in the regression analysis of derivatives use by hedge funds. The reason for dropping out these variables is that the relation between these variables and derivatives use may be biased due to look-ahead bias. Specifically, the problem is that derivatives use by a hedge fund may be indicated at the beginning of the sample period while the size variable may be based on later information. To alleviate this problem the size variable used in this study is the average size of a hedge fund over the period January 1994 – December 2006. Nevertheless, the results on the relation between the size of a hedge fund and its derivatives use should be interpreted with a caution.

Incentive fees can also be important in explaining hedge fund performance. Better performance-based compensation which aligns investors' interests with managers interests (see Holmström 1979) should attract informed managers. Thus, it is sensible to control for this characteristic. If manager skill could be explained merely by higher incentive fees, it does not yet show that investors could benefit from options use by these skilled managers. From an alternative point of view, Chen (2008) similarly notices that higher incentive fees may attract more talented managers. Therefore, management and incentive fees can be considered as indicators of fund quality, and therefore these variables may imply lower risk and better performance. In fact, Ackermann et al. (1999) and Liang (1999) find evidence that incentive fees can explain hedge fund performance.

It is assumed that auditing a hedge fund and the openness of a hedge fund to public may be substituted with higher auditing effectiveness and transparency of a hedge fund due to more regulations related to retail investors (see Liang 2003). As hedge funds do not in practice report whether they are audited but may not report auditing date in the TASS database, non-missing auditing dates are used as

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[12] Multi-strategy is used as an omitted variable category to avoid the dummy trap. Hedge fund strategies included as control variables are the convertible arbitrage, event-driven, dedicated short bias, equity long-short, emerging market, equity market-neutral, fixed-income arbitrage, global/macro, and managed futures.

a proxy for auditing similar to Liang (2003) and Chen (2009)[13]. Personal capital invested by a manager may be associated with better fund quality and as lower risk gaming (see Hodder et al. 2007; Kouwenberg et al. 2007) and, in theory, higher quality (see Leland et al. 1997).

Two additional control variables which indicate the sophistication of a hedge fund and are included in the analysis are the natural logarithms of fund size and age. These variables can be considered to be proxies for the economies of scale, evolution and sophistication of a hedge fund.

TASS reports the lockup, redemption notice and payout periods of hedge funds. These characteristics may indicate higher illiquidity risk, which may be replaced by higher returns through illiquidity risk premium (see, e.g. Amihud and Mendelson 1986). For hedge funds, the results by Aragon (2007) suggest that the share restrictions of a hedge fund are associated with higher risk premium in the hedge fund investment strategy. Thus, redemption and payout periods and lockup periods revisiting of the share restrictions, are also combined in the performance and risk analysis in addition to the closed-end dummy variable. Following Agarwal et al. (2009) and Klebanov (2008), redemption and payout periods in days are combined to a single restriction variable in the analysis of this study. Lockup period in months is still included in the analysis as an individual variable.

Leverage must be considered as a dummy variable in the regression analysis (1 = leverage) because the use of leverage may have an impact on risk. In the Lipper TASS hedge fund database, hedge fund managers report the average and maximum leverage that they use in addition to information on whether they use leverage. A dummy variable of leverage use is mainly used in this study given that fewer hedge funds report further information regarding their leverage use. Also, the information for maximum and average leverage used by hedge funds may vary over time, and thus the information contained in the variable may not be fully reliable. However, a complimentary analysis using the average leverage of a hedge fund will be presented.

High watermarks may also have an impact on the risk of a hedge fund as managers may increase risk if their performance is under the high watermark, and vice versa. For instance, the analysis by Goetzmann, Ingersoll, and Ross (2003) suggests that high variance strategies and strategies which are associated with higher

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[13] Auditing date of a hedge fund refers to “financial audit date” presented in the Lipper TASS Questionaire. Thus, auditing of a hedge fund is not clearly defined in the questionnaire and the information is based on managers’ own judgement.

sensitivity of investors to withdraw their money especially should motivate to use high watermark contracts.

The models of this study are augmented using time dummies to account for the time-varying performance of hedge funds. Specifically, for each year from 1994 to 2006, a dummy variable which takes a value of 1 if a hedge fund has a return history more than 6 months during the year. The choice of a 6-month threshold is simply compromising for selection funds for each year between their inclusions from 1 to 12 months.

6.2 Performance and Risk Measures

The first performance measure examined in cross-sectional analysis is the arithmetic mean return of a hedge fund and the first risk measure used for cross-sectional analysis is the sample standard deviation. The second risk measure is VaR that is used to measure the worst return of a hedge fund with 99% certainty. The VaR used in this study relies on the assumption of normally distributed hedge fund returns and is defined as:

(38) $$VaR = \mu + z(\alpha)\sigma,$$

where $z(\alpha)$ defines the critical value corresponding to 99 % confidence level; μ defines the sample mean, and σ defines the sample standard deviation. The third risk measure, which accounts for skewness and kurtosis, is MVaR that is defined as:

(39) $$MVaR = \mu + \left(z(\alpha) + \frac{1}{6}\left(z(\alpha)^2 - 1\right)S + \frac{1}{24}\left(z(\alpha)^3 - 3z(\alpha)\right)K - \frac{1}{36}\left(2z(\alpha)^3 - 5z(\alpha)\right)S^2\right)\sigma$$

where S defines skewness, K defines excess kurtosis. MVaR is a popular risk measure for hedge funds (see, e.g., Liang and Park 2007; Bali et al. 2007). The expansion which is used in the construction of MVaR is known as the Cornish-Fischer (CF) expansion, specifically:

(40) $$CF = z(\alpha) + \frac{1}{6}\left(z(\alpha)^2 - 1\right)S + \frac{1}{24}\left(z(\alpha)^3 - 3z(\alpha)\right)K - \frac{1}{36}\left(2z(\alpha)^3 - 5z(\alpha)\right)S^2.$$

Lower (higher) value for the Cornish-Fischer measure of a hedge fund implies a fatter (thinner) left tail of its return distribution. In addition to the use of VaR and MVaR in the analysis of this study, the Cornish-Fischer expansion, skewness, and excess kurtosis of hedge fund returns are used in the cross-sectional analysis. These measures are needed to test Hypotheses 5a and 5b. The expansion is examined on the same variables as VaR and MVaR. This approach is interesting because these determinants should explain the differences between the results for the VaR and MVaR measures. The critical value of the examined CF expansion also corresponds to the 99 % confidence level.

In addition to the sample standard deviation and VaR methodology, downside deviation of hedge fund returns is used. Formally, the downside volatility is the following:

(41) $$D_p = \sqrt{\sum_{t=0\ R_{p,t}<\bar{R}_h}^{T} (R_{p,t} - \bar{R}_p)^2 \Big/ N},$$

where $\bar{R}_p$ defines the mean of the returns of a hedge fund, and $R_{p,t}$ defines the return of a hedge fund at time *t*, and D_p defines the downside volatility of the returns of a hedge fund.

In addition to the arithmetic mean return, four different performance measures are used for the cross-sectional analysis. The first performance measure is the Sharpe ratio (1966, 1994) that is defined as

(42) $$Sharpe_p = \frac{1}{N}\sum_{t=0}^{T}\left(R_{p,t} - R_{f,t}\right) \Big/ \hat{\sigma}\left(R_p - R_f\right),$$

where $\hat{\sigma}\left(R_p - R_f\right)$ defines the volatility of excess returns of a hedge fund; R_h defines the return of a hedge fund, and R_f defines the risk-free rate. In practice, the Sharpe ratio is a popular and traditional performance indicator. However, the Sharpe ratio relies heavily on normality of returns, yet this assumption may not be applied to individual hedge fund returns. Accordingly, the Sharpe ratio with downside volatility that considers only volatility of returns below the average return is used to account for the asymmetry as

(43) $$SharpeD_p = \frac{1}{N}\sum_{t=0}^{T}\left(R_{p,t} - R_{f,t}\right) \Big/ D_p,$$

where D_p is calculated from the excess returns (small difference from the risk analysis of downside volatility). This version of the Sharpe ratio is close to the symmetric downside-risk Sharpe ratio proposed by Ziemba (2005). The particular difference from Ziemba's (2005) Sharpe ratio is that he calculates the downside risk on the returns below zero. However, some successful hedge funds may have been able to sustain constantly positive returns, and thus the downside volatility on the returns below zero could not be calculated for all hedge funds. This problem could cause a serious bias. Therefore, Ziemba's (2005) approach to model downside-risk Sharpe ratio is applied for downside volatility, which is calculated on returns below the mean return. This choice should be more sensible for hedge fund analysis. Also, the standard deviation of the downside Sharpe ratio is not scaled by the square root of 2, since the purpose in the analysis of this study is to compare the performance between hedge funds using the same measures. The scaling would make the downside Sharpe ratio more comparable with the ordinary Sharpe ratio.

Admittedly, the choice of performance measure does not necessarily alter the rank of a hedge fund according to Eling and Schuhmacher (2007), but comparison of these performance measures demonstrates the implications of the use of derivatives with asymmetry considered and contrasted between the variables.

A viable alternative for the Sharpe ratio with downside volatility would be the Modified Sharpe ratio, which applies the MVaR risk measure instead of the standard deviation, and is often used for hedge funds, for example, by Gregoriou and Gueyie (2003). However, the risk-return relationship for the expected return and the MVaR may be complicated. Bali et al. (2007) find that the relation between the downside risk of a hedge fund measured using the VaR methodology and its return is positive for live funds and negative for defunct funds. The result implies that the risk-return relation is positive for live funds and negative for dead funds. The authors' explanation for the phenomenon is that by taking a high risk fund may spend fund capital and become liquidated after a poor performance resulting as negative risk-return relation. These characteristics may be problematic in the performance measurement as the risk-return relation is not conclusive. As a result, this study uses the Sharpe ratio with downside volatility which is also closely associated with the original Sharpe ratio.

In addition to the conventional Sharpe ratio statistics, it is advisable to account for the market-based factors of hedge fund returns and focus on abnormal performance. Therefore, this study employs an empirical factor model to estimate the alphas (see Jensen 1967) and appraisal ratios (Treynor et al. 1973) of hedge fund performance. The empirical factors chosen for the model are motivated by earlier research. The following set of risk factors is chosen:

Buy-and-hold option writing strategies for put and call options. These factors are chosen based on the evidence of Agarwal et al. (2004) that hedge fund returns can resemble option writing strategies. Therefore, three different buy-and-hold strategies are chosen: returns in excess of risk-free rate on CBOE S&P 500 Buy-Write Index, CBOE S&P 500 2% OTM BuyWrite Index, and CBOE S&P 500 PutWrite Index. The first index returns replicates the performance of a strategy which involves buying an S&P 500 stock index portfolio and writing an at-the-money S&P 500 index call option. The second index returns replicate the performance of a strategy which involves buying a S&P 500 stock index portfolio and writing an out-of-the-money S&P 500 index call option. The third index returns replicates the performance of a strategy which involves investing in cash U.S. T-Bill rate and writing an at-the-money S&P 500 index put option.

The choice of above mentioned simple buy-and-hold indices is a reasonable benchmark to test whether hedge funds are able to produce performance in excess of the factors as the strategies could well be investable for investors. As a result, the use of the factors especially advocates investigating the benefits from the use of derivatives from the investors' viewpoint.

Asset-Based Style Factors: Following Fung et al. (2004b), the six-asset based style factors are chosen: returns in excess of risk-free rate on the U.S. stock market, end of the month difference of the yield on constant-maturity T-bond, and PTFS factors for equity, interest rates, bonds, currency, and commodities[14].

Volatility Risk Factor: The end of the month difference in the VIX implied volatility is chosen to account for volatility risk**.** This factor is extremely relevant in this study to capture systematic risk in hedge fund returns as the focus is on derivatives. The relevance of this factor for this study is the reason for not using a closely related variable in the asset based style analysis, end of the month difference in the credit spread (see Fung et al. 2004a).

*Factors for Market Anomalies***:** The SMB, HML, and UMD factors are also chosen as empirical risk factors. The factors are motivated by the Capocci's et al. (2004) study which suggests that these factors are strong explanatory variables for

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[14] The proxy for the excess return on the market is the value-weight return on stocks listed on the U.S. stock markets. Specifically, the stock markets are the NYSE, AMEX, and NASDAQ stock markets. Data for this factor is downloaded from Kenneth French webpage. Data for PTFS factors is downloaded from David Hsieh's webpage: http://faculty.fuqua.duke.edu/%7Edah7/HFData.htm.

hedge fund returns. Data for these factors is downloaded from the Kenneth French data library along with the market factor[15].

In time-series analysis, all the hedge fund returns examined are in excess of risk-free rate. The risk-free rate for this study is the 1-month U.S. T-bill from Ibbotson Associates. The model in the empirical time-series analysis is analogous to Equation (9) and the model is formally the following:

$$R_{p,t} - R_{f,t} = \alpha_p + \sum_{n=1}^{12} b_{p,n} f_{n,t} + e_{p,t}, \tag{44}$$

where α_p defines the abnormal return of a hedge fund; $R_{p,t}$ defines the return of a hedge fund; $R_{f,t}$ defines the risk-free return; $\sum_{n=1}^{12} b_{p,n} f_{n,t}$ defines the set of above mentioned empirical risk factors; $e_{p,t}$ defines the residual return of a hedge fund. The alpha and the appraisal ratios described in Section Two are then used in the empirical analysis of this study. The fitted returns of regression Equation (47) are used to estimate the market-based risk of a hedge fund including the standard deviation, skewness, excess kurtosis, and Cornish-Fischer expansion. The residual returns of regression Equation (47) are likewise used to estimate idiosyncratic risk of a hedge fund including the standard deviation, skewness, excess kurtosis, and Cornish-Fischer expansion.

6.3 Determinants of Derivatives Use by Hedge Funds

To test determinants of derivatives use by hedge funds, LR analysis is used. The empirical model for testing the cross-sectional analysis of options use is the following (Model 1):

$$\log\left[\frac{\Pr(DERIVATIVE_{ji} = 1)}{1 - \Pr(DERIVATIVE_{ji} = 1)}\right] = \tag{45}$$

$$\alpha_i + \beta_1 SPECIALIZATION_i + \beta_2 LEVERAGE + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + e_i$$

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15 http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

where $DERIVATIVE_{ji}$ defines the use of derivative j by fund i; $SPECIALIZATION_i$ defines a dummy variable for the specialization for the same asset as the asset class of $DERIVATIVE_{ji}$, and $CONTROL_i$ defines an additional control variable j of fund i. In addition to the above-mentioned fund characteristics these control variables also include dummy variables for invested asset classes, other asset focuses than that of $DERIVATIVE_{ji}$. This model does not test any of the hypotheses of this study. It rather provides supportive information for its conclusions. The variables for the invested asset classes are important as they take into account if a hedge fund reports that it invests in the asset class but does not yet imply a focus on the asset class. The association between options use and asset specialization is seen particularly as a statistically significant coefficient of $DERIVATIVE_{ji}$ for the options use for the same asset as the funds in the sample have a focus on (asset specialization).

6.4 Cross-Sectional Analysis of Performance and Risk

The empirical analyses of this study continue with cross-sectional analysis of hedge fund performance after examining the determinants of options use. The purpose of cross-sectional performance and risk analysis is to provide a detailed picture of the use of options and control for other variables that may explain hedge fund performance and risk. The dummy variables for the use of other derivatives and options for each asset class (1 = use options or other derivatives) form variables for asset classes respectively. These variables are used to indicate whether the use of particular derivatives has an impact on hedge fund performance and risk. Other primary focuses, other invested asset classes, and hedge fund strategies are controlled for as in the previous analysis.

The empirical model for the cross-sectional performance and risk characteristic analyses of hedge funds is the following (Model 2):

$$MEASURE_{ji} = \alpha_i + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \sum_{j=1}^{N} \beta_j DERIVATIVE_{ji} + e_i, \tag{46}$$

where $MEASURE_{ji}$ defines a risk/performance measure j of fund i; $CONTROL_{ji}$ defines an additional control variable j of fund i, and $DERIVATIVE_{ji}$ defines a dummy variable for the use of a derivative j by fund i (1 if the derivative is used, and 0 otherwise). Model 2 is used to test Hypotheses 1, 2 and 5a. Statistically significant values of β_j imply derivatives use affecting the performance and risk characteristics of hedge funds.

To test the impact of the complexity of derivative strategies on the risk and performance characteristics of a hedge fund Model 2 is reformulated and the empirical model for the cross-sectional analysis of the complexity, which tests Hypotheses 3, 4, and 5b, is the following (Model 3):

$$MEASURE_{ji} = \alpha_i + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \beta_1 COMPLEX_i + e_i, \tag{46}$$

where $MEASURE_{ji}$ defines a measure associated with higher moments j of fund i; $CONTROL_{ji}$ defines an additional control variable j of fund i, and $COMPLEX_i$ defines the number of different derivatives used by a hedge fund. Statistically significant and positive values of β_1 imply supportive evidence for the hypotheses examined.

The number of different derivatives used by a hedge fund is considered to be a proxy for complexity of derivative strategies. As there is no more detailed information available on the use of derivatives for a sufficient sample of hedge funds, the variable constructed may be considered as the most reasonable proxy for the complexity of derivative strategy. Intuitively, the more a hedge fund uses different types of derivatives, the more complex its derivative strategy is. The variable for the complexity is slightly similar to the variable for complexity of a hedge fund used by Tiu (2005) as the complexity variable used by Tiu (2005) counts for the number of significant strategy exposures of a hedge fund to 15 different indices.

Different options counted in the construction of the complexity variable are options for equity, fixed-income, commodity, and currency. Futures and forwards, respectively, for fixed-income, currency, and commodity are counted for the variable but for equity the Lipper TASS database reports only the use of equity index futures. Also, warrants issued with equity securities, warrants issued with fixed-income securities, interest rate swaps, and cross-currency interest rate swaps are counted for the variable. To sum up, data in the Lipper TASS database allows a proxy variable to be constructed for the complexity of derivative strategies by a hedge fund ranging from 0 to 15. As an example of the complexity, if a hedge fund uses equity index futures and equity index options, the strategy is assumed to be more complex than if the hedge fund had used only one of these two derivatives. A hedge fund may have a long position on an index futures option and short position on the same index using index futures as an attempt to profit from price inefficiency between the securities. The strategy appears to be simple and hedged but a hedge fund may be exposed to many other risk factors such as the liquidity of the underlying assets. This risk may be intensified as a result of leverage use once the market exposure is hedged. As such, the term “complexity” comprehends risks that may be unexpected or should be nonexistent as a result of hedging and diversification. A practical example of such complexity is the failure of the LTCM, a hedge fund, which used a wide range of different derivatives and derivative strategies. The fund positions were supposed to be hedged and diversified but the fund was eventually exposed to liquidity squeeze during the Russian Crisis 1998 (see, e.g., Lowenstein 2002). Considering the complexity from the viewpoint of a formal model, it appears that the more financial derivatives are used, the more inputs there are in the model used. For example, also investing also in stock options in addition to fixed-income options increases the number of the inputs by definition as for these options the underlying assets are different.

The model presented above assumes a linear relation between the complexity of a derivative strategy of a hedge fund and its performance but the relation may also be nonlinear. For instance, the use of a few derivatives may be relatively less profitable than the use of many derivatives as a result of economies of scale. Therefore, a polynomial relation of degree 2 between $MEASURE_{ji}$ and $COMPLEX_i$ is also analysed using the following model (Model 4):

(48) $$MEASURE_{ji} =$$

$$\alpha_i + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \beta_1 COMPLEX_i + \beta_2 (COMPLEX_i)^2 + e_i,$$

where the only difference from Model 3 is that the series of squared numbers of different derivatives used is included in the model. Thus, Model 4 also tests Hypotheses 3, 4, 5b. Models 3 and 4 are compared with one another using the Akaike information criterion (AIC) and the Schwarz information criterion (SIC).

A disadvantage of the OLS analysis is that it can only consider the relation between the mean of performance and risk measures and the complexity of derivative strategy. However, the complexity may affect the performance and risk of a hedge fund differently for different segments of the sample. For instance, the complexity may have a relation only with best performing funds but not with those performing poorly. Thus, quantile regression can provide more insights into the analysis of this study. Thus, the results of quantile regression analysis is presented for nine equally spaced quantiles of the sample using selected risk and performance measures which are alpha, appraisal ratio, the Sharpe ratio, the Cornish-Fischer expansion and standard deviation.

6.5 Further Analysis

The existing analysis on the complexity of derivative strategy and hedge fund risk does not separate the returns into market-based and idiosyncratic components. As an additional analysis, the empirical factor model of this study is used to separate the systematic and idiosyncratic components of hedge fund returns. These analyses include skewness, standard deviation, excess kurtosis and Cornish-Fischer expansion of the market-based and idiosyncratic components which are estimated using Model 3. The idiosyncratic components are calculated using the residual returns of the OLS on Equation (44) and market-based components are calculated using the fitted returns of the OLS on the same Equation.

6.6 Derivatives Use and Management of Hedge Fund Portfolios

This study performs two separate analyses to investigate the use of derivatives in fund of hedge funds management: first, the relation between the complexity of the derivative strategy of a fund of hedge funds and its performance and risk characteristics are investigated using Model 3. Second, investigate whether the impact of the derivatives use of a hedge fund is different when it invests in other hedge funds. All the above-mentioned performance and risk measures are applied to these funds. For the second analysis, the following model is used:

(49)
$$MEASURE_{ji} = \alpha_i + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \beta_1 COMPLEX_i$$
$$+\beta_2 COMPLEX_i * OTHER_i + \beta_3 OTHER_i + e_i,$$

where $OTHER_i$ defines a dummy variable for investing in other funds by fund i (1 if the fund invests in other funds, and otherwise 0). Statistically significant values of β_2 imply that the relation between the complexity of the derivative strategy of a hedge fund and its risk and performance is different for hedge funds which invest in other funds from that of ordinary hedge funds.

6.7 Autocorrelation and Relevance of the Variable for the Complexity of Derivative Strategy

There is a chance that the results may be biased due to autocorrelation in hedge fund returns, which may be caused most likely by illiquid investments and/or return smoothing (see Getmansky et al. 2004). The results would be most biased if the use of derivatives by a hedge fund were associated with higher return persistence. But the literature does not offer evident guidance for such a characteristic. However, the possibility of the characteristic is considered by obtaining the return persistence slope coefficient from the following restricted regression:

$$(50) \qquad R_{p,t} = b_p R_{p,t-1} + e_{p,t},$$

where $R_{p,t}$ defines the excess return of a hedge fund at time t, and b_p defines the slope coefficient for the persistence. Alternatively, the autocorrelation coefficient may have been used but the values of correlation variable is restricted between -1 and 1, and thus it would not be a proper dependent variable in a regression.

The series of slope coefficients is then regressed on the empirical models used in the empirical analysis of this study. Specifically, the slope coefficient for the entire hedge fund sample is regressed on Model 3 and the slope coefficient for subsamples of hedge funds (equity, fixed-income, currency, and commodity) is regressed on Model 2.

The variable for the complexity used in this study can be seen as an expansion of the binary variable of derivatives use used by Chen (2009). Therefore, it is important to consider whether such an expansion provides new information on the previously used binary variable. Thus, it is reasonable to evaluate the relevance of the extension using the following regression which includes the binary variable of derivatives use and the complexity:

$$(51) \qquad MEASURE_{ji} = \alpha_i + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \beta_1 COMPLEX_i$$
$$+\beta_2 BINARY_i + e_i,$$

where $BINARY_i$ defines a dummy variable for the use of derivatives by fund i (1 if the fund uses derivatives, and otherwise 0). Three different variations of the above model are investigated: a model with all parameters, a reduced form of the model of which the variable for the complexity of derivatives is excluded, and a reduced form of the model of which the binary variable of derivatives use is excluded. The adjusted R^2, the statistics for β_1 and β_2 and the AIC and SIC criteria are presented for the performance and risk measures of hedge funds. The statistics allows one to evaluate whether the inclusion of the variable for the complexity increases the fit of the model, and thus being a relevant component of the analysis of hedge fund risk and performance.

The leverage use may also bias the results as it can be used in replicating the returns of derivatives and derivative strategies. The use of the binary variable of leverage use as a control variable in the previous models may not be sufficient. Therefore, it is reasonable to consider the use of average leverage by a hedge fund in the analysis of its performance and risk. The model for the analysis of average leverage use by a hedge fund is the following:

$$(51)\qquad MEASURE_{ji} = , \quad \alpha + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \beta_1 AVGL_i + \beta_2 COMPLEX_i + e,$$

where $AVGL_i$ defines the average leverage of a hedge fund. If the average leverage is a good explanatory variable of the performance and risk of a hedge fund it raises a concern of a biased result for the complexity as leverage can be used to replicate derivative payoffs.

6.8 Sample Selectivity Bias

In cross-sectional analysis of asset specialized derivatives use, factors which affect derivatives use may bias the derivatives use-performance relation. This problem is mitigated using the Heckman's (1979) two-stage estimation procedure. In the first stage of the estimation procedure, a probit analysis of a dummy variable of derivatives use indicating 1 if derivatives are used and 0 otherwise on the independent variables is used. The independent variables are the same as in the earlier analysis of derivatives use by hedge funds excluding the natural logarithms of size and age. These variables are excluded due to possible look-ahead bias (see e.g. Chen 2009) minimize all bias in this further estimation procedure. The first stage is carried using the full sample of hedge funds.

In the second stage of Heckman's (1979) procedure, the predicted probabilities from the first-stage are used to mitigate the sample selection bias using the inverse Mills ratio. The inverse Mills ratio is then included in as an additional variable in Model 2. The coefficient for inverse Mills ratio indicates whether the results obtained earlier may suffer from sample selectivity bias. The analysis also provides corrected test statistics to test Hypotheses 1, 2, and 5a. Regarding these hypotheses, the results may be interpreted in the same way as earlier.

7 EMPIRICAL RESULTS

The empirical analysis can be divided into three parts. The first part (Chapter 7.1.) provides information of the determinants of options use. The first part of the empirical section also provides information about hedge fund characteristics which may incidence with the use of other different derivatives. The second part (Chapters 7.2., 7.3., 7.4 and 7.5) of the empirical analysis examines whether derivatives use has an impact on the performance and risk characteristics of a hedge fund. These performance and risk characteristics are the standard derivation, downside volatility, skewness, excess kurtosis, mean return, the Sharpe ratio, the Sharpe ratio with downside volatility, alpha, and appraisal ratio. Thus, the second part of the empirical section addresses the first research problem: *does the use of options by a hedge fund for the primary asset class of a fund affect its performance and risk characteristics?* The second part also addresses the second research problem: *does the use of equity index futures by a hedge fund affect its performance and risk characteristics?*

The third part of the empirical section (Chapters 7.6. and 7.7.) examines whether the use of a more complex derivative strategy has an impact on the same examined performance and risk characteristics of a hedge fund as in the second. As such, the third part regards the third problem: *does the use of a more complex derivative strategy affect the performance and risk characteristics of a hedge fund?* Chapter 7.8. is devoted to examining whether the complexity of the derivative strategy of a fund of hedge funds affects the risk and performance. Lastly, Chapter 7.9. presents discussion and analyses on robustness, relevance and validity of the findings of this study.

7.1 Determinants of Derivatives Use

Table 9 presents the logistic regression statistics for the determinants of the use of different derivatives by hedge funds. The results are controlled for different hedge fund strategies. However, when the number of funds in the strategy category is less than 10, the strategy is not included because the variable may capture information which only concerns just an individual hedge fund.

The regression statistics in Table 9 provide evidence that, as the use of leverage and asset specialization for the underlying asset class of an option increases, so does the probability of a hedge fund to use the option. Excluding warrants issued with fixed-income securities, the use of leverage coincides statistically significantly with the use of all derivatives by hedge funds at the 1% level. This result may also support the view that these options for speculative trading are inferior to other derivatives in hedge funds. Asset specialization coincides statistically significantly with the use of all derivatives examined except other derivatives for currency than options, at least at the 5% level. To sum up the results in Table 9, the use of leverage and asset specializations are important factors of the use of options by hedge funds, but also other derivatives.

The results for other variables than leverage and asset specialization partly differ from the results of Chen (2009) suggesting that the use of derivatives by hedge funds is associated with higher incentive fees, less restrictive redemption policy, managerial ownership and effective auditing. In particular, higher incentive fee is only found to coincidence statistically significantly with the use of derivatives in the case of equity options. By contrast, higher incentive fee has a negative and statistically significant coincidence with derivatives use in the cases of warrants issued with fixed-income securities and other derivatives than options for commodities. If performance based compensation attracts skilled managers, those managers who use options for equity should be outperformers while those managers who use options for commodity should be underperformers. This evidence is thus consistent with the expectation that equity options are used for informed trading, and thus also consistent with the evidence of Aragon et al. (2007).

The evidence for the coincidence of personal capital and the use of derivatives is found to be fairly consistent with the results of Chen (2008) as the incidence is statistically significant in 4 out of 10 regressions. The use of auditing services, instead, is not found to have any positive coincidence with the use of derivatives in contrast to Chen (2009). Also, the evidence for the coincidence of less restrictive redemption policy and the use of derivatives is mixed in this study. Longer restriction periods are, in fact, associated with the use of warrants, which is a reasonable finding as warrants may be highly illiquid and managers need longer redemption periods when investing in these assets. Consistent with Pinnuck (2004), the test statistics of this study also yield evidence that all options and warrants examined are more popular among bigger hedge funds.

The AE_OTHER variable indicates whether a fund using equity index futures as the derivative is the only equity derivative reported by TASS which has a linear payoff. The results are consistent with the assumption related to the first hypothesis that the derivative is a substitute for illiquidity risk premium. This consistency is the statistically highly significant and negative incidence between the use of the derivative and longer restriction and lockup periods which are related to higher illiquidity risk premium (see Aragon 2007).

Table 9. Logistic Regression Statistics of Derivatives Use on Leverage and Asset Specialization

This table presents parameter the estimates of cross-sectional analysis for the use of the derivatives of hedge funds. The model for the cross-sectional analysis is the following (Model 1):

$$\log\left[\frac{\Pr\left(DERIVATIVE_{ji}=1\right)}{1-\Pr\left(DERIVATIVE_{ji}=1\right)}\right]=\alpha_i+\beta_1 SPECIALIZATION_i+$$

$$\beta_2 LEVERAGE_i+\sum_{j=1}^{N}\lambda_j CONTROL_{ji}+e_i$$

where $DERIVATIVE_{ji}$ defines the use of derivative *j* by a fund *i*; $SPECIALIZATION_i$ defines a dummy variable for the specialization for the same asset as the asset class of $DERIVATIVE_i$, and $CONTROL_i$ defines an additional control variable *j* of fund *i*. These control variables include dummy variables for invested asset classes, other asset focuses than same of $DERIVATIVE_i$. The standard errors are QML (Huber/White) heteroskedasticity robust *z*-statistics are given in italics. The sample includes 3,382 observations. See Table 1 for definitions of the variables.

	AE_OPTION		AF_OPTION		AC_OPTION		ACUR_OPTION	
Variable	Coef.	*z*	Coef.	*z*	Coef.	*z*	Coef.	*z*
C	-6.626***	*-4.16*	-7.862***	*-4.06*	-9.954***	-3.73	-6.777***	*-3.19*
PRIMARY	0.369***	*3.80*	0.681***	*4.82*	0.990***	3.55	0.859***	*4.36*
LEVERAGED	0.647***	*7.18*	0.712***	*5.02*	0.677***	2.80	0.635***	*3.45*
S_CA	-0.768***	*-2.86*	-1.001***	*-3.32*				
S_DS	0.204	*0.48*						
S_ED	0.028	*0.13*	-1.178***	*-4.35*				
S_ELS	-0.026	*-0.13*	-0.575**	*-2.25*	-0.265	-0.78	-0.157	*-0.69*
S_EM	-0.807***	*-3.48*	-0.153	*-0.58*	1.482***	2.97	0.427*	*1.89*
S_EMN	-0.811***	*-3.40*	-0.187	*-0.52*				
S_FI	-0.693*	*-1.83*	0.189	*0.66*				
S_GM	-0.841***	*-2.90*	0.031	*0.10*	-0.136	-0.40	0.619**	*2.48*
S_MF	-2.442***	*-7.64*	-1.739***	*-5.21*	-1.127***	-3.16	-0.716**	*-2.47*
LNSIZE	0.069**	*2.42*	0.071*	*1.84*	0.122**	1.98	0.086*	*1.87*
LNAGE	0.137	*0.63*	0.195	*0.74*	0.143	0.40	0.000	*0.00*
HMARK	0.007	*0.06*	-0.083	*-0.49*	-0.314	-1.13	-0.537***	*-2.89*
IFEE	0.018*	*1.96*	0.005	*0.50*	0.012	0.69	-0.011	*-0.90*
MFEE	-0.186**	*-2.47*	0.056	*0.67*	-0.002	-0.02	-0.103	*-1.22*
MIN(Million$)	-0.022	*-0.68*	0.077*	*1.66*	0.000	0.03	0.089	*1.62*
RESTRICTION	0.001	*0.70*	-0.004*	*-1.81*	0.006***	2.78	0.001	*0.28*
LOCKUP	0.016**	*2.18*	0.002	*0.23*	0.018	1.00	-0.026*	*-1.67*
AUDIT	-0.148	*-1.38*	0.231	*1.56*	-0.106	-0.46	0.017	*0.10*
PERCAPITAL	0.204**	*2.26*	0.027	*0.22*	0.106	0.55	0.063	*0.45*
OPEN	0.052	*0.46*	-0.073	*-0.49*	0.028	0.12	-0.257	*-1.46*
OPENENDED	-0.092	*-0.97*	0.141	*1.03*	0.016	0.08	0.275	*1.64*
Time-Dummies	Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes	
Log likelihood	-1775.686		-1014.254		-408.884		-744.271	
McFadden R²	0.238		0.357		0.536		0.411	
LR statistic (43	1106.751		1127.133		945.366		1037.465	
Probability (LR	0.000		0.000		0.000		0.000	
Obs with Dep=0	1851		2784		3136		2965	
Obs with Dep=1	1531		598		246		417	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level

Table 9. Continued

	AE_OTHER		AF_OTHER		AC_OTHER		ACUR_OTHER	
Variable	Coef.	*z*	Coef.	*z*	Coef.	*z*	Coef.	*z*
C	-8.073***	*-4.52*	-	*-2.83*	-6.814**	*-2.10*	-5.477**	*-2.29*
PRIMARY	0.483***	*4.03*	0.415***	*4.91*	1.330***	*3.57*	0.285	*1.15*
LEVERAGED	0.821***	*7.05*	0.671***	*7.55*	1.776***	*5.50*	0.842***	*4.91*
S_CA	-0.434	*-1.48*	-0.442**	*-2.40*			-0.558	*-1.29*
S_ED	-0.739***	*-3.00*	-	*-4.78*			-0.146	*-0.41*
S_ELS	0.184	*0.94*	-0.408**	*-2.51*	-0.424	*-1.21*	-0.216	*-0.64*
S_EM	-0.279	*-1.15*	-0.287*	*-1.66*	-0.079	*-0.15*	-0.194	*-0.53*
S_EMN	-0.009	*-0.03*	-0.329	*-1.55*	-0.099	*-0.16*	-1.084**	*-2.42*
S_FI	0.218	*0.43*	0.484**	*2.53*			-0.631	*-1.53*
S_GM	1.083***	*3.43*	0.225	*1.16*	1.167***	*2.77*	0.845**	*1.97*
S_MF	1.861***	*5.99*	0.880***	*4.49*	2.529***	*5.95*	1.014**	*2.30*
LNSIZE	0.053**	*1.62*	0.082***	*3.34*	0.037	*0.52*	0.089*	*1.89*
LNAGE	0.138	*0.56*	-0.114	*-0.68*	0.063	*0.14*	-0.068	*-0.21*
HMARK	0.235*	*1.75*	0.160	*1.56*	0.110	*0.33*	0.170	*0.93*
IFEE	0.001	*0.07*	-0.008	*-1.17*	-0.023	*-1.15*	-0.032**	*-2.57*
MFEE	0.247**	*2.52*	0.143***	*2.83*	0.000	*0.00*	0.046	*0.38*
MIN(Million$)	0.201***	*4.67*	0.216***	*4.76*	0.147***	*3.00*	0.271***	*5.91*
RESTRICTION	-0.006***	*-3.12*	-0.002	*-1.34*	-0.003	*-0.68*	0.000	*0.12*
LOCKUP	-0.030***	*-3.35*	-0.008	*-1.27*	-0.035	*-1.54*	-	*-4.51*
AUDIT	-0.236*	*-1.95*	0.088	*1.00*	-0.175	*-0.58*	0.065	*0.35*
PERCAPITAL	0.227**	*2.26*	0.184**	*2.51*	0.176	*0.76*	0.407**	*2.65*
OPENTOPUBLIC	0.163	*1.29*	0.106	*1.15*	0.310	*1.06*	0.261	*1.34*
OPENENDED	0.381***	*3.32*	-0.011	*-0.13*	0.074	*0.28*	0.346	*1.95*
Time-Dummies	Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes	
Log likelihood	-1417.850		-877.697		-344.853		-718.906	
McFadden R^2	0.313		0.553		0.756		0.654	
LR statistic (38 df)	1291.770		2171.461		2137.032		2723.135	
Probability (LR stat)	0.000		0.000		0.000		0.000	
Obs with Dep=0	2370		2478		2884		2350	
Obs with Dep=1	1012		904		498		1032	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

Table 9. Continued

	AE_WARRANT		AF_WARRANT	
Variable	Coef.	*z*	Coef.	*z*
C	-10.521***	*-5.64*	-10.280***	*-3.92*
PRIMARY	0.765***	*6.43*	0.358**	*1.99*
LEVERAGED	0.447***	*4.15*	0.007	*0.04*
S_CA	0.988***	*3.78*	0.639**	*2.15*
S_ED	1.427***	*7.46*	0.262	*0.93*
S_ELS	0.948***	*5.94*	-0.310	*-0.98*
S_EM	0.878***	*4.22*	-0.017	*-0.06*
S_EMN			-0.331	*-0.67*
S_FI	-0.415	*-0.78*		
S_GM	0.026	*0.10*	-0.056	*-0.16*
S_MF				
LNSIZE	0.154***	*4.45*	0.105**	*1.91*
LNAGE	0.045	*0.18*	0.010	*0.03*
HMARK	-0.334***	*-2.58*	0.312	*1.55*
IFEE	-0.015	*-1.62*	-0.030**	*-2.19*
MFEE	-0.178**	*-2.26*	-0.217**	*-2.04*
MIN(Million$)	0.012	*0.38*	0.105**	*2.06*
RESTRICTION	0.007***	*4.16*	0.009***	*4.32*
LOCKUP	-0.006	*-0.69*	-0.024*	*-1.91*
AUDIT	0.059	*0.48*	0.296	*1.43*
PERCAPITAL	0.136	*1.32*	0.009	*0.06*
OPEN	0.143	*1.12*	-0.027	*-0.14*
OPENENDED	0.314***	*2.84*	0.521***	*2.81*
Time-Dummies	Yes		Yes	
Asset Dummies	Yes		Yes	
Log likelihood	-1406.788		-628.524	
McFadden R²	0.241		0.329	
LR statistic (38 df)	891.461		616.016	
Probability (LR stat)	0.000		0.000	
Obs with Dep=0	2580.000		3114.000	
Obs with Dep=1	802.000		268	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level

Generally, the results do not reveal any other consistent patterns for the determinants of options use and other derivatives use. Admittedly, higher minimum investment seems to coincidence with the use of other derivatives than options and warrants at the 1% statistical significance level.

7.2 Univariate Analysis of Derivatives Use

Table 10 presents a univariate analysis of asset specialized options use of a hedge fund for its performance and risk measures. The results provide information for testing Hypotheses 1 and 5a. The test statistics suggest that asset specialized equity options users on average achieve better performance than nonusers which supports Hypothesis 1. However, the difference in performance is not statistically significant for alpha and the statistical significance is weaker for the appraisal ratio. This finding is not surprising as the Sharpe ratio cannot account for nonlinear characteristics and alpha is estimated using the empirical risk factors which include simple option writing strategies. The results also suggest that equity option users have lower risk and higher returns. The evidence for lower risk could be caused by risk management consistent use of equity options.

For the asset specialized use of fixed-income options, the results suggest that the options use causes weaker Sharpe ratios but higher returns. Accordingly, this evidence for asset specialized use of options and hedge fund performance does not support Hypothesis 1. For the asset specialized use of other options, the results do not yield evidence of a statistically significant difference between users and nonusers. In conclusion, the univariate analysis provides support for Hypothesis 1 only for equity specialized use of options.

The results for the asset specialized use of fixed-income, commodity, currency show that it is associated with a fatter left tail of the return distribution of a hedge fund, which is measured using the Cornish-Fischer expansion. The results for asset specialized use of equity options, instead, show weak evidence only at the 10 % significance level that the use of equity options is associated with fatter left tails. All in all, these characteristics together support Hypothesis 5a.

The results in Table 11 present the univariate analysis for the equity specialized use of equity index futures and the analysis is denoted for testing Hypothesis 2. The results suggest that equity specialized users of equity index futures show poorer performance statistics in the terms of the Sharpe ratio, Sharpe ratio with downside volatility, and appraisal ratio which is in line with Hypothesis 2. However, the results do not provide support for a statistically significant difference between the alpha of the users and nonusers. The users of equity index futures also show higher risk in the terms of VaR, MVaR, standard deviation, and downside volatility estimates.

Table 10. Univariate Analysis of Asset Specialized Options Use

This table presents the univariate analysis of asset specialized options use. *t*-statistics are given in italics and the level of statistical significance is presented below the *t*-statistics. The number of observations for funds using derivatives (Yes) and funds not using options (No) is presented in parentheses on the right of the indicator. The highest mean is given in bold face. The initial sample is 3,403 funds.

AE_OPTION	SHARPE	SHARPED	APPRAISAL	ALPHA	MEAN	SKEW
	Mean	Mean	Mean	Mean	Mean	Mean
No (795)	0.16	0.18	0.17	0.42	0.89	**0.19**
Yes (1059)	**0.22**	**0.24**	**0.21**	**0.46**	**0.99**	0.12
t-statistic	*5.01*	*4.73*	*1.93*	*0.52*	*2.24*	*1.29*
Probability	0.000	0.000	0.053	0.606	0.025	0.198
AE_OPTION	STDEV	VAR	MVAR	EXKURT	CF	DD
	Mean	Mean	Mean	Mean	Mean	Mean
No (795)	**4.92**	-10.56	-10.47	2.43	**-2.39**	**4.67**
Yes (1059)	4.46	**-9.38**	**-9.46**	**3.23**	-2.47	4.24
t-statistic	*2.74*	*-3.05*	*-1.96*	*-3.33*	*1.66*	*2.72*
Probability	0.006	0.002	0.050	0.001	0.098	0.007
AF_OPTION	SHARPE	SHARPED	APPRAISAL	ALPHA	MEAN	SKEW
	Mean	Mean	Mean	Mean	Mean	Mean
No (487)	**0.28**	**0.32**	**0.31**	**0.44**	**0.79**	**-0.12**
Yes (359)	0.20	0.21	0.23	0.33	0.61	-0.64
t-statistic	*2.54*	*2.96*	*1.61*	*1.21*	*3.17*	*4.58*
Probability	0.011	0.003	0.108	0.226	0.002	0.000
AF_OPTION	STDEV	VAR	MVAR	EXKURT	CF	DD
	Mean	Mean	Mean	Mean	Mean	Mean
No (487)	**3.66**	-7.71	**-8.42**	4.30	**-2.57**	3.65
Yes (359)	3.47	**-7.46**	-9.29	**6.18**	-2.91	**3.70**
t-statistic	*0.78*	*-0.46*	*1.27*	*-2.55*	*4.30*	*-0.24*
Probability	0.435	0.646	0.205	0.011	0.000	0.813
AC_OPTION	SHARPE	SHARPED	APPRAISAL	ALPHA	MEAN	SKEW
	Mean	Mean	Mean	Mean	Mean	Mean
No (132)	**0.11**	**0.15**	**0.25**	**1.03**	**0.89**	**0.40**
Yes (117)	0.09	0.11	0.21	0.99	0.84	0.20
t-statistic	0.72	0.97	0.65	0.13	0.41	1.88
Probability	0.472	0.332	0.519	0.896	0.682	0.062
AC_OPTION	STDEV	VAR	MVAR	EXKURT	CF	DD
	Mean	Mean	Mean	Mean	Mean	Mean
No (132)	5.89	**-12.81**	**-11.19**	1.66	**-2.09**	5.37
Yes (117)	**6.57**	-14.44	-13.23	**2.20**	-2.38	**5.99**
t-statistic	-0.85	0.91	1.81	-1.29	3.32	-1.09
Probability	0.393	0.361	0.072	0.197	0.001	0.277
ACUR_OPTION	SHARPE	SHARPED	APPRAISAL	ALPHA	MEAN	SKEW
	Mean	Mean	Mean	Mean	Mean	Mean
No (192)	0.07	0.09	0.14	**0.60**	**0.70**	**0.35**
Yes (176)	**0.09**	**0.10**	**0.16**	0.41	0.56	0.10
t-statistic	-0.78	-0.69	-0.35	1.09	1.54	2.20
Probability	0.437	0.488	0.728	0.275	0.124	0.028
ACUR_OPTION	STDEV	VAR	MVAR	EXKURT	CF	DD
	Mean	Mean	Mean	Mean	Mean	Mean
No (192)	5.38	-11.82	-10.97	2.14	**-2.21**	**4.97**
Yes (176)	4.43	**-9.75**	**-10.02**	**3.24**	-2.47	4.19
t-statistic	2.33	-2.23	-1.08	-2.07	3.01	2.28
Probability	0.020	0.027	0.281	0.039	0.003	0.023

Table 11. Univariate Analysis of Asset Specialized Equity Index Futures Use

This table presents the univariate analysis of asset specialized equity index futures use. *t*-statistics are given in italics and the level of statistical significance is presented below the *t*-statistics. The number of observations for funds using derivatives (Yes) and funds not using options (No) is presented in parentheses on the right of the indicator. The highest mean is given in bold face. The sample includes 1,854 funds.

	SHARPE	SORTINO	APPRAISAL	ALPHA	MEAN	SKEW
No (132)	**0.22**	**0.24**	**0.20**	**0.47**	**1.00**	0.12
Yes (117)	0.16	0.18	0.17	0.39	0.84	**0.20**
t-statistic	5.19	4.72	1.77	1.40	3.64	-1.45
Probability	0.000	0.000	0.077	0.162	0.000	0.148
	STDEV	VAR	MVAR	EXKURT	CF	D
No (132)	3.94	**-9.51**	**-9.54**	2.85	-2.45	3.79
Yes (117)	**4.60**	-10.53	-10.51	**2.96**	**-2.41**	**4.39**
t-statistic	-4.82	2.55	1.83	-0.47	-0.86	-4.87
Probability	0.000	0.011	0.067	0.639	0.391	0.000

7.3 Derivatives Use and Risk and Return in Hedge Funds

Table 12 presents the results of a multivariate analysis for the impact of the use of derivatives on the mean, standard deviation, VaR, MVaR, and downside volatility estimates of hedge funds. The results in Table 12 do not directly relate to any hypothesis of this study but rather provide additional information.

In Table 12, it is a slightly puzzling finding that the asset specialized use of options does not have a statistically significant and positive impact on the mean return of a hedge fund since informed trading could yield higher returns. However, risk adjusted return is more important as mean returns are not sufficient to judge the performance. The use of equity index futures, instead, is associated with lower mean return of a hedge fund. This result may be related to the lower illiquidity risk premium of the return of a hedge fund which is a finding supportive of Hypothesis 2.

Table 12. Regression Statistics of Mean Return and Risk Measures on Derivatives Use

This table presents the parameter estimates of the cross-sectional analysis for the mean return and risk estimates of hedge funds. The model for the cross-sectional analysis is the following (Model 2):

$$MEASURE_{ji} = \alpha + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \sum_{j=1}^{N} \beta_j DERIVATIVE_{ji} + e,$$

where $MEASURE_{ji}$ defines a mean return or a risk measure *j* of fund *i*; $CONTROL_{ji}$ defines an additional control variable *j* of fund *i*, and $DERIVATIVE_{ji}$ defines a dummy variable for the use of a derivative *j* by fund *i* (1 if the derivative is used, otherwise 0). Asset dummies include controls for assets and primary assets in which hedge funds report investing. This table also presents the Durbin-Watson test for the first-order serial correlation. The standard errors are White (1980) heteroskedasticity robust *t*-statistics are given in italics. See Table 1 for definitions of the variables.

Dep.: MEAN	All		Equity		Fixed-Income		Commodity		Currency	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-2.734***	*-4.68*	-2.161***	*-2.71*	0.001	*0.00*	-0.634	*-0.39*	-2.116	*-1.57*
LNSIZE	0.064***	*6.28*	0.074***	*5.31*	0.070***	*3.24*	0.025	*0.59*	0.082***	*2.85*
LNAGE	0.300***	*3.81*	0.196**	*1.82*	-0.127	*-1.08*	0.088	*0.39*	0.107	*0.61*
HMARK	0.000	*-0.01*	0.073	*1.50*	0.165**	*2.18*	0.306	*1.43*	0.162	*1.14*
IFEE	0.009***	*2.89*	0.005	*1.18*	0.012**	*2.46*	0.025**	*1.99*	0.002	*0.25*
MFEE	0.036	*1.41*	0.043	*1.10*	0.039	*0.95*	-0.077	*-1.27*	-0.046	*-0.97*
LEVERAGED	0.079**	*2.57*	0.098**	*2.36*	0.031	*0.51*	-0.026	*-0.13*	-0.021	*-0.16*
LOCKUP	0.010***	*3.97*	0.008**	*2.15*	0.010**	*2.42*	0.007	*0.26*	0.026*	*1.95*
MIN(Million$)	-0.030***	*-3.17*	-0.029**	*-2.14*	-0.043**	*-2.16*	-0.144**	*-2.07*	-0.119	*-0.48*
RESTRICTION	0.002***	*4.38*	0.003***	*3.14*	0.000	*0.46*	0.007	*1.76*	0.001	*0.34*
AUDIT	-0.008	*-0.19*	0.027	*0.43*	0.087	*0.89*	-0.504**	*-2.27*	-0.035	*-0.26*
PERCAPITAL	0.072**	*2.49*	0.108***	*2.62*	0.077	*1.50*	0.138	*0.94*	0.109	*1.12*
OPEN	-0.069*	*-1.68*	-0.014	*-0.22*	-0.087	*-1.41*	-0.021	*-0.11*	-0.090	*-0.72*
OPENENDED	0.005	*0.14*	0.020	*0.42*	-0.046	*-0.74*	-0.113	*-0.70*	-0.022	*-0.18*
AE_OPTION	-0.023	*-0.63*	0.012	*0.26*	-0.033	*-0.44*	-0.218	*-1.13*	0.139	*0.88*
AF_OPTION	-0.159***	*-2.95*	-0.223***	*-2.61*	-0.162**	*-1.98*	-0.406*	*-1.72*	-0.197	*-1.20*
AC_OPTION	0.076	*0.79*	-0.017	*-0.10*	0.126	*0.73*	0.209	*0.88*	-0.054	*-0.32*
ACUR_OPTION	-0.018	*-0.30*	0.001	*0.01*	-0.094	*-0.84*	-0.006	*-0.02*	-0.060	*-0.48*
AE_WARRANT	0.073	*1.53*	0.099	*1.63*	-0.079	*-0.75*	0.104	*0.17*	0.132	*0.58*
AF_WARRANT	-0.037	*-0.63*	-0.010	*-0.11*	0.010	*0.10*	0.295	*0.41*	-0.212	*-0.83*
AE_OTHER	-0.095**	*-2.41*	-0.113**	*-2.14*	-0.024	*-0.27*	0.051	*0.17*	0.149	*0.99*
AF_OTHER	0.096*	*1.79*	0.141*	*1.72*	-0.016	*-0.17*	0.229	*0.61*	0.091	*0.47*
AC_OTHER	-0.167*	*-1.84*	-0.350**	*-2.00*	-0.227	*-1.38*	0.141	*0.53*	-0.161	*-0.90*
ACUR_OTHER	0.008	*0.15*	-0.064	*-0.85*	0.142	*1.69*	-0.132	*-0.49*	0.113	*0.69*
Strategy Dummies	Yes		Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes		Yes	
Adjusted R^2	0.17		0.20		0.175		0.165		0.141	
F-statistic	14.33		10.27		4.62		2.07		2.29	
Durbin-Watson	1.91		1.95		1.75		1.79		1.95	
N	3382		1841		838		245		363	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level

Options use for fixed-income has a negative and statistically significant impact on the mean return in the sample of all funds. This impact is also evident in the sub-samples of equity, fixed-income, and commodity specialized funds. Also, in the samples of both equity and fixed-income specialized funds, the use of other derivatives than options and warrants for equity and commodity have a statistically significant and negative impact on the mean return of a hedge fund. The result is consistent with the view that the use of these derivatives may be costly, as the returns are net-of-fee returns although the transaction costs are usually low for derivatives. In contrast, the use of other fixed-income derivatives than options has a statistically significant and positive impact on the mean return. In conclusion, the use of options and other derivatives of a hedge fund is not associated with higher returns but fixed-income derivatives may be cost effective.

Table 12. Continued

Dep.: STDEV	All		Equity		Fixed-Income		Commodity		Currency	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	3.806*	*1.66*	10.505***	*4.26*	4.555	*1.22*	0.267	*0.03*	0.392	*0.06*
LNSIZE	-0.282***	*-6.89*	-0.258***	*-5.13*	-0.328***	*-2.95*	-0.624***	*-2.61*	-0.439**	*-2.40*
LNAGE	0.449	*1.31*	-0.439	*-1.26*	0.289	*0.43*	1.179	*0.76*	0.760	*0.70*
HMARK	-0.333**	*-2.39*	-0.389**	*-2.16*	0.132	*0.47*	1.346	*1.37*	-0.029	*-0.05*
IFEE	0.049***	*4.48*	0.030**	*2.02*	0.093***	*3.97*	0.285***	*3.60*	0.172***	*3.29*
MFEE	0.229**	*2.00*	0.128	*0.95*	0.133	*0.81*	-0.130	*-0.42*	-0.003	*-0.02*
LEVERAGED	0.554***	*5.24*	0.824***	*5.64*	0.464**	*2.43*	0.314	*0.32*	-0.180	*-0.43*
LOCKUP	0.035***	*3.88*	0.044***	*3.42*	0.028*	*1.76*	0.056	*0.56*	0.075	*1.25*
MIN(Million$)	-0.089***	*-3.10*	-0.074**	*-2.05*	-0.145**	*-2.10*	-0.128	*-0.36*	-0.081	*-0.51*
RESTRICTION	0.000	*0.01*	0.002	*0.69*	0.001	*0.27*	-0.002	*-0.06*	0.006	*0.31*
AUDIT	-0.211	*-1.33*	-0.207	*-0.98*	-0.496	*-1.19*	-2.883*	*-1.77*	-1.098	*-1.15*
PERCAPITAL	0.141	*1.20*	0.343**	*2.34*	0.205	*0.91*	-1.087	*-1.17*	-0.626	*-1.17*
OPEN	-0.047	*-0.36*	0.153	*0.80*	-0.713***	*-3.14*	-1.184*	*-1.67*	-1.143**	*-2.52*
OPENENDED	-0.038	*-0.35*	-0.182	*-1.21*	0.280	*1.12*	0.489	*0.66*	0.447	*0.93*
AE_OPTION	-0.159	*-1.18*	-0.425**	*-2.36*	0.286	*0.74*	0.606	*0.54*	1.769**	*2.04*
AF_OPTION	-0.427**	*-2.24*	-0.490	*-1.52*	-0.157	*-0.55*	-1.476	*-1.24*	-0.337	*-0.52*
AC_OPTION	0.429	*0.99*	0.271	*0.62*	-0.487	*-0.95*	1.415	*0.96*	-0.119	*-0.18*
ACUR_OPTION	0.216	*0.96*	0.357	*1.05*	0.215	*0.67*	-0.907	*-0.77*	-0.915*	*-1.81*
AE_WARRANT	0.354**	*2.27*	0.454**	*2.31*	-0.284	*-0.99*	-1.304	*-0.62*	0.078	*0.08*
AF_WARRANT	0.198	*0.86*	0.133	*0.36*	0.309	*1.21*	3.164	*1.17*	0.528	*0.58*
AE_OTHER	-0.260*	*-1.69*	-0.132	*-0.67*	-0.351	*-0.84*	-1.082	*-0.86*	-0.644	*-1.01*
AF_OTHER	0.146	*0.82*	0.282	*1.01*	-0.195	*-0.67*	2.035	*1.29*	0.140	*0.19*
AC_OTHER	0.537*	*1.87*	0.401	*0.94*	1.112**	*2.01*	1.481	*1.44*	1.920**	*2.20*
ACUR_OTHER	-0.017	*-0.10*	-0.298	*-1.19*	0.666**	*2.38*	0.490	*0.42*	0.866*	*1.78*
Strategy Dummies	Yes		Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes		Yes	
Adjusted R^2	0.28		0.32		0.311		0.064		0.201	
F-statistic	25.94		18.05		8.71		1.37		2.98	
Durbin-Watson	1.90		1.91		1.97		2.11		1.98	
N	3382		1841		838		245		363	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level

The regression statistics of standard deviation on derivatives use provide partial support for risk management consistent use of derivatives by hedge funds. However, the results show contradictory evidence for equity options and warrants issued with equity securities. The results are also mixed for different samples. For instance, the use of equity options increases standard deviation of a fund by 1.769 % for funds specialized in currency. But the use of these options by funds that are equity specialized decreases standard deviation by 0.425 %. The latter result is consistent with those of Aragon et al. (2008) and Chen (2009). The mixed results suggest that, after accounting for the heterogeneity of derivatives, the impact of the use of derivatives on the standard deviation of a hedge fund is not conclusive. Moreover, the result suggests that asset specialized use of equity options may decrease the risk of a hedge fund.

Table 12. Continued

Dep..: D	All		Equity		Fixed-Income		Commodity		Currency	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	3.619*	*1.83*	9.482***	*4.06*	3.653	*1.04*	4.982	*0.65*	3.681	*0.72*
LNSIZE	-	*-6.72*	-	*-4.69*	-	*-2.64*	-0.501***	*-2.67*	-0.321**	*-2.36*
LNAGE	0.388	*1.34*	-0.328	*-0.99*	0.201	*0.37*	0.240	*0.22*	0.130	*0.17*
HMARK	-	*-2.64*	-0.391**	*-2.42*	0.035	*0.13*	1.132	*1.34*	-0.057	*-0.11*
IFEE	0.038***	*3.93*	0.021	*1.61*	0.079***	*3.65*	0.239***	*4.08*	0.142***	*3.73*
MFEE	0.181*	*1.84*	-0.014	*-0.12*	0.079	*0.54*	0.016	*0.06*	-0.036	*-0.23*
LEVERAGED	0.534***	*5.62*	0.828***	*6.40*	0.606***	*3.06*	0.173	*0.25*	-0.073	*-0.19*
LOCKUP	0.027***	*3.36*	0.039***	*3.51*	0.019	*1.30*	0.017	*0.20*	0.067	*1.34*
MIN(Million$)	-0.073**	*-2.17*	-0.058*	*-1.88*	-0.124*	*-1.78*	-0.124	*-0.45*	-0.148	*-1.15*
RESTRICTION	-0.001	*-0.30*	0.001	*0.53*	0.001	*0.42*	-0.001	*-0.04*	0.000	*0.01*
AUDIT	-0.166	*-1.21*	-0.197	*-1.03*	-0.512	*-1.36*	-1.747*	*-1.66*	-0.706	*-1.09*
PERCAPITAL	0.256**	*2.47*	0.370***	*2.71*	0.587***	*2.71*	-0.383	*-0.60*	-0.262	*-0.62*
OPEN	-0.103	*-0.88*	0.014	*0.08*	-	*-3.48*	-1.112**	*-2.04*	-0.866**	*-2.40*
OPENENDED	-0.051	*-0.54*	-0.161	*-1.19*	0.255	*1.22*	0.216	*0.37*	0.385	*1.02*
AE_OPTION	-0.118	*-0.99*	-0.296*	*-1.83*	0.338	*1.01*	0.239	*0.26*	1.118*	*1.69*
AF_OPTION	-0.283	*-1.37*	-0.502	*-1.64*	-0.204	*-0.56*	-0.999	*-1.08*	-0.205	*-0.36*
AC_OPTION	0.328	*0.97*	0.151	*0.35*	-0.580	*-1.17*	1.142	*1.16*	0.017	*0.03*
ACUR_OPTION	0.192	*0.95*	0.198	*0.70*	0.254	*0.72*	-0.602	*-0.66*	-0.771*	*-1.71*
AE_WARRANT	0.218	*1.63*	0.317*	*1.87*	-0.288	*-0.97*	-0.791	*-0.43*	0.178	*0.20*
AF_WARRANT	0.186	*0.83*	0.180	*0.52*	0.284	*0.96*	2.680	*1.18*	0.678	*0.76*
AE_OTHER	-0.209	*-1.51*	-0.194	*-1.05*	-0.156	*-0.41*	-0.924	*-0.84*	-0.568	*-1.05*
AF_OTHER	0.257	*1.33*	0.559**	*1.97*	-0.053	*-0.14*	2.031	*1.53*	0.165	*0.24*
AC_OTHER	0.456	*1.61*	0.348	*0.87*	0.956*	*1.91*	1.233	*1.45*	1.732***	*2.60*
ACUR_OTHER	-0.052	*-0.32*	-0.291	*-1.31*	0.622**	*2.20*	0.153	*0.16*	0.689	*1.45*
Strategy Dummies	Yes		Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes		Yes	
Adjusted R^2	0.31		0.34		0.295		0.096		0.203	
F-statistic	29.07		19.85		8.16		1.58		3.00	
Durbin-Watson	1.87		1.90		1.89		2.21		2.02	
N	3382		1841		838		245		363	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level

In Table 12, there are some contradictions between the standard deviation and downside volatility. The impact of the asset specialized use of options for equity is -0.425 % and statistically significant (5 % level) on standard deviation while the impact on the downside deviation is weaker -0.296 % (10 % level) while the fit of the estimated model is better for downside volatility than the standard deviation (R^2: 34 % vs. 23 %). The same characteristic also applies to the asset specialized use of warrants for equity. Moreover, incentive fee seems to have a stronger impact on the standard deviation than the downside volatility of a hedge fund for the samples of all, equity, fixed-income-, commodity, and currency hedge funds. For the sample of equity specialized funds, the coefficient for incentive fee is statistically significant and positive when the standard deviation is fitted while the coefficient is not statistically significant when the downside volatility is fitted.

Table 12. Continued

Dep.: VAR	All		Equity		Fixed-Income		Commodity		Currency	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-	*-2.23*	-	*-4.77*	-10.596	*-1.22*	-1.255	-0.05	-3.028	*-0.20*
LNSIZE	0.721***	*7.70*	0.675***	*5.80*	0.833***	*3.28*	1.476***	*2.76*	1.103**	*2.67*
LNAGE	-0.745	*-0.96*	1.219	*1.55*	-0.799	*-0.53*	-2.655	*-0.76*	-1.661	*-0.68*
HMARK	0.774**	*2.53*	0.978**	*2.44*	-0.141	*-0.23*	-2.825	*-1.31*	0.228	*0.18*
IFEE	-	*-4.25*	-0.064*	*-1.88*	-	*-3.75*	-	*-3.55*	-	*-3.37*
MFEE	-0.497*	*-1.92*	-0.254	*-0.83*	-0.271	*-0.71*	0.225	*0.32*	-0.039	*-0.09*
LEVERAGED	-	*-5.12*	-1.820***	*-5.54*	-1.048**	*-2.37*	-0.756	*-0.34*	0.396	*0.42*
LOCKUPPERIOD	-0.070	*-3.61*	-0.093***	*-3.30*	-0.055	*-1.55*	-0.124	*-0.57*	-0.148	*-1.12*
MIN(Million$)	0.177***	*2.81*	0.124*	*1.82*	0.294*	*1.92*	0.153	*0.20*	0.169	*0.49*
RESTRICTION	0.002	*0.50*	-0.002	*-0.28*	-0.002	*-0.23*	0.011*	*0.21*	-0.012	*-0.30*
AUDIT	0.483	*1.35*	0.509	*1.07*	1.242	*1.29*	6.203	*1.70*	2.520	*1.18*
PERCAPITAL	-0.256	*-0.97*	-0.689**	*-2.10*	-0.400	*-0.77*	2.667	*1.28*	1.565	*1.29*
OPEN	0.042	*0.15*	-0.369	*-0.89*	1.572***	*3.07*	2.734*	*1.76*	2.569**	*2.58*
OPENENDED	0.092	*0.39*	0.443	*1.34*	-0.698	*-1.24*	-1.249	*-0.76*	-1.062	*-0.99*
AE_OPTION	0.347	*1.15*	1.001**	*2.45*	-0.698	*-0.79*	-1.627	*-0.65*	-3.976**	*-2.04*
AF_OPTION	0.835	*1.90*	0.917	*1.26*	0.203	*0.30*	3.028	*1.14*	0.587	*0.41*
AC_OPTION	-0.921	*-0.95*	-0.646	*-0.65*	1.259	*1.04*	-3.083	*-0.94*	0.222	*0.15*
ACUR_OPTION	-0.521	*-1.03*	-0.829	*-1.09*	-0.594	*-0.79*	2.104	*0.80*	2.069*	*1.79*
AE_WARRANT	-0.751**	*-2.15*	-0.957**	*-2.16*	0.582	*0.88*	3.138	*0.69*	-0.049	*-0.02*
AF_WARRANT	-0.498	*-0.95*	-0.320	*-0.38*	-0.709	*-1.16*	-7.066	*-1.18*	-1.441	*-0.71*
AE_OTHER	0.510	*1.46*	0.194	*0.43*	0.792	*0.83*	2.569	*0.91*	1.647	*1.12*
AF_OTHER	-0.244	*-0.60*	-0.515	*-0.82*	0.438	*0.61*	-4.505	*-1.28*	-0.234	*-0.14*
AC_OTHER	-1.416**	*-2.19*	-1.283	*-1.34*	-2.815**	*-2.22*	-3.305	*-1.46*	-4.627**	*-2.37*
ACUR_OTHER	0.048	*0.13*	0.629	*1.15*	-1.408**	*-2.23*	-1.273	*-0.49*	-1.902	*-1.63*
Strategy Dummies	Yes		Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes		Yes	
Adjusted R-squared	0.29		0.33		0.326		0.078		0.216	
F-statistic	27.49		18.93		9.25		1.46		3.17	
Durbin-Watson stat.	1.89		1.91		1.98		2.13		1.99	
N	3382		1841		838		245		363	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

The results for MVaR and VaR are contradictiory. Specifically, the asset specialized use of options for equity decreases risk in terms of VaR estimate by 1.001 % and the statistical significance is at the 5 % level. However, the impact is not statistically significant when the MVaR estimate, which accounts for asymmetry and fat tails of hedge fund returns, is used instead of VaR estimate. The asset specialized use of warrants issued with equity securities also has a negative and statistically significant impact on the VaR estimates at the 5 % level but the impact on the MVaR estimate is not statistically significant. The results suggest that the relation between the use of options and hedge fund risk is altered by the choice of risk measures accounting for skewness and kurtosis of returns.

In general, the use of options by a hedge fund, except for asset specialized use of options for equity and currency does not support the view that the use of derivatives for risk management or that they otherwise coincidence with lower risk. The results for the use of the above-mentioned two derivatives also hold for the VaR measure, which assumes that the returns are normally distributed and does not account for skewness and kurtosis of the returns. This finding is significantly inconsistent with the results of Chen (2009) for risk management motivated use of derivatives.

Table 12. Continued

Dep.: MVAR	All		Equity		Fixed-Income		Commodity		Currency	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-	*-2.57*	-	*-3.59*	-	*-1.35*	-	*-1.29*	-9.738	*-0.78*
LNSIZE	0.654***	*6.05*	0.632***	*3.91*	0.807***	*3.13*	1.233	*3.07*	0.777***	*2.67*
LNAGE	0.144	*0.17*	1.710	*1.50*	-0.183	*-0.14*	0.764	*0.36*	-0.436	*-0.26*
HMARK	0.095	*0.23*	0.516	*0.88*	-1.283	*-1.57*	-2.515**	*-1.33*	-0.241	*-0.12*
IFEE	-0.049	*-1.58*	-0.036	*-0.86*	-0.156**	*-2.14*	-0.501	*-3.99*	-	*-3.42*
MFEE	-0.249	*-0.70*	0.493	*0.85*	0.033	*0.08*	-0.438	*-0.88*	0.009	*0.02*
LEVERAGED	-	*-4.30*	-1.883***	*-4.14*	-1.438**	*-2.14*	0.379	*0.24*	0.151	*0.14*
LOCKUP	-0.054**	*-2.11*	-0.101**	*-2.46*	-0.001	*-0.02*	0.079	*0.43*	-0.128	*-1.05*
MIN(Million$)	0.296***	*3.27*	0.115	*1.11*	0.435**	*2.19*	-0.095	*-0.15*	0.516	*1.61*
RESTRICTION	0.003	*0.56*	-0.003	*-0.44*	0.003	*0.44*	0.012	*0.33*	0.015	*0.63*
AUDIT	-0.095	*-0.24*	0.165	*0.26*	0.674	*0.79*	1.718*	*1.05*	1.216	*0.97*
PERCAPITAL	-0.642**	*-2.00*	-1.016**	*-2.16*	-1.570**	*-2.46*	-0.493	*-0.41*	0.731	*0.71*
OPEN	0.542	*1.36*	0.672	*0.97*	2.081***	*3.43*	2.473**	*2.02*	1.984**	*2.14*
OPENENDED	-0.178	*-0.57*	0.047	*0.10*	-0.855	*-1.38*	-0.344	*-0.27*	-1.486	*-1.64*
AE_OPTION	0.052	*0.13*	0.372	*0.65*	-0.718	*-0.67*	-0.190	*-0.10*	-2.335	*-1.59*
AF_OPTION	-0.177	*-0.23*	1.007	*0.67*	-0.463	*-0.49*	0.898	*0.48*	0.721	*0.50*
AC_OPTION	-1.431	*-1.59*	-1.474	*-1.15*	1.077	*0.82*	-2.034	*-1.19*	-0.353	*-0.25*
ACUR_OPTION	0.059	*0.07*	0.118	*0.07*	-0.192	*-0.19*	0.214	*0.11*	0.876	*0.61*
AE_WARRANT	0.014	*0.03*	0.089	*0.16*	0.641	*0.57*	-2.225	*-0.37*	-1.388	*-0.44*
AF_WARRANT	-0.435	*-0.46*	0.154	*0.09*	-1.374	*-1.45*	-2.420	*-0.37*	-1.212	*-0.39*
AE_OTHER	0.370	*0.80*	0.356	*0.50*	0.084	*0.07*	3.025	*1.03*	0.385	*0.26*
AF_OTHER	-0.894	*-1.49*	-3.026***	*-2.96*	0.229	*0.21*	-5.833*	*-1.74*	0.227	*0.10*
AC_OTHER	-0.854	*-0.94*	-0.827	*-0.60*	-2.848*	*-1.70*	-3.197	*-1.53*	-	*-2.88*
ACUR_OTHER	0.510	*0.83*	1.343	*1.36*	-1.084	*-1.15*	0.719	*0.29*	-1.695	*-1.13*
Strategy Dummies	Yes		Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes		Yes	
Adjusted R^2	0.23		0.22		0.272		0.179		0.136	
F-statistic	19.79		11.28		7.39		2.19		2.24	
Durbin-Watson	1.86		1.89		1.94		2.35		1.95	
N	3382		1841		838		245		363	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

7.4 Derivatives Use and Hedge Fund Performance

Table 13 presents the results for the impact of derivatives use on the Sharpe ratio, the Sharpe ratio with downside volatility, alpha, and appraisal ratio of a hedge fund. The results are denoted for testing Hypotheses 1 and 2. The results support Hypothesis 1 only in the case of hedge funds which are equity specialized, and thus have a primary asset focus on equity. More specifically, the impact of the asset specialized use of equity options increases the Sharpe ratio of a hedge fund by 0.023 % and the impact is statistically significant at the 5% level.

In relation to the study by Holmström (1979), the positive impact on the Sharpe ratio is consistent with a characteristic that performance based-compensation of managers attracts skilled managers which is also considered by Chen (2008). But this study does indeed find further evidence. More specifically, the use of options is consistent with higher incentive fees only when the performance is higher in the terms of Sharpe ratios. Thus, the results so far provide an explanation that informed hedge funds seem to use equity options and receive higher incentive fees. The other explanation, which is also consistent with the results by Aragon et al. (2008), is that equity options are used for risk management. This use can better explain Sharpe ratio associated with equity options use, and therefore investors may reward equity options users with higher incentive fees for better risk management.

Table 13 also presents the results for the impact of option use on the Sharpe ratio with downside volatility of a hedge fund. The asset specialized use of options for equity does not have a positive and statistically significant impact on the performance measure.

The results for alpha and appraisal ratio are different in relation to the results of the Sharpe ratio. Specifically, the asset specialized use of equity options does not have a statistically significant impact on the performance and the impact is rather negative according to these statistics. This result clearly implies that the empirical factor model is capable of accounting for the positive performance impact of the asset specialized use of equity options. Thus, Hypothesis 1 is supported for equity specialized use of options only when the Sharpe ratio is used. Overall, the results for the multivariate analysis of hedge fund performance are consistent with those of the univariate analysis.

Table 13. Regression Statistics of Performance Measures on Derivatives Use

This table presents parameter estimates of cross-sectional analysis for performance estimates of hedge funds. The model for the cross-sectional analysis is the following (Model 2):

$$MEASURE_{ji} = \alpha + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \sum_{j=1}^{N} \beta_j DERIVATIVE_{ji} + e,$$

where $MEASURE_{ji}$ defines a performance measure *j* of fund *i*; $CONTROL_{ji}$ defines an additional control variable *j* of fund *i*, and $DERIVATIVE_{ji}$ defines a dummy variable for the use of a derivative *j* by fund *i* (1 if the derivative is used, otherwise 0). Asset dummies include controls for assets and primary assets in which hedge funds report investing. This table also presents the Durbin-Watson test for the first-order serial correlation. *t*-statistics are given in italics. The standard errors are White (1980) heteroskedasticity robust. *t*-statistics are given in italics. See Table 1 for definitions of the other variables.

Dep.: SHARPE	All		Equity		Fixed-Income		Commodity		Currency	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-0.634**	*-2.24*	-0.904***	*-4.75*	0.323	*0.47*	-0.618*	*-1.71*	-0.543**	*-2.04*
LNSIZE	0.034***	*11.52*	0.032***	*8.42*	0.040***	*5.25*	0.019***	*2.75*	0.025***	*4.22*
LNAGE	0.052	*1.30*	0.087***	*3.20*	-0.096	*-0.96*	0.071	*1.37*	0.039	*1.13*
HMARK	0.000	*-0.03*	0.022*	*1.93*	0.048	*0.80*	0.009	*0.26*	0.012	*0.40*
IFEE	0.000	*-0.08*	0.001	*1.09*	-0.003	*-0.75*	-0.003	*-0.74*	-0.004*	*-1.92*
MFEE	-0.001	*-0.15*	0.002	*0.30*	0.011	*1.01*	-0.018	*-1.84*	-0.013	*-1.54*
LEVERAGED	0.008	*0.60*	-0.003	*-0.32*	0.031	*0.80*	-0.016	*-0.31*	0.001	*0.02*
MIN(Million$)	-0.004	*-0.96*	0.003	*0.82*	-0.018	*-1.47*	-0.034*	*-1.86*	0.004	*0.28*
RESTRICTION	0.001***	*3.86*	0.001**	*2.50*	0.001*	*1.88*	0.003***	*2.64*	0.002***	*3.13*
LOCKUP	0.002**	*2.18*	-0.001	*-0.62*	0.006**	*2.51*	0.008	*1.57*	0.003	*1.13*
AUDIT	-0.009	*-0.63*	-0.013	*-0.91*	0.018	*0.43*	-0.031	*-0.99*	-0.041	*-1.41*
PERCAPITAL	0.009	*0.81*	0.016	*1.70*	-0.001	*-0.04*	-0.010	*-0.35*	0.010	*0.49*
OPEN	-0.051***	*-3.54*	-0.033***	*-2.62*	-0.042	*-0.98*	-0.048	*-1.37*	-0.054**	*-1.98*
OPENENDED	0.013	*0.89*	-0.001	*-0.05*	0.019	*0.41*	-0.014	*-0.45*	0.006	*0.26*
AE_OPTION	-0.003	*-0.26*	0.023**	*2.00*	-0.037	*-1.54*	-0.036	*-0.90*	0.001	*0.02*
AF_OPTION	-0.041	*-1.53*	-0.024	*-1.15*	-0.083	*-1.40*	0.012	*0.21*	-0.027	*-0.63*
AC_OPTION	0.044	*1.94*	-0.015	*-0.61*	0.093**	*2.20*	-0.020	*-0.49*	-0.024	*-0.80*
ACUR_OPTION	-0.026	*-1.62*	-0.015	*-0.76*	-0.019	*-0.67*	-0.013	*-0.22*	0.016	*0.48*
AE_WARRANT	-0.007	*-0.59*	-0.001	*-0.09*	0.069**	*2.36*	0.214	*1.65*	0.044	*0.95*
AF_WARRANT	-0.019	*-0.94*	-0.004	*-0.18*	-0.071**	*-2.26*	-0.164	*-1.20*	-0.083	*-1.24*
AE_OTHER	0.015	*1.26*	-0.018	*-1.52*	0.062*	*1.83*	0.007	*0.12*	0.037	*1.03*
AF_OTHER	-0.025	*-1.00*	-0.009	*-0.46*	-0.025	*-0.44*	-0.056	*-0.73*	0.028	*0.67*
AC_OTHER	-0.049**	*-2.23*	-0.032	*-1.07*	-0.097*	*-1.85*	0.055	*0.92*	-0.038	*-1.13*
ACUR_OTHER	0.000	*0.03*	-0.032*	*-1.77*	0.054*	*1.84*	-0.051	*-0.92*	-0.016	*-0.39*
Strategy Dummies	Yes		Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes		Yes	
Adjusted R^2	0.227		0.333		0.212		0.406		0.311	
F-statistic	19.76		19.39		5.60		4.70		4.56	
Durbin-Watson	1.95		1.86		2.02		2.03		1.83	
N	3382		1841		838		245		363	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level

Table 13. Continued

Dep.: SHARPED	All		Equity		Fixed-Income		Commodity		Currency	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-0.585*	*-1.85*	-0.940***	*-4.49*	0.483	*0.65*	-0.768	*-1.74*	-0.571**	*-2.03*
LNSIZE	0.036***	*10.27*	0.033***	*7.75*	0.041***	*4.59*	0.023**	*2.34*	0.026***	*3.98*
LNAGE	0.050	*1.12*	0.090***	*3.02*	-0.101	*-0.94*	0.076	*1.21*	0.043	*1.14*
HMARK	-0.020	*-0.90*	0.021	*1.61*	0.007	*0.09*	-0.006	*-0.11*	0.007	*0.23*
IFEE	0.000	*0.22*	0.002	*1.59*	-0.005	*-0.86*	-0.004	*-0.86*	-0.004	*-1.60*
MFEE	-0.002	*-0.23*	0.009	*1.02*	0.010	*0.82*	-0.020	*-1.64*	-0.014	*-1.56*
LEVERAGED	0.007	*0.42*	-0.008	*-0.62*	0.054	*1.10*	0.045	*0.51*	0.001	*0.02*
MIN(Million$)	-0.002	*-0.31*	0.003	*-0.65*	-0.013	*-0.84*	-	*-2.22*	0.004	*0.28*
RESTRICTION	0.002***	*3.93*	0.001**	*2.44*	0.001*	*1.93*	0.006**	*-2.53*	0.002***	*2.90*
LOCKUP	0.003**	*2.36*	-0.001	*-0.84*	0.007**	*2.27*	0.015*	*1.80*	0.004	*1.09*
AUDIT	-0.008	*-0.45*	-0.020	*-1.27*	0.026	*0.52*	-0.037	*-0.93*	-0.047	*-1.48*
PERCAPITAL	0.003	*0.26*	0.020	*1.78*	-0.008	*-0.24*	-0.031	*-0.80*	0.012	*0.52*
OPEN	-0.053***	*-3.31*	-0.029*	*-1.96*	-0.029	*-0.65*	-0.073	*-1.45*	-0.044	*-1.50*
OPENENDED	0.009	*0.51*	-0.005	*-0.34*	0.006	*0.11*	-0.012	*-0.26*	0.000	*0.01*
AE_OPTION	-0.010	*-0.79*	0.022	*1.65*	-0.042	*-1.57*	-0.030	*-0.59*	0.003	*0.09*
AF_OPTION	-0.053*	*-1.77*	-0.029	*-1.20*	-0.095	*-1.50*	0.057	*0.69*	-0.037	*-0.80*
AC_OPTION	0.038	*1.34*	-0.012	*-0.44*	0.111***	*2.26*	-0.061	*-1.05*	-0.020	*-0.59*
ACUR_OPTION	-0.010	*-0.52*	-0.011	*-0.47*	-0.017	*-0.54*	-0.018	*-0.22*	0.019	*0.51*
AE_WARRANT	-0.006	*-0.44*	0.006	*0.39*	0.073**	*2.24*	0.227	*1.41*	0.047	*0.85*
AF_WARRANT	-0.020	*-0.84*	0.005	*0.20*	-0.081**	*-2.36*	-0.149	*-0.88*	-0.084	*-1.13*
AE_OTHER	0.027*	*1.70*	-0.016	*-1.11*	0.078**	*2.10*	0.046	*0.58*	0.029	*0.73*
AF_OTHER	-0.059*	*-1.91*	-0.026	*-1.14*	-0.075	*-1.07*	-0.117	*-1.07*	0.040	*0.89*
AC_OTHER	-0.047*	*-1.74*	-0.043	*-1.23*	-0.118**	*-1.99*	0.060	*0.72*	-0.069*	*-1.72*
ACUR_OTHER	0.005	*0.29*	-0.032	*-1.55*	0.059*	*1.76*	-0.049	*-0.63*	-0.010	*-0.22*
Strategy Dummies	Yes		Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes		Yes	
Adjusted R^2	0.198		0.299		0.199		0.392		0.272	
F-statistic	16.72		16.67		5.24		4.49		3.94	
Durbin-Watson	1.98		1.88		2.01		1.94		1.87	
N	3382		1841		838		245		363	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level

The asset specialized use of these derivatives has a statistically significant and negative impact so that the use of these derivatives decreases the alpha of a hedge fund by -0.188 %. Consequently, the statistics for alpha suggest that the equity specialized use of index futures is associated with poorer performance providing support for Hypothesis 2. The result may be explained by the primary use of these securities for uninformed trading and their substitute for share restrictions, and thus less illiquidity risk premium. Admittedly, appraisal ratio, the Sharpe ratio and the Sharpe ratio with downside volatility of hedge funds are not associated with the use of equity index futures, which may be explained by the affect of risk characteristics associated with equity index futures on the denominator of these performance measures.

The lack of support for Hypothesis 2 in the univariate analysis is a concern of bias associated with the inclusion of variables in the multivariate analysis. As a further analysis it is tested whether dropping the asset and strategy dummies results in an insignificant relation between the use of equity index futures and the alpha of a hedge fund. The logic of this test is that the use of equity index futures and its liquidity characteristic has no relevance for some strategies which use the futures primarily to perform their trading. For example, managed futures funds may use only futures to perform trend-following strategies and the use of equity index futures has less implication regarding their liquidity management. Consequently, the statistical significance of the results may be weak when hedge fund strategies are not controlled. The further analysis is performed by testing the use equity index futures separately for two subsamples. The first group of strategies (GROUP 1) includes all equity-based strategies which more likely manage their liquidity using equity index futures. These strategies are the dedicated short bias, event-driven, equity long/short, emerging market, and equity market neutral strategies. The second group of strategies (GROUP 2) includes the remaining strategies which may use equity index futures for their primary strategy or do not invest heavily in equities. These strategies are the managed futures, global/macro, convertible arbitrage, and fixed-income strategies. The result for these groups and hedge fund performance are presented in Appendix 2, which clearly demonstrates that the negative relation between the index futures and the alpha of a hedge fund is negative and statistically significant for the first group which potentially may use these derivatives for cash management.

The results in Table 13 also provide some evidence for other type of use of derivatives than that of asset specialized use. In contrast to the use of equity options, the use of other currency derivatives than options has a statistically significant (10% level) and negative impact on the Sharpe ratio of equity specialized funds. Equity specialized funds may use these derivatives to hedge currency related risk, and therefore this finding is slightly surprising. Alternatively, the result may suggest that risk management by derivatives is not efficient for fund performance. It may also imply that hedging is expensive. For fixed-income specialized funds, the use of options for commodity has also a statistically significant and positive impact on the Sharpe ratio of a hedge fund.

Table 13. Continued

Dep.: ALPHA	All		Equity		Fixed-Income		Commodity		Currency	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-4.309***	*-4.01*	-3.022**	*-2.37*	-0.653	*-0.41*	-3.474	*-0.80*	-6.603**	*-2.02*
LNSIZE	0.067***	*3.90*	0.074***	*3.59*	0.061	*1.41*	0.019	*0.19*	0.075	*0.99*
LNAGE	0.436***	*2.86*	0.160	*0.91*	-0.117	*-0.45*	0.304	*0.49*	0.661	*1.38*
HMARK	0.039	*0.66*	0.075	*1.09*	0.314***	*2.83*	0.075	*0.22*	0.190	*0.73*
IFEE	0.017***	*3.25*	0.021***	*3.39*	0.023***	*2.68*	0.057**	*2.00*	0.015	*0.68*
MFEE	0.121**	*2.34*	0.175***	*2.80*	0.093	*1.20*	-0.024	*-0.16*	-0.044	*-0.44*
LEVERAGED	0.101**	*2.10*	0.006	*1.32*	0.008	*1.44*	0.057	*1.36*	0.025	*1.37*
MIN(Million$)	-0.028**	*-2.17*	-0.027	*-1.53*	-0.049*	*-1.86*	-0.222*	*-1.87*	0.062	*0.89*
RESTRICTION	0.002**	*2.31*	0.002**	*2.22*	0.001	*0.90*	0.008	*0.89*	0.001	*0.14*
LOCKUP	0.007**	*2.11*	0.053	*0.56*	-0.134	*-0.74*	-1.105*	*-1.69*	-0.226	*-0.57*
AUDIT	-0.062	*-0.86*	0.058	*0.96*	0.067	*0.74*	-0.206	*-0.56*	0.051	*0.23*
PERCAPITAL	0.037	*0.76*	-0.015	*-0.18*	-0.107	*-1.03*	-0.489	*-1.46*	-0.210	*-0.96*
OPEN	-0.151**	*-2.59*	0.117*	*1.82*	0.095	*0.91*	0.513	*1.55*	0.275	*1.41*
OPENENDED	0.051	*1.08*	0.086	*1.36*	-0.004	*-0.05*	0.123	*0.27*	-0.089	*-0.32*
AE_OPTION	-0.021	*-0.37*	-0.026	*-0.34*	-0.088	*-0.64*	-0.238	*-0.52*	0.208	*0.60*
AF_OPTION	-0.040	*-0.54*	0.070	*0.60*	0.005	*0.05*	0.062	*0.15*	-0.096	*-0.38*
AC_OPTION	-0.078	*-0.43*	-0.275	*-1.32*	-0.184	*-0.69*	0.108	*0.19*	-0.397	*-1.39*
ACUR_OPTION	0.050	*0.52*	0.132	*1.02*	0.087	*0.55*	-0.031	*-0.07*	-0.019	*-0.08*
AE_WARRANT	-0.004	*-0.05*	0.075	*0.83*	-0.041	*-0.29*	0.092	*0.11*	-0.046	*-0.14*
AF_WARRANT	0.035	*0.39*	0.066	*0.48*	-0.044	*-0.35*	0.121	*0.12*	-0.240	*-0.62*
AE_OTHER	-0.173***	*-2.61*	-0.188**	*-2.29*	-0.187	*-1.09*	0.402	*0.82*	-0.081	*-0.30*
AF_OTHER	0.052	*0.69*	0.000	*0.00*	-0.052	*-0.48*	-0.013	*-0.02*	0.042	*0.11*
AC_OTHER	0.138	*0.98*	-0.017	*-0.07*	0.130	*0.50*	0.890*	*1.70*	0.258	*0.60*
ACUR_OTHER	0.021	*0.27*	-0.046	*-0.48*	0.038	*0.31*	-0.717	*-1.16*	0.200	*0.57*
Strategy Dummies	Yes		Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes		Yes	
Adjusted R^2	0.068		0.067		0.119		-0.043		0.043	
F-statistic	5.62		3.64		3.30		0.780		1.35	
Durbin-Watson	1.90		1.88		1.81		1.95		1.93	
N	3382		1841		838		245		363	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

Table 13. Continued

Dep.: APPRAISAL	All		Equity		Fixed-Income		Commodity		Currency	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-0.952*	*-1.75*	-1.068**	*-2.25*	0.874	*0.76*	-0.590	*-0.64*	-1.520**	*-2.00*
LNSIZE	0.049***	*7.32*	0.039***	*4.64*	0.056***	*4.19*	0.040*	*1.79*	0.049***	*3.12*
LNAGE	0.046	*0.61*	0.061	*0.90*	-0.228	*-1.39*	-0.032	*-0.27*	0.128	*1.24*
HMARK	0.012	*0.44*	0.005	*0.24*	0.136	*1.37*	-0.069	*-0.77*	0.019	*0.22*
IFEE	0.002	*0.82*	0.008***	*3.35*	-0.002	*-0.34*	-0.002	*-0.23*	-0.003	*-0.74*
MFEE	0.028**	*2.10*	0.048***	*2.85*	0.031*	*1.71*	-0.007	*-0.25*	-0.011	*-0.51*
LEVERAGED	0.031	*1.35*	0.000	*0.16*	0.001	*0.39*	0.027*	*1.94*	0.005	*0.70*
MIN(Million$)	-0.001	*-0.13*	0.012	*1.12*	-0.035*	*-1.84*	-0.090**	*-2.49*	0.010	*0.38*
RESTRICTION	0.002***	*3.40*	0.001**	*2.32*	0.001*	*1.78*	0.006**	*2.10*	0.000	*0.30*
LOCKUP	0.002	*1.24*	-0.001	*-0.04*	0.033	*0.45*	0.023	*0.26*	-0.008	*-0.10*
AUDIT	-0.010	*-0.33*	0.007	*0.33*	0.023	*0.51*	-0.054	*-0.91*	0.046	*0.89*
PERCAPITAL	0.013	*0.66*	-0.049*	*-1.81*	-0.076	*-1.23*	-0.161*	*-1.87*	-0.089	*-1.44*
OPEN	-0.111***	*-4.29*	0.035	*1.38*	0.002	*0.03*	0.096	*1.17*	0.011	*0.20*
OPENENDED	0.041	*1.53*	0.022	*0.91*	0.058	*0.88*	0.003	*0.02*	-0.014	*-0.15*
AE_OPTION	0.005	*0.25*	0.006	*0.25*	-0.092**	*-2.08*	-0.081	*-0.94*	0.012	*0.14*
AF_OPTION	-0.050	*-1.09*	0.035	*0.97*	-0.085	*-0.90*	0.210*	*1.94*	-0.086	*-1.06*
AC_OPTION	-0.003	*-0.07*	-0.071	*-1.38*	0.084	*1.09*	-0.125*	*-1.54*	-0.074	*-0.99*
ACUR_OPTION	-0.018	*-0.53*	0.003	*0.06*	0.016	*0.29*	-0.005	*-0.05*	0.075	*1.00*
AE_WARRANT	-0.052**	*-2.15*	-0.013	*-0.52*	0.102*	*1.96*	0.333	*1.63*	-0.083	*-0.81*
AF_WARRANT	0.033	*0.83*	0.040	*0.99*	-0.077	*-1.44*	-0.225	*-0.90*	-0.044	*-0.35*
AE_OTHER	-0.003	*-0.12*	-0.040	*-1.61*	0.029	*0.49*	0.040	*0.35*	-0.039	*-0.43*
AF_OTHER	-0.004	*-0.08*	-0.008	*-0.21*	-0.005	*-0.05*	-0.252	*-1.17*	0.127	*1.18*
AC_OTHER	0.010	*0.19*	0.021	*0.32*	-0.084	*-0.72*	0.447	*2.13*	-0.085	*-0.51*
ACUR_OTHER	-0.012	*-0.38*	-0.036	*-1.00*	0.038	*0.64*	-0.271	*-1.34*	-0.034	*-0.32*
Strategy Dummies	Yes		Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes		Yes	
Adjusted R^2	0.116		0.126		0.111		0.176		0.063	
F-statistic	9.34		6.32		3.12		2.16		1.53	
Durbin-Watson.	1.91		1.90		2.04		1.95		1.94	
N	3382		1841		838		245		363	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

Fixed-income specialized hedge funds seem to benefit from the use of other derivatives than options and warrants for both equity and currency as the use of these variables is associated with better performance of these funds. They also seem to benefit from the use of warrants issued with equity securities. This result is the opposite in the case of warrants issued with fixed-income and commodity derivatives other than options which are associated with poorer performance. In general, the asset specialized use of options has an impact on the Sharpe ratios of hedge funds but only in the case of equity specialized hedge funds. This finding is indeed interesting as the use of equity options as the only derivative instrument coincidences with higher incentive fees (see Table 5) in accordance with the first hypothesis concerning informed trading.

In relation to the study by Aragon (2007), it is an interesting finding that lockup period has a statistically significant affect on the alpha of a hedge fund only when using the sample of all hedge funds. Restriction period also has a statistically significant affect on the alpha of a hedge fund only when using the samples of all funds and equity specialized funds. Moreover, the result suggests that lockup period does not have statistically significant affect on the appraisal ratio of a hedge fund. These findings may imply that controlling for asset specialization of hedge funds can explain much of illiquidity risk premium in hedge fund returns.

7.5 Derivatives Use and Higher Moments of Hedge Fund Returns

Investigation of the impact of derivatives use on the higher moments of hedge fund returns can provide information on factors contrasting the results of different risk measures such as VaR and MVaR. Table 9 presents the results for the impact of derivatives use on skewness, excess kurtosis, and the Cornish-Fischer expansion with 99 % confidence level, which accounts for both skewness and excess kurtosis. The results are denoted for testing Hypothesis 5a.

The results in Table 14 support Hypothesis 5a. The regression statistics of the skewness of hedge fund return distribution on derivatives use suggest that the asset specialized use of options is generally associated with lower skewness although the result is statistically significant only for equity specialized and commodity specialized use of options. Specifically, equity specialized use of options has an impact of -0.153 on skewness. Commodity specialized use of options in turn has an impact of -0.395 on skewness. For commodity specialized hedge funds, the asset specialized use of options, for instance, has a statistically significant and negative (-0.215) impact on skewness of hedge fund returns. Clearly, the results for the association between the asset specialized use of options for commodity and equity show similar pattern to the case of asset specialized use of options and skewness of return distributions. The use of options for equity also decreases skewness of fixed-income specialized funds. Incentive fee and management fee, by contrast, positively increases the skewness for equity specialized funds. As hedge fund returns are found to exhibit negative skewness (see Brooks et al. 2002), these findings provide evidence that asset specialized use of options may be associated with the asymmetry.

Table 14. Regression Statistics of Higher Moments on Derivatives Use

This table presents the parameter estimates of cross-sectional analysis for Value-at-Risk estimates of hedge funds. The model for the cross-sectional analysis is the following (Model 2):

$$MEASURE_{ji} = \alpha + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \sum_{j=1}^{N} \beta_j DERIVATIVE_{ji} + e,$$

where $MEASURE_{ji}$ defines a measure *j* associated with higher moments of the returns of fund *i*; $CONTROL_{ji}$ defines an additional control variable *j* of fund *i*, and $DERIVATIVE_{ji}$ defines a dummy variable for the use of a derivative *j* by fund *i* (1 if the derivative is used, otherwise 0). Asset dummies include controls for assets and primary assets in which hedge funds report investing. This table also presents the Durbin-Watson test for the first-order serial correlation. The standard errors are White (1980) heteroskedasticity robust *t*-statistics are given in italics. *t*-statistics are given in italics. See Table 1 for definitions of the variables.

Dep.: SKEW	All		Equity		Fixed-Income		Commodity		Currency	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	0.348	*0.49*	-0.015	*-0.02*	2.986**	*2.38*	-1.705	*-1.08*	0.588	*0.37*
LNSIZE	-0.025*	*-1.93*	-0.007	*-0.52*	-0.038	*-1.13*	0.036	*0.86*	-0.042	*-1.14*
LNAGE	-0.062	*-0.61*	-0.060	*-0.52*	-0.338*	*-1.87*	0.183	*0.90*	-0.086	*-0.39*
HMARK	-0.092	*-1.40*	-0.081	*-1.10*	0.015	*0.06*	-0.101	*-0.60*	0.237	*1.17*
IFEE	0.013***	*3.02*	0.017***	*3.64*	-0.006	*-0.63*	0.003	*0.27*	0.001	*0.06*
MFEE	0.060	*1.83*	0.111**	*2.45*	0.043	*0.79*	-0.084*	*-1.78*	-0.012	*-0.26*
LEVERAGED	-0.018	*-0.39*	-0.062	*-1.11*	0.105	*0.96*	-0.128	*-0.67*	0.081	*0.53*
MINMillion$)	-0.026	*-1.12*	-0.020	*-1.48*	-0.150**	*-1.98*	-0.013	*-0.24*	0.053	*1.06*
RESTRICTION	0.002**	*2.45*	0.001	*1.03*	0.002	*0.80*	0.008**	*2.11*	0.002	*0.59*
LOCKUP	0.007*	*1.81*	0.001	*0.16*	0.004	*0.37*	0.013	*0.67*	-0.018	*-0.88*
AUDIT	-0.024	*-0.47*	0.010	*0.15*	0.065	*0.47*	-0.051	*-0.29*	0.040	*0.24*
PERCAPITAL	-0.072	*-1.52*	-0.011	*-0.20*	-0.245**	*-2.08*	-0.261**	*-2.27*	-0.169	*-1.36*
OPEN	-0.003	*-0.05*	0.108	*1.38*	0.018	*0.13*	0.020	*0.14*	-0.440**	*-2.66*
OPENENDED	-0.091*	*-1.91*	-0.020	*-0.34*	-0.272**	*-2.05*	0.083	*0.56*	-0.091	*-0.68*
AE_OPTION	-0.068	*-1.42*	-0.153**	*-2.57*	-0.253**	*-2.04*	0.285	*1.52*	0.171	*0.98*
AF_OPTION	-0.235**	*-2.52*	-0.011	*-0.09*	-0.230	*-1.45*	0.193	*0.99*	0.009	*0.05*
AC_OPTION	0.032	*0.32*	0.074	*0.57*	0.303	*1.64*	-0.396**	*-2.08*	0.085	*0.49*
ACUR_OPTION	0.052	*0.56*	-0.014	*-0.11*	0.083	*0.50*	-0.058	*-0.25*	-0.217	*-1.24*
AE_WARRANT	0.095*	*1.69*	0.111	*1.66*	0.100	*0.71*	-0.089	*-0.27*	-0.466	*-1.10*
AF_WARRANT	0.013	*0.13*	-0.084	*-0.59*	-0.059	*-0.41*	-0.255	*-0.69*	-0.047	*-0.10*
AE_OTHER	0.056	*1.09*	0.126*	*1.94*	-0.043	*-0.28*	-0.102	*-0.42*	-0.268	*-1.25*
AF_OTHER	-0.110	*-1.33*	-0.185*	*-1.79*	-0.095	*-0.59*	-0.183	*-0.62*	0.102	*0.41*
AC_OTHER	0.094	*0.78*	-0.076	*-0.42*	-0.219	*-0.89*	-0.003	*-0.01*	-0.273	*-1.14*
ACUR_OTHER	0.039	*0.50*	-0.037	*-0.35*	-0.037	*-0.21*	0.277	*1.02*	-0.077	*-0.36*
Strategy Dummies	Yes		Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes		Yes	
Adjusted R^2	0.12		0.08		0.218		0.062		0.119	
F-statistic	9.49		4.21		5.77		1.36		2.06	
Durbin-Watson	1.84		1.88		1.83		1.92		1.71	
N	3382		1841		838		245		363	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level

Table 14. Continued

Dep.: EXKURT	All		Equity		Fixed-Income		Commodity		Currency	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-7.553**	-	-7.510**	-	-	-	-4.470	*-0.89*	-7.267	-
LNSIZE	0.045	*0.67*	0.014	*0.20*	0.181	*0.95*	0.210	*1.37*	-0.003	-
LNAGE	1.590***	*3.34*	1.028**	*2.12*	2.054**	*2.05*	0.308	*0.50*	1.571*	*1.71*
HMARK	-0.877**	-	-0.306	-	-2.925	-	-0.401	*-0.65*	-1.413	-
IFEE	0.066***	*3.43*	0.082***	*4.14*	0.087*	*1.70*	0.038	*0.83*	0.139*	*1.85*
MFEE	0.058	*0.34*	0.180	*0.75*	-0.056	-	-0.137	*-0.77*	-0.320*	-
LEVERAGED	0.042	*0.17*	0.168	*0.63*	0.248	*0.45*	-0.053	*-0.07*	-1.342	-
MIN(Million$)	-0.279	*1.43*	-	-	1.140*	*1.69*	-0.014	*-0.06*	-0.239	-
RESTRICTION	0.003	*0.72*	0.000	*0.09*	0.018	*1.27*	0.048***	*3.16*	-0.011	-
LOCKUP	-0.022	-	-0.012	-	-0.042	-	0.069	*1.12*	0.136	*0.97*
AUDIT	-0.082	-	-0.384	-	0.651	*0.93*	-0.944	*-1.26*	-0.728	-
PERCAPITAL	0.400	*1.40*	0.107	*0.39*	0.840	*1.04*	-0.626	*-1.30*	-0.038	-
OPEN	-0.013	-	0.430	*1.02*	-0.790	-	-1.121***	*-2.81*	0.951	*1.14*
OPENENDED	0.258	*0.95*	-0.004	-	1.375	*1.46*	1.263**	*2.30*	0.641	*1.27*
AE_OPTION	0.497**	*2.03*	0.344	*1.15*	0.952	*1.37*	0.965	*1.36*	1.101	*1.39*
AF_OPTION	0.414	*0.69*	-0.233	-	0.426	*0.36*	1.416**	*2.02*	1.828**	*2.01*
AC_OPTION	-0.110	-	0.233	*0.43*	-0.481	-	-0.215	*-0.34*	-1.356	-
ACUR_OPTION	0.454	*0.95*	0.711	*1.16*	-0.392	-	-0.880	*-1.10*	0.061	*0.08*
AE_WARRANT	0.126	*0.49*	0.218	*0.74*	0.521	*0.68*	-1.814	*-1.48*	1.611	*0.63*
AF_WARRANT	-0.809	-	-0.073	-	-1.408	-	-0.678	*-0.53*	-3.184	-
AE_OTHER	0.140	*0.57*	0.060	*0.19*	0.491	*0.59*	0.417	*0.57*	0.743	*0.77*
AF_OTHER	0.194	*0.42*	-0.009	-	0.242	*0.23*	0.412	*0.51*	-0.936	-
AC_OTHER	-1.060	-	0.418	*0.53*	-1.858	-	-0.600	*-0.67*	1.443	*1.32*
ACUR_OTHER	-0.446	-	-0.189	-	0.052	*0.05*	0.633	*0.71*	1.681	*1.65*
Strategy Dummies	Yes		Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes		Yes	
Adjusted R-squared	0.12		0.05		0.175		0.094		0.123	
F-statistic	9.66		2.99		4.62		1.56		2.11	
Durbin-Watson stat.	1.83		1.94		1.71		2.13		1.90	
N	3382		1841		838		245		363	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

The use of equity options is found to have a positive impact on kurtosis in the sample of all funds but not in the subsamples, which are sorted according to the asset specialization of a hedge fund. In conclusion, the association between kurtosis of the return distribution of a hedge fund and the use of options is heterogeneous.

In Table 14, the asset specialized use of options for fixed-income, commodity, and currency has a statistically significant and negative impact on the Cornish-Fischer expansion which supports Hypothesis 5a. The coefficient for the asset specialized use of equity options is also negative but not statistically significant. Thus, the aggregate impact of the asset specialized option use is negative on the Cornish-Fischer expansion (increases the left tail of the return distribution) even though the impact on the excess kurtosis is not statistically significant. Intuitively, the test statistics of the Cornish-Fischer expansion on the option use implies that the asset specialized use of options is related to hidden risks in the left tail of the return distribution of a hedge fund. In the samples of all funds and equity specialized funds, higher incentive and management fees, instead, are rather associated with less fat left tails.

Table 14. Continued

Dep.: CF	All		Equity		Fixed-Income		Commodity		Currency	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-	*-3.84*	-	*-2.91*	-1.106	*-1.11*	-	*-2.35*	-1.331	*-0.99*
LNSIZE	-0.006	*-0.54*	0.005	*0.39*	-0.009	*-0.37*	0.037	*1.14*	-0.007	*-0.27*
LNAGE	-0.012	*-0.14*	-0.054	*-0.51*	-0.169	*-1.18*	-0.013	*-0.08*	-0.242	*-1.30*
HMARK	-	*-3.23*	-0.093	*-1.38*	-	*-2.79*	-0.117	*-0.83*	0.017	*0.08*
IFEE	0.010***	*2.65*	0.008**	*2.09*	-0.004	*-0.50*	0.006	*0.58*	0.008	*0.70*
MFEE	0.069**	*2.48*	0.093**	*2.15*	0.066*	*1.86*	-0.034	*-0.93*	0.029	*0.72*
LEVERAGED	-0.040	*-0.94*	-0.056	*-0.97*	0.197**	*2.06*	-0.054	*-0.31*	-0.024	*-0.19*
MIN(Million$)	0.034**	*1.98*	-0.008	*-0.67*	0.044	*0.98*	-0.043	*-0.85*	-0.047	*1.15*
RESTRICTION	0.001**	*2.13*	0.000	*0.28*	0.003*	*1.93*	0.007**	*2.03*	0.002	*0.80*
LOCKUP	0.003	*0.90*	-0.001	*-0.11*	0.003	*0.40*	0.017	*1.00*	-0.006	*-0.38*
AUDIT	-0.018	*-0.41*	-0.017	*-0.29*	0.099	*1.02*	0.063	*0.48*	0.080	*0.66*
PERCAPITAL	-0.031	*-0.80*	-0.040	*-0.76*	-0.078	*-0.96*	-	*-2.22*	-0.018	*-0.19*
OPEN	0.027	*0.54*	0.127	*1.58*	0.020	*0.22*	0.060	*0.50*	-0.178	*-1.58*
OPENENDED	-0.078*	*-1.89*	-0.036	*-0.61*	-0.159*	*-1.86*	0.030	*0.23*	-0.156	*-1.49*
AE_OPTION	-0.066	*-1.50*	-0.093	*-1.53*	-0.176*	*-1.70*	0.147	*0.96*	-0.020	*-0.16*
AF_OPTION	-	*-2.71*	0.025	*0.19*	-0.209**	*-2.04*	0.014	*0.09*	0.129	*0.84*
AC_OPTION	-0.070	*-0.84*	-0.050	*-0.44*	0.104	*0.76*	-	*-2.07*	0.023	*0.18*
ACUR_OPTION	0.066	*0.77*	-0.050	*-0.38*	0.095	*0.78*	-0.041	*-0.22*	-0.262*	*-1.67*
AE_WARRANT	0.095*	*1.88*	0.126**	*2.09*	0.065	*0.54*	-0.149	*-0.42*	-0.126	*-0.40*
AF_WARRANT	-0.037	*-0.38*	-0.017	*-0.11*	-0.184	*-1.60*	0.088	*0.24*	-0.038	*-0.11*
AE_OTHER	0.042	*0.88*	0.064	*1.00*	0.043	*0.34*	0.056	*0.26*	-0.198	*-1.14*
AF_OTHER	-0.115*	*-1.67*	-0.245**	*-2.49*	-0.104	*-0.85*	-0.362	*-1.35*	0.070	*0.33*
AC_OTHER	0.001	*0.01*	-0.090	*-0.51*	-0.294	*-1.46*	-0.117	*-0.45*	-	*-2.00*
ACUR_OTHER	0.038	*0.54*	0.002	*0.02*	-0.065	*-0.49*	0.349	*1.48*	-0.011	*-0.06*
Strategy Dummies	Yes		Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes		Yes	
Adjusted R-squared	0.092		0.065		0.215		0.087		0.095	
F-statistic	7.44		3.55		5.67		1.51		1.83	
Durbin-Watson stat.	1.90		1.94		1.93		1.99		1.76	
N	3382		1841		838		245		363	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

7.6 Complexity of Derivative Strategies and Hedge Fund Risk and Performance

Table 15 presents the results for the impact of complexity of derivative strategies on fund risk and performance characteristics assuming a linear relation between the complexity and dependent variables which describe hedge fund risk and performance characteristics. The results are denoted for testing Hypotheses 3, 4 and 5b. The complexity of a derivative strategy of a hedge fund does not have a statistically significant impact on its risk measured in terms of standard deviation, downside volatility, VaR, and MVaR Thus, Hypothesis 3 is not supported and the result is different from a closely related study by Chen (2009). The following reasons may explain the difference: the exclusion of funds of hedge funds from the sample, the inclusion of managed futures funds in the sample of this study, updated dataset, the use of complexity variable instead of binary variable of derivatives use, and the use of asset class dummies. The regression statistics suggest that the impact of the use of a more complex derivative strategy is negative and statistically significant on the performance, mean returns, and skewness of the returns of a hedge fund. The impact on the excess kurtosis of the returns of a hedge fund is positive and statistically significant.

The impact of the use of a more complex derivative strategy on the Cornish-Fischer expansion of the returns of a hedge fund is also negative and statistically significant. This result is also consistent with the results for skewness and kurtosis as higher kurtosis and lower skewness would decrease the value of this expansion as is also found in Table 15. To quantify the impact of a fatter left tail resulting from the use of 10 different derivatives for a hedge fund which has the mean standard deviation 4.13, the impact on the MVaR would be (-0.023*10*4.130 = -0.949) nearly -1 %. The impact of the use of 15 different derivatives would be (-0.023*15*4.130 = -1.425) nearly -1.5 %. Taken all in all, these statistics show evidence that a more complex derivative strategy of a hedge fund causes fatter left tails of its return distribution. This finding is consistent with the prediction of John et al. (2006) that managers prefer to employ complex derivative strategies which result in a higher probability of sustaining large losses. Consequently, the results support Hypothesis 5b, which implies that the more complex derivative strategy of a hedge fund is associated with fatter left tails of its return distribution. This result again contradicts the view of risk management motivated use of derivatives as evidenced by Chen's (2009). These results imply that those complex derivative strategies play a minor role in risk management and are rather related to managers' incentives to hide risk in the left tail.

The results for performance ratios are not consistent with Hypothesis 4 of this study and the findings of John et al. (2006). The impact of the complexity of the derivative strategy of a hedge fund is negative and statistically highly significant for the three performance measures used in this study: the Sharpe ratio, the Sharpe ratio with downside volatility, and appraisal ratio. The only performance measure for which the impact is not statistically significant is the alpha. Thus, the complexity of derivative strategy does not seem to have a strong impact on abnormal returns of a hedge fund alone. Nevertheless, the result is consistent with the empirical study by Tiu (2005). Tiu's (2005) results provide evidence for a negative relation between complexity of a hedge fund and its performance.

Table 15. The Impact of Complexity of Derivative Strategies on Hedge Fund Performance

This table presents the parameter estimates of the cross-sectional analysis of performance and risk estimates of hedge funds. The model for the cross-sectional analysis is the following (Model 3):

$$MEASURE_{ji} = \alpha + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \beta_1 COMPLEX_i + e,$$

where $MEASURE_{ji}$ defines a measure associated with higher moments *j* of fund *i*; $CONTROL_{ji}$ defines an additional control variable *j* of fund *i*, and $COMPLEX_i$ defines the number of different derivatives used by fund *i*. Asset dummies include controls for assets and primary assets in which hedge funds report investing. The sample includes 3,382 hedge funds. This table also presents the Durbin-Watson test for the first-order serial correlation. The standard errors are White (1980) heteroskedasticity robust. *t*-statistics are given in italics. See Table 1 for definitions of the variables.

	SHARPE		SHARPED		ALPHA		APPRAISAL	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-0.653**	*-2.33*	-0.608*	*-1.94*	-4.251***	*-3.97*	-0.962*	*-1.78*
LNSIZE	0.034***	*11.59*	0.036***	*10.33*	0.068***	*3.98*	0.049***	*7.37*
LNAGE	0.053	*1.33*	0.052	*1.17*	0.433***	*2.85*	0.048	*0.62*
HMARK	-0.001	*-0.05*	-0.022	*-0.97*	0.036	*0.60*	0.015	*0.54*
IFEE	0.000	*-0.09*	0.000	*0.19*	0.016***	*3.19*	0.002	*0.77*
MFEE	-0.001	*-0.09*	-0.002	*-0.24*	0.117**	*2.28*	0.028**	*2.14*
LEVERAGED	0.008	*0.60*	0.006	*0.35*	0.101**	*2.16*	0.034	*1.46*
MIN(Million$)	-0.036	*-0.95*	-0.017	*-0.32*	0.000**	*-2.08*	0.000	*0.06*
RESTRICTION	0.001***	*3.91*	0.002***	*3.99*	0.002**	*2.47*	0.002***	*3.41*
LOCKUP	0.002**	*2.14*	0.002**	*2.26*	0.007**	*2.11*	0.002	*1.18*
AUDIT	-0.011	*-0.78*	-0.011	*-0.63*	-0.057	*-0.78*	-0.011	*-0.38*
PERCAPITAL	0.009	*0.83*	0.003	*0.24*	0.039	*0.80*	0.014	*0.73*
OPEN	-0.050***	*-3.51*	-0.053***	*-3.29*	-0.151***	*-2.58*	-0.110***	*-4.30*
OPENENDED	0.014	*0.94*	0.011	*0.62*	0.048	*1.03*	0.041	*1.54*
COMPLEXITY	-0.009***	*-3.41*	-0.011***	*-3.64*	-0.017	*-1.54*	-0.014**	*-2.45*
Strategy Dummies	Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes	
Adjusted R^2	0.227		0.196		0.068		0.118	
F-statistic	23.55		19.77		6.59		11.28	
Durbin-Watson.	1.94		1.97		1.89		1.91	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

The regression statistics in Table 15 also imply that the performance loss in terms of the Sharpe ratio is associated with lower mean return but not with higher standard deviation. This characteristic is revealed by the statistically significant impact at the 1 % level of the complexity of the derivative strategy of a hedge fund on its mean return. Thus, the poorer performance associated with the complex derivative strategy is closely related to weaker returns of the users of complex derivative strategies.

The weakness of the impact of complexity of derivative strategy on the alpha of a hedge fund is different from the statistically significant impact of the complexity on the mean returns of a hedge fund. Indeed, the results are seemingly different when the empirical risk factors are considered. However, the result for the appraisal ratio should be weighted more as it also considers idiosyncratic risk (see Treynor et al. (1973). The idiosyncratic risk may be especially important for some hedge funds as they may not be well diversified and have focused investment strategies.

The results in Table 15 for the use of leverage and hedge fund performance suggest that the use of leverage would imply higher alpha of a hedge fund. This result is consistent with the prediction arising from Ross's (1977) study that skilled managers who know their type would use leverage. But the result is inconsistent with Schneeweis et al. (2005) who find that the use of leverage does not have an impact on hedge fund performance. The result in this study, however, should be treated with caution as the use of leverage does not have a statistically significant impact on the appraisal ratio of a hedge fund which considers idiosyncratic risk of a hedge fund. Intuitively, leveraged hedge funds may focus on more specific strategies which may require the use of leverage to boost returns while hedging systematic risk. This possibility could also explain the results.

When compared to the other hedge fund characteristics, the use of derivatives and the openness of a fund to the public is considered, the impact of using one more type of derivative on performance ratios is relatively small respect to whether a hedge fund is open to the public. Clearly, the openness of a hedge fund to public is related to weaker performance beside the complexity of the derivative strategy of a hedge fund. In summary, important factors which have an impact on hedge fund performance according to the results measured using the appraisal ratio and the Sharpe ratio of this study are the following:

1. size (positive)
2. restriction period (positive)
3. management fee (positive)
4. lockup period (positive)
5. complexity of derivative strategy (negative)
6. openness to public (negative)

Table 15. Continued

	MEAN		STDEV		D	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-2.737***	*-4.7*	3.850*	*1.68*	3.668**	*1.86*
LNSIZE	0.066***	*6.42*	-0.279***	*-6.85*	-0.235***	*-6.67*
LNAGE	0.298***	*3.78*	0.448	*1.32*	0.384	*1.34*
HMARK	-0.008	*-0.19*	-0.361**	*-2.59*	-0.343***	*-2.76*
IFEE	0.009***	*2.81*	0.047***	*4.33*	0.037***	*3.83*
MFEE	0.037	*1.44*	0.221*	*1.92*	0.177*	*1.80*
LEVERAGED	0.078**	*2.54*	0.549***	*5.39*	0.537***	*5.77*
MIN(Million$)	-0.295***	*-3.10*	-0.870***	*-3.16*	-0.690**	*-2.12*
RESTRICTION	0.002***	*4.62*	0.001	*0.29*	0.000	*-0.08*
LOCKUP	0.011***	*4.08*	0.034***	*3.84*	0.026***	*3.34*
AUDIT	-0.007	*-0.16*	-0.204	*-1.28*	-0.157	*-1.15*
PERCAPITAL	0.074**	*2.55*	0.148	*1.26*	0.263**	*2.54*
OPEN	-0.063	*-1.55*	-0.037	*-0.28*	-0.097	*-0.82*
OPENENDED	0.003	*0.10*	-0.029	*-0.28*	-0.048	*-0.51*
COMPLEXITY	-0.019***	*-2.85*	0.006	*0.22*	0.014	*0.55*
Strategy Dummies	Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes	
Adjusted R^2	0.171		0.279		0.304	
F-statistic	16.82		30.70		34.62	
Durbin-Watson	1.90		1.89		1.87	

	SKEW		EXKURT		CF		VAR		MVAR	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	0.289	*0.41*	-7.505**	*-2.37*	-2.282***	*-3.93*	-11.694**	*-2.25*	-15.292***	*-2.61*
LNSIZE	-0.08	*-1.87*	0.043	*0.64*	-0.005	*-0.50*	0.715***	*7.69*	0.646***	*5.93*
LNAGE	-0.056	*-0.55*	1.575***	*3.27*	-0.007	*-0.08*	-0.746	*-0.97*	0.157	*0.18*
HMARK	-0.102	*-1.54*	-0.903**	*-2.20*	-0.184***	*-3.43*	0.832***	*2.71*	0.076	*0.18*
IFEE	0.012***	*2.81*	0.071***	*3.66*	0.010	*2.47*	-0.101***	*-4.10*	-0.050	*-1.62*
MFEE	0.058*	*1.81*	0.049	*0.28*	0.068**	*2.49*	-0.476*	*-1.84*	-0.254	*-0.75*
LEVERAGED	-0.017	*-0.36*	0.041	*0.16*	-0.043	*-0.99*	-1.200***	*-5.27*	-1.368***	*-4.60*
MIN(Million$)	-0.245	*-1.05*	2.480	*1.28*	0.345**	*2.07*	1.730***	*2.86*	2.850***	*3.24*
RESTRICTION	0.002***	*2.66*	0.003	*0.65*	0.001**	*2.34*	0.001	*0.23*	0.002	*0.54*
LOCKUP	0.006	*1.59*	-0.016	*-0.76*	0.002	*0.65*	-0.068***	*-3.55*	-0.055**	*-2.19*
AUDIT	-0.030	*-0.60*	-0.091	*-0.39*	-0.023	*-0.53*	0.467	*1.30*	-0.122	*-0.31*
PERCAPITAL	-0.069	*-1.47*	0.387	*1.37*	-0.030	*-0.78*	-0.270	*-1.02*	-0.657**	*-2.06*
OPEN	0.003	*0.05*	-0.039	*-0.13*	0.031	*0.63*	0.023	*0.08*	0.540	*1.34*
OPENENDED	-0.080*	*-1.67*	0.220	*0.79*	-0.069*	*-1.66*	0.071	*0.30*	-0.155	*-0.50*
COMPLEXITY	-0.021*	*-1.78*	0.112*	*1.77*	-0.023**	*-2.56*	-0.032	*-0.53*	-0.061	*-0.84*
Strategy Dummies	Yes		Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes		Yes	
Adjusted R^2	0.115		0.119		0.088		0.291		0.227	
F-statistic	10.96		11.41		8.37		32.58		23.60	
Durbin-Watson.	1.83		1.82		1.90		1.89		1.85	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

Thus the results of this study suggest that there are five significant factors of hedge fund performance. The result for the size is very likely too naïve and the characteristic may vary for different strategies (see Getmansky 2005). The impact of the restriction and lockup periods may be related to the premium of illiquidity risk following the study by Aragon (2007). The impact of openness to the public can be explained simply; hedge funds which are open to the public focus more on marketing which aims to compensate for lower performance. The result for this characteristic may also relate to the transparency of a hedge fund (see Liang

2003). This result also implies that those hedge funds which are open to the public and therefore closer to small investors yield weaker performance. These results for performance are also otherwise similar to the results in Table 11 when applicable.

Many other factors than the complexity of derivative strategy also have an impact on the Cornish-Fischer expansion of the returns of a hedge fund. Specifically, the results in Table 15 suggests that both minimum investment and the restriction period of a hedge fund have a positive impact on the Cornish-Fischer expansion in the distribution of its returns, and thus these fund characteristics are associated with a less heavy left tail of the return distribution. The use of a high watermark and open to the public status in turn are associated with a heavier left tail of the return distribution of a hedge fund. A reasonable explanation for these results is protection against heavy losses resulting from investors' fire liquidations; a longer restriction period can be seen as a protection against changes in investor sentiment while the open-end status of a hedge fund to the public makes it more exposed to the changes. The result for minimum investment also implies that hedge funds for more wealthy investors have less heavy left tails of their return distributions. Better performance statistics associated with the restriction period are seen as a compensation for illiquidity risk (see, e.g., Aragon 2007).

Table 16 presents the regression statistics estimated using Model 4, which also accounts for the nonlinear impact of the complexity of the derivative strategy of a hedge fund on its risk and performance characteristics. The regression statistics suggest that the complexity has a statistically significant and nonlinear impact only on the performance of a hedge fund in terms of both the Sharpe ratio and the Sharpe ratio with downside volatility. Thus, the statistics imply that this impact is convex and it decreases with the complexity of the derivative strategy of a hedge fund. For instance, this characteristic implies that when the number of different derivatives used by a hedge fund is increased, for example, from the use of 1 to 2 derivatives, the impact is much more severe than when the number of different derivatives is increased from 5 to 6. Admittedly, the convex relation between the complexity of derivative strategy and hedge fund performance is not supported for appraisal ratio due to the test statistics in Table 16. This result implies that once the abnormal returns with idiosyncratic risk of a hedge fund are considered alone the relation is not asymmetric.

Table 16. Nonlinear Impact of Complexity of Derivative Strategies on Hedge Fund Performance

This table presents the parameter estimates of the cross-sectional analysis of performance and risk estimates of hedge funds. The model for the cross-sectional analysis is the following (Model 4):

$$MEASURE_{ji} = \alpha + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \beta_1 COMPLEX_i + \beta_2 (COMPLEX_i)^2 + e,$$

where $MEASURE_{ji}$ defines a measure associated with higher moments *j* of fund *i*; $CONTROL_{ji}$ defines an additional control variable *j* of fund *i*, and $COMPLEX_i$ defines the number of different derivatives used by fund *i*. The sample includes 3,382 hedge funds. This table also presents the Durbin-Watson test for the first-order serial correlation. The standard errors are White (1980) heteroskedasticity robust. *t*-statistics are given in italics. Asset dummies include controls for assets and primary assets in which hedge funds report to investing. See Table 1 for definitions of the variables.

	SHARPE		SHARPED		ALPHA		APPRAISAL	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
Fund Characteristics	Yes		Yes		Yes		Yes	
COMPLEXITY	-0.030***	*-4.37*	-0.038***	*-4.49*	-0.014	*-0.62*	-0.033**	*-2.41*
COMPLEXITY^2	0.002***	*3.63*	0.003***	*3.84*	0.000	*-0.14*	0.002	*1.33*
Strategy Dummies	Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes	
Adjusted R^2	0.230		0.200		0.068		0.119	
F-statistic	23.47		19.80		6.45		11.13	
Durbin-Watson	1.94		1.967		1.90		1.91	

	MEAN		STDEV		D	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*
Fund Characteristics	Yes		Yes		Yes	
COMPLEXITY	-0.020	*-1.37*	0.063	*1.11*	0.035	*0.68*
COMPLEXITY^2	0.000	*0.12*	-0.006	*-1.17*	-0.002	*-0.45*
Strategy Dummies	Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes	
Adjusted R^2	0.170		0.279		0.304	
F-statistic	16.44		30.05		33.84	
Durbin-Watson	1.90		1.90		1.87	

	SKEW		EXKURT		CF		VAR		MVAR	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
Fund Characteristics	Yes		Yes		Yes		Yes		Yes	
COMPLEXITY	-0.004	*-0.18*	0.136	*1.04*	-0.023	*-1.13*	-0.167	*-1.31*	-0.141	*-0.87*
COMPLEXITY^2	-0.002	*-0.73*	-0.002	*-0.20*	0.000	*-0.02*	0.013	*1.23*	0.008	*0.58*
Strategy Dummies	Yes		Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes		Yes	
Adjusted R^2	0.115		0.119		0.087		0.291		0.227	
F-statistic	10.73		11.16		8.18		31.89		23.08	
Durbin-Watson	1.83		1.82		1.90		1.89		1.86	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

To compare differences between live and dead hedge funds Models 3 and 4 are estimated for the samples of these hedge funds. Table 17 presents the results for Model 3 estimated for live hedge funds. The results for the complexity of the derivative strategy of a hedge fund and its performance are likewise similar to the model estimated for the full sample. The use of a more complex derivative strategy has a statistically highly significant and negative impact on the Sharpe ratio of a hedge fund. The impact is also statistically significant for the Cornish-Fischer expansion and skewness of the returns of a hedge fund. Nevertheless, the impact on excess kurtosis is not statistically significant as it is for the sample of all funds.

Table 17. Impact of Complexity of a Derivative Strategy on Live Hedge Funds

This table presents the parameter estimates of the cross-sectional analysis of the performance and risk estimates of hedge funds. The model for the cross-sectional analysis is the following (Model 3):

$$MEASURE_{ji} = \alpha + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \beta_1 COMPLEX_i + e,$$

where $MEASURE_{ji}$ defines a measure associated with higher moments j of fund i; $CONTROL_{ji}$ defines an additional control variable j of fund i, and $COMPLEX_i$ defines the number of different derivatives used by fund i. Asset dummies include controls for assets and primary assets in which hedge funds report investing. The sample includes 2,070 hedge funds. This table also presents the Durbin-Watson test for the first-order serial correlation. The standard errors are White (1980) heteroskedasticity robust. *t*-statistics are given in italics. See Table 1 for definitions of the variables.

	SHARPE		SHARPED		ALPHA		APPRAISAL	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-	*-3.21*	-0.686***	*-2.96*	-2.102	*-1.32*	-0.796*	*-1.79*
LNSIZE	0.033***	*9.45*	0.035***	*8.47*	0.068***	*3.16*	0.047***	*6.03*
LNAGE	0.050*	*1.82*	0.055*	*1.81*	0.110	*0.51*	0.024	*0.41*
HMARK	-0.040*	*-1.74*	-0.071**	*-2.13*	-0.004	*-0.05*	-0.069**	*-2.01*
IFEE	0.000	*0.05*	0.000	*0.2*	0.017***	*2.75*	0.002	*0.85*
MFEE	0.002	*0.32*	-0.002	*-0.25*	0.077	*1.34*	0.021	*1.56*
LEVERAGED	0.000	*0*	0.009	*0.41*	0.075	*1.28*	0.033	*1.17*
MIN(Million$)	-0.004	*-0.94*	-0.004	*-0.58*	0.000	*-1.29*	0.000	*0.55*
RESTRICTION	0.002***	*4.82*	0.003***	*4.75*	0.001	*1.16*	0.002***	*3.25*
LOCKUP	0.002**	*2.04*	0.002*	*1.79*	0.006	*1.53*	0.003	*1.48*
AUDIT	-0.023	*-1.24*	-0.018	*-0.74*	-0.086	*-0.78*	-0.029	*-0.80*
PERCAPITAL	0.009	*0.67*	-0.001	*-0.05*	0.062	*1.02*	0.012	*0.53*
OPEN	-0.035*	*-1.84*	-0.037*	*-1.73*	-	*-2.71*	-0.095***	*-2.97*
OPENENDED	0.021	*1.09*	0.016	*0.64*	0.101*	*1.78*	0.050	*1.55*
COMPLEXITY	-	*-3.07*	-0.012***	*-3.1*	-0.012	*-0.89*	-0.010*	*-1.87*
Strategy Dummies	Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes	
Adjusted R^2	0.291		0.234		0.087		0.20	
F-statistic	20.34		15.39		5.49		12.36	
Durbin-Watson	1.97		2.01		1.94		1.50	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

Table 17. Continued

Variable	MEAN Coef.	*t*	STDEV Coef.	*t*	D Coef.	*t*
C	-1.312*	*-1.8*	6.604*	*1.85*	6.317**	*2.22*
LNSIZE	0.060***	*4.87*	-0.269***	*-5.13*	-0.220***	*-4.98*
LNAGE	0.085	*0.85*	0.092	*0.18*	0.028	*0.07*
HMARK	-0.006	*-0.11*	-0.063	*-0.37*	-0.042	*-0.27*
IFEE	0.009**	*2.27*	0.053***	*3.83*	0.039***	*3.24*
MFEE	0.034	*1.19*	0.065	*0.49*	0.04	*0.37*
LEVERAGED	0.027	*0.70*	0.270**	*2.07*	0.254**	*2.22*
MINIMUM(Million$)	-0.026**	*-2.31*	-0.093***	*-2.69*	-0.090***	*-2.69*
RESTRICTION	0.003***	*3.65*	-0.001	*-0.56*	-0.002	*-0.99*
LOCKUP	0.010***	*3.21*	0.026**	*2.44*	0.022**	*2.28*
AUDIT	-0.007	*-0.12*	-0.236	*-0.96*	-0.066	*-0.36*
PERCAPITAL	0.067**	*1.98*	0.097	*0.65*	0.200*	*1.62*
OPEN	-0.087*	*-1.93*	0.037	*0.23*	-0.027	*-0.19*
OPENENDED	0.036	*0.93*	0.047	*0.36*	0.000	*0.000*
COMPLEXITY	-0.022***	*-2.72*	0.006	*0.18*	0.015	*0.49*
Strategy Dummies	Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes	
Adjusted R^2	0.207		0.255		0.304	
F-statistic	13.30		17.11		21.56	
Durbin-Watson	1.89		1.94		1.91	

Variable	SKEW Coef.	*t*	EXKURT Coef.	*t*	CF Coef.	*t*	VAR Coef.	*t*	MVAR Coef.	*t*
C	-0.147	*-0.14*	-2.398	*-0.54*	-3.022***	*-3.88*	-16.676**	*-2.06*	-21.150**	*-2.49*
LNSIZE	-0.022	*-1.36*	0.088	*1.06*	0.001	*0.10*	0.685***	*5.73*	0.605***	*4.37*
LNAGE	0.000	*0.00*	0.821	*1.30*	0.063	*0.58*	-0.128	*-0.11*	0.794	*0.66*
HMARK	-0.125	*-1.28*	-0.944	*-1.39*	-0.206***	*-2.81*	0.141	*0.37*	-0.422	*-0.80*
IFEE	0.012**	*2.43*	0.068***	*2.90*	0.008*	*1.83*	-0.114***	*-3.64*	-0.059	*-1.56*
MFEE	0.007	*0.19*	0.167	*0.89*	0.055*	*1.73*	-0.118	*-0.39*	0.172	*0.43*
LEVERAGED	0.049	*0.86*	0.244	*0.82*	0.020	*0.41*	-0.600**	*-2.08*	-0.576	*-1.51*
MINIMUM(Million$)	-0.022	*-1.01*	0.139	*0.81*	0.023	*1.47*	0.191**	*2.54*	0.271**	*2.43*
RESTRICTION	0.002	*1.53*	0.007	*1.16*	0.002**	*2.09*	0.006	*1.09*	0.009	*1.56*
LOCKUP	0.006	*1.34*	-0.028	*-1.01*	-0.001	*-0.15*	-0.051**	*-2.20*	-0.069**	*-2.05*
AUDIT	-0.097	*-1.38*	0.226	*0.67*	-0.009	*-0.17*	0.542	*0.98*	-0.142	*-0.29*
PERCAPITAL	-0.063	*-1.03*	0.348	*0.92*	-0.018	*-0.36*	-0.159	*-0.47*	-0.487	*-1.22*
OPEN	0.051	*0.72*	0.022	*0.05*	0.061	*0.92*	-0.174	*-0.49*	0.726	*1.36*
OPENENDED	-0.074	*-1.21*	0.075	*0.20*	-0.041	*-0.77*	-0.073	*-0.25*	-0.124	*-0.30*
COMPLEXITY	-0.026*	*-1.83*	0.124	*1.43*	-0.022**	*-1.97*	-0.036	*-0.46*	-0.042	*-0.44*
Strategy Dummies	Yes		Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes		Yes	
Adjusted R^2	0.150		0.150		0.110		0.274		0.228	
F-statistic	9.27		9.29		6.82		18.76		14.86	
Durbin-Watson	1.84		1.78		1.95		1.94		1.92	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

Table 18 presents the results for Model 3, which is estimated for the sample of dead hedge funds. In the case of dead hedge funds, the use of a more complex derivative strategy does not seem to have a statistically significant impact on the Sharpe ratio of a hedge fund but the impact on the Sharpe ratio with downside volatility is still statistically significant at the 10 % level. However, these results are significant only for a linear relation between the complexity of a derivative strategy of a hedge fund and its performance. The results for the Cornish-Fischer expansion are similar for both live and dead hedge funds. For dead hedge funds, however, a more complex derivative strategy does not seem to result as lower skewness but in turn as higher excess kurtosis, which differs from the characteristics of live hedge funds.

Table 18. Impact of the Complexity of a Derivative Strategy on Dead Hedge Funds

This table presents the parameter estimates of the cross-sectional analysis of the performance and risk estimates of hedge funds. The model for the cross-sectional analysis is the following (Model 3):

$$MEASURE_{ji} = \alpha + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \beta_1 COMPLEX_i + e,$$

where $MEASURE_{ji}$ defines a measure associated with higher moments *j* of fund *i*; $CONTROL_{ji}$ defines an additional control variable *j* of fund *i*, and $COMPLEX_i$ defines the number of different derivatives used by fund *i*. Asset dummies include controls for assets and primary assets in which hedge funds report investing. The sample includes 1,312 hedge funds. This table also presents the Durbin-Watson test for the first-order serial correlation. The standard errors are White (1980) heteroskedasticity robust. *t*-statistics are given in italics. See Table 1 for definitions of the variables.

	SHARPE		SHARPED		ALPHA		APPRAISAL	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-0.434	*-0.58*	-0.27	*-0.33*	-8.358***	*-4.28*	-1.224	*-0.87*
LNSIZE	0.034***	*6.41*	0.033***	*5.54*	0.064**	*2.47*	0.047***	*4.14*
LNAGE	0.021	*0.19*	0.011	*0.09*	1.072***	*3.84*	0.078	*0.38*
HMARK	0.022	*1.18*	0.009	*0.40*	0.055	*0.49*	0.064	*1.46*
IFEE	0.000	*-0.07*	0.001	*0.26*	0.013	*1.45*	0.001	*0.35*
MFEE	-0.009	*-0.52*	-0.003	*-0.16*	0.237*	*1.87*	0.038	*0.98*
LEVERAGED	0.022	*1.04*	0.006	*0.25*	0.137*	*1.68*	0.048	*1.12*
MINIMUM(Million$)	-0.008	*-1.11*	-0.002	*-0.21*	0.000**	*-1.97*	0.000*	*-1.84*
RESTRICTION	0.000	*1.20*	0.001	*1.59*	0.002**	*1.99*	0.001	*1.53*
LOCKUP	0.001	*0.87*	0.002	*1.31*	0.010	*1.51*	-0.001	*-0.35*
AUDIT	0.013	*0.55*	0.009	*0.32*	-0.032	*-0.34*	0.025	*0.50*
PERCAPITAL	0.013	*0.73*	0.015	*0.79*	-0.001	*-0.01*	0.024	*0.62*
OPEN	-0.080***	*-3.34*	-0.091***	*-3.30*	-0.070	*-0.61*	-0.157***	*-3.19*
OPENENDED	0.017	*0.67*	0.021	*0.73*	-0.041	*-0.53*	0.038	*0.79*
COMPLEXITY	-0.008	*-1.60*	-0.009*	*-1.75*	-0.037*	*-1.77*	-0.023*	*-1.79*
Strategy Dummies	Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes	
Adjusted R^2	0.133		0.132		0.040		0.045	
F-statistic	5.56		5.52		2.24		2.41	
Durbin-Watson	1.90		1.91		1.87		1.89	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

The impact of complexity of derivative strategy on the appraisal ratio is similar for both live and dead hedge funds. However, the results are different for live and dead hedge funds for alpha. Specifically, the impact of the complexity of derivative strategy on the alpha is statistically significant and negative for dead hedge funds but it is not statistically significant for live hedge funds. This result may imply that dead hedge funds have employed derivative strategies rather unsuccessfully. This poor skill is not related to their exposure to market-based risk factors. All in all, the results do not support Hypothesis 4 either for dead or live hedge funds.

Table 17. Continued

	MEAN		STDEV		D	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-5.027***	*-4.51*	2.279	*0.62*	1.897	*0.52*
LNSIZE	0.073***	*4.38*	-0.286***	*-4.72*	-0.251***	*-4.34*
LNAGE	0.659***	*4.19*	0.603	*1.05*	0.611	*1.10*
HMARK	-0.015	*-0.2*	-0.449*	*-1.95*	-0.414**	*-1.97*
IFEE	0.008	*1.43*	0.029	*1.60*	0.024	*1.52*
MFEE	0.081	*1.33*	0.602***	*2.66*	0.535**	*2.21*
LEVERAGED	0.125**	*2.52*	0.915***	*5.31*	0.879***	*5.41*
MINIMUM(Million$)	-0.042**	*-2.14*	-0.025	*-0.36*	0.035	*0.35*
RESTRICTION	0.002***	*2.69*	0.002	*0.91*	0.002	*0.85*
LOCKUP	0.013**	*2.59*	0.049***	*3.32*	0.034***	*2.64*
AUDIT	0.002	*0.03*	-0.150	*-0.75*	-0.237	*-1.14*
PERCAPITAL	0.086	*1.61*	0.163	*0.85*	0.293	*1.56*
OPEN	0.028	*0.32*	-0.034	*-0.14*	-0.072	*-0.32*
OPENENDED	-0.058	*-1.08*	-0.231	*-1.36*	-0.211	*-1.36*
COMPLEXITY	-0.014	*-1.11*	-0.002	*-0.06*	0.010	*0.23*
Strategy Dummies	Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes	
Adjusted R^2	0.125		0.319		0.311	
F-statistic	5.25		14.94		14.43	
Durbin-Watson	1.95		1.83		1.84	

	SKEW		EXKURT		CF		VAR		MVAR	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	0.084	*0.06*	-6.850	*-1.11*	-1.602	*-1.33*	-10.329	*-1.24*	-11.750	*-1.18*
LNSIZE	-0.033	*-1.48*	-0.065	*-0.57*	-0.017	*-0.87*	0.738***	*5.37*	0.710***	*4.22*
LNAGE	-0.037	*-0.17*	2.026*	*1.84*	-0.061	*-0.30*	-0.745	*-0.58*	0.028	*0.02*
HMARK	-0.131	*-1.35*	-0.431	*-0.91*	-	*-2.06*	1.030**	*2.02*	0.023	*0.03*
IFEE	0.016**	*1.98*	0.043	*1.23*	0.012	*1.65*	-0.059	*-1.49*	-0.031	*-0.60*
MFEE	0.211**	*2.57*	-0.228	*-0.49*	0.108	*1.70*	-	*-2.69*	-1.424**	*-2.07*
LEVERAGED	-0.085	*-1.04*	-0.478	*-1.05*	-0.145*	*-1.75*	-	*-5.16*	-	*-4.89*
MINIMUM(Million$)	-0.027	*-0.41*	0.578	*1.14*	0.065	*1.53*	0.015	*0.10*	0.200	*1.16*
RESTRICTION	0.002**	*2.16*	-0.001	*-0.10*	0.001	*1.15*	-0.004	*-0.58*	-0.005	*-0.97*
LOCKUP	0.007	*1.06*	0.010	*0.33*	0.007	*1.23*	-	*-3.14*	-0.042	*-1.06*
AUDIT	0.036	*0.47*	-0.510	*-1.46*	-0.049	*-0.68*	0.350	*0.77*	-0.238	*-0.37*
PERCAPITAL	-0.076	*-0.98*	0.456	*1.06*	-0.044	*-0.70*	-0.293	*-0.68*	-0.809	*-1.52*
OPEN	-0.108	*-1.08*	-0.455	*-1.03*	-0.027	*-0.34*	0.107	*0.20*	0.033	*0.05*
OPENENDED	-0.086	*-1.12*	0.487	*1.30*	-0.093	*-1.35*	0.479	*1.27*	0.127	*0.28*
COMPLEXITY	-0.021	*-1.11*	0.192**	*2.46*	-	*-1.96*	-0.008	*-0.09*	-0.122	*-1.04*
Strategy Dummies	Yes		Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes		Yes	
Adjusted R^2	0.060		0.082		0.041		0.323		0.227	
F-statistic	2.89		3.68		2.27		15.23		9.74	
Durbin-Watson	1.85		1.95		1.81		1.82		1.77	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

Table 19. Nonlinear Impact of the Complexity of a Derivative Strategy on Live Hedge Funds

This table presents the parameter estimates of the cross-sectional analysis of the performance and risk estimates of hedge funds. The model for the cross-sectional analysis is the following (Model 4):

$$MEASURE_{ji} = \alpha + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \beta_1 COMPLEX_i +$$
$$\beta_2 (COMPLEX_i)^2 + e,$$

where $MEASURE_{ji}$ defines a measure associated with higher moments *j* of fund *i*; $CONTROL_{ji}$ defines an additional control variable *j* of fund *i*, and $COMPLEX_i$ defines the number of different derivatives used by fund *i*. The sample includes 2,070 hedge funds. This table also presents the Durbin-Watson test for the first-order serial correlation. The standard errors are White (1980) heteroskedasticity robust. *t*-statistics are given in italics. Asset dummies include controls for assets and primary assets in which hedge funds report investing. See Table 1 for definitions of the variables.

	SHARPE		SHARPED		ALPHA		APPRAISAL	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
Fund Characteristics	Yes		Yes		Yes		Yes	
COMPLEXITY	-0.031***	*-3.710*	-0.042***	*-3.800*	0.001	*0.03*	-0.043***	*-3.21*
COMPLEXITY^2	0.002***	*3.070*	0.003***	*3.270*	-0.001	*-0.57*	0.003***	*2.96*
Strategy Dummies	Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes	
Adjusted R²	0.295		0.238		0.087		0.198	
F-statistic	20.23		15.39		5.37		12.32	
Durbin-Watson	1.97		2.01		1.94		1.95	

	MEAN		STDEV		D	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*
Fund Characteristics	Yes		Yes		Yes	
COMPLEXITY	-0.022	*-1.28*	0.057	*0.8*	0.028	*0.45*
COMPLEXITY^2	0.000	*0.00*	-0.005	*-0.81*	-0.001	*-0.21*
Strategy Dummies	Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes	
Adjusted R²	0.207		0.255		0.304	
F-statistic	13.00		16.74		21.07	
Durbin-Watson	1.89		1.94		1.91	

	SKEW		EXKURT		CF		VAR		MVAR	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
Fund Characteristics	Yes		Yes		Yes		Yes		Yes	
COMPLEXITY	-0.034	*-1.12*	0.245	*1.32*	-0.056**	*-2.14*	-0.155	*-0.96*	-0.213	*-0.99*
COMPLEXITY^2	0.001	*0.28*	-0.012	*-0.70*	0.003	*1.50*	0.012	*0.84*	0.017	*0.94*
Strategy Dummies	Yes		Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes		Yes	
Adjusted R²	0.149		0.150		0.111		0.274		0.228	
F-statistic	9.07		9.10		6.72		18.35		14.55	
Durbin-Watson	1.84		1.77		1.96		1.94		1.92	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

Table 19 reports the results for the nonlinear relation between the use of a more complex derivative strategy and the performance characteristics of live hedge funds. Table 20 in turn reports the results for dead hedge funds. The results suggest that the nonlinear relation between the use of a more complex derivative strategy of a hedge fund and its performance is also advocated for the samples of both live and dead hedge funds.

Table 20. Nonlinear Impact of the Complexity of a Derivative Strategy on Dead Hedge Funds

This table presents the parameter estimates of the cross-sectional analysis of the performance and risk estimates of hedge funds. The model for the cross-sectional analysis is the following (Model 4):

$$MEASURE_{ji} = \alpha + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \beta_1 COMPLEX_i +$$
$$\beta_2 (COMPLEX_i)^2 + e,$$

where $MEASURE_{ji}$ defines a measure associated with higher moments *j* of fund *i*; $CONTROL_{ji}$ defines an additional control variable *j* of fund *i*, and $COMPLEX_i$ defines the number of different derivatives used by fund *i*. The sample includes 1,312 hedge funds. This table also presents the Durbin-Watson test for the first-order serial correlation. The standard errors are White (1980) heteroskedasticity robust. *t*-statistics are given in italics. Asset dummies include controls for assets and primary assets in which hedge funds report investing. See Table 1 for definitions of the variables.

	SHARPE		SHARPED		ALPHA		APPRAISAL	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
Fund Characteristics	Yes		Yes		Yes		Yes	
COMPLEXITY	-0.028**	*-2.41*	-0.032**	*-2.52*	*-0.039*	*-0.88*	*-0.020*	*-0.73*
COMPLEXITY^2	0.002**	*2.07*	0.002**	*2.15*	*0.000*	*0.06*	*0.000*	*-0.10*
Strategy Dummies	Yes		Yes		*Yes*		*Yes*	
Time Dummies	Yes		Yes		*Yes*		*Yes*	
Asset Dummies	Yes		Yes		*Yes*		*Yes*	
Adjusted R²	0.135		0.134		0.039		0.045	
F-statistic	5.56		5.52		2.19		2.36	
Durbin-Watson	1.90		1.91		1.87		1.89	

	MEAN		STDEV		D	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*
Fund Characteristics	Yes		Yes		Yes	
COMPLEXITY	-0.011	*-0.40*	0.073	*0.75*	0.056	*0.61*
COMPLEXITY^2	0.000	*-0.11*	-0.007	*-0.95*	-0.005	*-0.60*
Strategy Dummies	Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes	
Adjusted R²	0.124		0.319		0.31	
F-statistic	5.13		14.62		14.11	
Durbin-Watson	1.95		1.83		1.84	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

Table 20. Continued

	SKEW		EXKURT		CF		VAR		MVAR	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
Fund Characteristics	Yes		Yes		Yes		Yes		Yes	
COMPLEXITY	0.037	*1.01*	0.024	*0.15*	0.019	*0.61*	-0.181	*-0.84*	-0.150	*-0.57*
COMPLEXITY^2	-0.006	*-1.61*	0.017	*1.23*	-0.005*	*-1.71*	0.017	*0.99*	0.003	*0.12*
Strategy Dummies	Yes		Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes		Yes	
Adjusted R^2	0.061		0.083		0.042		0.323		0.226	
F-statistic	2.91		3.62		2.29		14.91		9.52	
Durbin-Watson	1.85		1.95		1.81		1.82		1.77	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

The results in Tables 19 and 20 are markedly different for appraisal ratios. The test statistics show that the nonlinear impact of complexity of derivative strategy is statistically significant for live hedge funds. The same relation, however, is not statistically significant for dead hedge funds. One explanation for the result is that the evolution of hedge funds may have an impact on the result (live funds are biased toward new funds). The other explanation for the result is the possibility that live hedge funds have different performance characteristics associated with the use of derivatives in contrast to dead hedge funds.

Table 21 presents AIC and SIC statistics for the comparison of Models 3 and 4 which are presented in the previous tables. For these statistics, model having the lowest information criteria is considered having the best fit. Moreover, the values of SIC suffer more from the use of additional variables. For the conclusions of the analysis, the alpha statistics may be emphasized less due to their weak relation to the complexity of derivative strategy.

In general, the statistics in Table 21 suggest that the nonlinear relation is better suitable for the performance of a hedge fund and the complexity of its derivative strategy than the linear relation. In the case of dead hedge funds, the SIC statistic suggests that the linear relation is more suitable for the Sharpe ratio and the Sharpe ratio with downside volatility. The SIC statistic also implies that the relation between the appraisal ratio and the complexity of the derivative strategy is linear in contrast to that of the AIC statistic. Nevertheless, more emphasise may be given to the AIC statistics as the parameters in the analysis of nonlinear relation exhibit remarkably higher statistical significance. For the dependent variables examined other than performance ratios, the statistics suggest that the linear relation is more suitable between the complexity of the derivative strategy of a hedge fund and the risk measure.

Table 21. Information Criteria

This table presents the values of the Akaike Information Criterion (AIC) and the Schwarz Information Criterion (SIC) for the linear regression analyses presented in Tables 11, 13, and 14 (denoted as *Linear*) and the quadratic regression analyses presented in Tables 12, 15, and 16 (denoted as *Quadratic*). Panel A presents the results for the entire sample, Panel B presents the results for live hedge funds, and Panel C presents the results for dead hedge funds. See Table 1 for definitions of the variables.

Panel A.

	SHARPE	SHARPED	ALPHA	APPRAISAL	MEAN	STDEV
Linear						
AIC	0.5430	0.9683	**3.3946**	1.7641	**2.4234**	**5.1061**
SIC	0.6245	1.0498	**3.4762**	**1.8456**	**2.5050**	**5.1876**
Quadratic						
AIC	**0.5390**	**0.9639**	3.3952	**1.7635**	2.4240	5.1063
SIC	**0.6223**	**1.0472**	3.4786	1.8469	2.5074	5.1897
	DD	SKEW	EXKURT	CF	VAR	MVAR
Linear						
AIC	**4.8815**	**3.2141**	**6.6717**	**2.8965**	**7.2112**	**6.7265**
SIC	**4.9630**	**3.2956**	**6.7532**	**2.9780**	**7.2927**	**6.8081**
Quadratic						
AIC	4.8820	3.2145	6.6723	2.8971	7.2117	6.7267
SIC	4.9653	3.2978	6.7556	2.9804	7.2950	6.8101

Panel B.

	SHARPE	SHARPED	ALPHA	APPRAISAL	MEAN	STDEV
Linear						
AIC	0.4602	1.0122	**3.3670**	1.5199	**2.3153**	**5.1355**
SIC	0.5827	1.1347	**3.4895**	1.6424	**2.4378**	**5.258**
Quadratic						
AIC	**0.4558**	**1.0074**	3.3679	**1.5166**	2.3163	5.1362
SIC	**0.5810**	**1.1327**	3.4931	**1.6418**	2.4415	5.2614
	DD	SKEW	EXKURT	CF	VAR	MVAR
Linear						
AIC	**4.7925**	**3.2393**	**6.8178**	2.8594	**6.7519**	**7.2229**
SIC	**4.9150**	**3.3618**	**6.9403**	**2.9819**	**6.8744**	**7.3454**
Quadratic						
AIC	4.7935	3.2402	6.8185	**2.8592**	6.7525	7.2235
SIC	4.9187	3.3655	6.9437	2.9845	6.8778	7.3487

Panel C.

	SHARPE	SHARPED	ALPHA	APPRAISAL	MEAN	STDEV
Linear						
AIC	0.6617	0.8968	**3.4552**	**2.0639**	**2.5781**	**5.0875**
SIC	**0.8393**	**1.0744**	**3.6328**	**2.2415**	**2.7558**	**5.2651**
Quadratic						
AIC	**0.6593**	**0.8945**	3.4567	2.0654	2.5796	5.0884
SIC	0.8409	1.0761	3.6383	2.2469	2.7612	5.2699
	DD	SKEW	EXKURT	CF	VAR	MVAR
Linear						
AIC	**5.0300**	3.1909	**6.3739**	2.9878	**6.7111**	**7.2261**
SIC	**5.2077**	**3.3685**	6.5515	**3.1654**	6.8887	7.4037
Quadratic						
AIC	5.0313	**3.1898**	6.3745	**2.9870**	6.7120	7.2276
SIC	5.2129	3.3714	6.5561	3.1686	6.8935	7.4092

The results for the quantile regression analysis, which considers different segments of the risk and performance measures of the sample of hedge funds, are presented in Table 22. This analysis is devoted for complimenting the results of OLS analysis for Hypotheses 3, 4 and 5b. Therefore, the analysis is limited to the most relevant variables of performance and risk of a hedge fund used in this study. The variables are alpha, appraisal ratio, the Sharpe ratio, the Cornish-Fischer expansion, and standard deviation.

The results in Table 22 provide further support for Hypothesis 5b as a negative relation between the Cornish-Fischer expansion and the complexity of the derivative strategy of a hedge fund is still found. The results provide evidence for a negative relation between the complexity and hedge fund performance. Further, the results provide evidence for negative relation between the complexity and the alpha, a relation not seen using OLS analysis. The reason is also seen in Table 22. That is, only the lower segment of the performers in the hedge fund industry has a negative association with the complexity. This result implies that investing in a hedge fund using complex derivative strategy on average does not perform worse than the others. Instead, by investing in such a hedge fund one takes a higher risk the fund being even worse performer in the terms of abnormal returns. For appraisal and Sharpe ratios, the evidence suggests that the negative complexity-performance relation is also statistically significant for higher performance segments. The relation between risk and the complexity is not found to be significant, which is a characteristic to OLS analysis.

Table 22. Quantile Regression Analysis

This table presents the parameter estimates of the cross-sectional analysis of the performance and risk estimates of hedge funds. The model for the cross-sectional analysis is the following (Model 4):

$$MEASURE_{ji} = \alpha + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \beta_1 COMPLEX_i + e,$$

where $MEASURE_{ji}$ defines a measure associated with higher moments j of fund i; $CONTROL_{ji}$ defines an additional control variable j of fund i, and $COMPLEX_i$ defines the number of different derivatives used by fund i. Only the coefficient for the "COMPLEX" is presented for nine different quantiles. The sample includes 3,382 hedge funds. The standard errors and covariance are Huber-Sandwich heteroskedasticity robust. *t*-statistics are given in italics. Independent variables in the model also include, time dummies, strategy dummies, and asset dummies. Asset dummies include controls for assets and primary assets in which hedge funds report investing. See Table 1 for definitions of the variables.

Quantile	ALPHA		APPRAISAL		SHARPE		CF		STDEV	
	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
0.1	-0.022**	*-2.13*	-	*-3.50*	-0.004	*-1.11*	-0.019	*-1.15*	-0.021	*-1.40*
0.2	-	*-3.41*	-	*-3.22*	-0.003*	*-1.70*	-0.024**	*-2.16*	-0.020	*-1.40*
0.3	-0.016**	*-2.50*	-	*-3.05*	-0.004**	*-2.39*	-0.022**	*-2.52*	0.005	*0.30*
0.4	-0.017**	*-2.47*	-	*-2.62*	-0.004**	*-2.52*	-	*-2.94*	0.005	*0.30*
0.5	-0.011	*-1.59*	-0.007**	*-2.33*	-0.003	*-1.56*	-0.017**	*-2.33*	0.017	*0.89*
0.6	-0.011	*-1.50*	-0.005	*-1.45*	-0.004*	*-1.89*	-	*-2.78*	0.022	*1.01*
0.7	-0.008	*-0.94*	-0.003	*-1.00*	-0.004*	*-1.78*	-	*-2.66*	0.032	*1.10*
0.8	-0.005	*-0.49*	-0.008**	*-2.11*	-	*-2.86*	-0.013	*-1.33*	0.038	*1.06*
0.9	-0.023	*-1.61*	-0.013**	*-2.28*	-0.009**	*-2.34*	0.005	*0.35*	0.033	*0.50*

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

7.7 Further Analysis of the Complexity of Derivative Strategy and Hedge Fund Risk

Table 23 presents the regression statistics for the market-based and idiosyncratic components of hedge fund risk. The regression statistics presented in Table 23 clearly imply that the impact of the complexity of the derivative strategy of a hedge fund is related to the market-based risk of a hedge fund. This result is seen as the complexity has statistically significant association with the skewness, kurtosis, and the Cornish-Fischer expansion of market-based returns. Therefore, the result also suggests that the empirical model used in this study is capable of capturing nonnormality in hedge fund returns arising from their derivative strategies. The skewness and kurtosis of residual returns and the Cornish-Fischer expansion estimated on these returns are weakly explained by Model 3. Thus, the results apparently suggest that the complexity of derivative strategy increases the fat left tails for market-based returns rather than idiosyncratic returns.

Table 23. Market-Based and Idiosyncratic Components of Hedge Fund Risk

This table presents the parameter estimates of the cross-sectional analysis for the performance and risk estimates of hedge funds. The model for the cross-sectional analysis is the following (Model 3):

$$MEASURE_{ji} = \alpha + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \beta_1 COMPLEX_i + e,$$

where $MEASURE_{ji}$ defines a measure associated with higher moments *j* of fund *i*; $CONTROL_{ji}$ defines an additional control variable *j* of fund *i*, and $COMPLEX_i$ defines the number of different derivatives used by fund *i*. Asset dummies include controls for assets and primary assets in which hedge funds report investing. The sample includes 3,382 hedge funds. This table also presents the Durbin-Watson test for the first-order serial correlation. The standard errors are White (1980) heteroskedasticity robust. *t*-statistics are given in italic. See Table 1 for definitions of the variables.

	SSTDEV		SSKEW		SKURT		SCF	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	6.048***	*3.63*	0.484	*0.83*	-5.547**	*-2.14*	-0.544	*-0.59*
LNSIZE	-	*-6.40*	-0.013	*-1.62*	0.052*	*1.72*	-0.022**	*-2.06*
LNAGE	-0.127	*-0.53*	-0.114	*-1.38*	0.932**	*2.50*	-0.302**	*-2.33*
HMARK	-	*-3.39*	-0.005	*-0.14*	-0.208	*-1.55*	0.045	*1.00*
IFEE	0.022***	*2.96*	0.009***	*2.76*	0.023	*1.53*	0.001	*0.20*
MFEE	0.091	*1.15*	0.098***	*4.09*	-0.084	*-0.82*	0.092**	*2.49*
LEVERAGED	0.434***	*5.75*	-0.025	*-0.92*	-0.014	*-0.15*	-0.015	*-0.45*
MIN(Million$)	-	*-2.64*	0.014	*1.51*	-0.063**	*-2.34*	0.025**	*2.47*
RESTRICTION	0.000	*0.28*	0.002***	*3.74*	-0.002	*-1.51*	0.002***	*3.46*
LOCKUP	0.023***	*3.69*	0.000	*-0.23*	-0.011*	*-1.70*	0.002	*0.98*
AUDIT	-0.197*	*-1.70*	0.015	*0.46*	0.088	*0.75*	-0.009	*-0.22*
PERCAPITAL	0.110	*1.29*	-0.026	*-0.98*	0.057	*0.57*	-0.033	*-0.94*
OPEN	-0.042	*-0.44*	-0.025	*-0.74*	0.064	*0.48*	-0.034	*-0.72*
OPENENDED	-0.096	*-1.26*	-0.012	*-0.47*	-0.020	*-0.22*	-0.004	*-0.14*
COMPLEXITY	0.004	*0.22*	-0.015*	*-1.93*	0.064**	*2.00*	-0.026**	*-2.26*
Strategy Dummies	Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes	
Adjusted R^2	0.276		0.182		0.143		0.202	
F-statistic	30.34		18.15		13.80		20.41	
Durbin-Watson	1.89		1.89		1.89		1.90	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

It is also an interesting characteristic that Model 3 is better capable of explaining the Cornish-Fischer expansion estimated for market-based and idiosyncratic components than the expansion estimated for raw returns. The adjusted R-squares in the estimation of market-based and idiosyncratic components respectively are 0.202 and 0.105 against the adjusted R-square 0.088 in the estimation of raw returns. The results also suggest that higher management fees, higher minimum investment, and restriction periods can be important components which can reduce fat left tails of the distribution of market-based hedge returns.

Table 23. Continued

	RSTDEV		RSKEW		RKURT		ICF	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-1.119	*-0.67*	0.762	*1.62*	-	*-4.79*	0.849	*1.23*
LNSIZE	-	*-6.48*	-0.017*	*-1.88*	0.005	*0.12*	-0.014	*-1.06*
LNAGE	0.786***	*3.07*	-0.116*	*-1.69*	1.722***	*5.05*	-	*-4.67*
HMARK	-0.152	*-1.47*	-0.074	*-1.56*	-0.215	*-0.72*	-0.004	*-0.05*
IFEE	0.045***	*5.17*	0.007***	*2.84*	0.040***	*3.36*	-0.004	*-1.11*
MFEE	0.214**	*2.43*	0.018	*0.79*	0.028	*0.20*	0.007	*0.17*
LEVERAGED	0.325***	*4.33*	-0.027	*-0.79*	-0.020	*-0.11*	-0.015	*-0.31*
MIN(Million$)	-	*-3.48*	-0.026	*-1.35*	0.258*	*1.68*	-0.079*	*-1.71*
RESTRICTION	0.000	*0.29*	0.001	*1.55*	0.004	*1.43*	0.000	*-0.48*
LOCKUP	0.025***	*3.79*	0.004	*1.34*	-0.018	*-1.19*	0.007	*1.54*
AUDIT	-0.092	*-0.81*	-0.036	*-1.05*	-0.062	*-0.38*	-0.012	*-0.31*
PERCAPITAL	0.083	*0.95*	-0.031	*-0.87*	0.373*	*1.74*	-0.110	*-1.73*
OPEN	-0.004	*-0.04*	-0.024	*-0.62*	-0.104	*-0.55*	0.007	*0.13*
OPENENDED	0.062	*0.80*	-0.035	*-0.97*	0.222	*1.07*	-0.077	*-1.29*
COMPLEXITY	0.000	*0.00*	-0.002	*-0.23*	0.016	*0.44*	-0.005	*-0.46*
Strategy Dummies	Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes	
Adjusted R^2	0.266		0.079		0.105		0.105	
F-statistic	28.82		7.57		10.01		10.06	
Durbin-Watson	1.88		1.85		1.79		1.76	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

7.8 Complexity of Derivative Strategy and Management of Hedge Fund Portfolios

To investigate the use of derivatives in the management of hedge funds' portfolios this study tests Hypotheses 3, 4, and 5b using the samples of hedge funds and funds of hedge funds. Table 24 presents the results for funds of funds. In contrast to the results for hedge funds, the results for funds of hedge funds provide support for Hypothesis 3. The complexity of derivative strategy has a statistically significant and negative impact on the standard deviation of the returns of a fund of hedge funds implying that the complexity is associated with less risk. The statistics for the standard deviation of both residual and market-based returns suggest that the impact can be related to both market-based and idiosyncratic components of the returns. The results for downside volatility, VaR and MVaR provide complimentary evidence for this complexity-risk relation. Thus, only the results for funds of hedge funds are consistent with the risk management use of derivative found by Chen (2008), who does not distinguish between funds of hedge funds and hedge funds in multivariate analysis. This seemingly explains different results for multivariate analysis of hedge funds, other than funds of hedge funds, from the study by Chen (2009). In conclusion, only funds of hedge funds seem to use derivatives consistent with risk management. This is very reasonable as funds of funds may need to hedge exchange rate risk from foreign currency denominated funds. They are also able to monitor risk characteristics of hedge funds in their portfolios and hedge some of the risk exposures if they desire to do so.

The results in Table 24 do not provide any statistically significant evidence that the complexity of the derivative strategy of a fund of hedge funds affects its performance. Thus, the results do not provide support for Hypothesis 4. They are also different from hedge funds for which a negative and statistically significant relation is found for performance and the complexity of derivative strategy.

Table 24. Complexity of Derivative Strategy and Funds of Hedge Funds

This table presents the parameter estimates of the cross-sectional analysis for the performance and risk estimates of funds of hedge funds. The model for the cross-sectional analysis is the following (Model 3):

$$MEASURE_{ji} = \alpha + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \beta_1 COMPLEX_i + e,$$

where $MEASURE_{ji}$ defines a measure associated with higher moments j of fund i; $CONTROL_{ji}$ defines an additional control variable j of fund i, and $COMPLEX_i$ defines the number of different derivatives used by fund i. The sample includes 761 funds of hedge funds. This table also presents the Durbin-Watson test for the first-order serial correlation. The standard errors are White (1980) heteroskedasticity robust. t-statistics are given in italic. See Table 1 for definitions of the variables.

	SHARPE		SHARPED		ALPHA		APPRAISAL	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-0.779**	*-2.53*	-0.813**	*-2.63*	-1.858	*-1.54*	-1.615**	*-2.20*
LNSIZE	0.037***	*8.11*	0.036***	*7.44*	0.062***	*3.79*	0.055***	*5.70*
LNAGE	0.045	*0.97*	0.052	*1.11*	0.118	*0.67*	0.134	*1.27*
HMARK	-0.017	*-0.88*	-0.010	*-0.50*	-0.015	*-0.30*	-0.062*	*-1.77*
IFEE	0.001	*1.09*	0.002	*1.23*	0.010**	*2.23*	0.005**	*2.33*
MFEE	-0.044***	*-3.64*	-0.041***	*-3.34*	-0.055	*-1.21*	-0.060**	*-2.46*
LEVERAGED	-0.016	*-1.06*	-0.017	*-1.01*	0.006	*0.11*	-0.004	*-0.12*
MIN(Million$)	0.000	*0.69*	0.000	*1.06*	0.000	*0.14*	0.000	*0.24*
RESTRICTION	0.002***	*7.87*	0.002***	*6.85*	0.001*	*1.66*	0.002***	*4.76*
LOCKUP	0.000	*-0.20*	0.000	*-0.20*	-0.009***	*-2.79*	-0.005*	*-1.84*
AUDIT	0.014	*0.86*	0.013	*0.70*	0.061	*1.04*	0.036	*1.07*
PERCAPITAL	0.050***	*3.22*	0.059***	*3.34*	-0.024	*-0.50*	0.041	*1.33*
OPEN	-0.028*	*-1.78*	-0.016	*-0.84*	-0.053	*-1.08*	-0.035	*-1.13*
OPENENDED	-0.022	*-1.34*	-0.020	*-1.11*	0.002	*0.05*	-0.027	*-0.82*
COMPLEXITY	0.000	*0.15*	0.000	*-0.23*	-0.002	*-0.39*	-0.003	*-1.06*
Time Dummies	Yes		Yes		Yes		Yes	
Adjusted R^2	0.378		0.319		0.152		0.259	
F-statistic	18.09		14.17		6.03		10.86	
Durbin-Watson	1.78		1.77		2.01		2.00	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

Table 24. Continued

	MEAN		STDEV		D	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-0.936	*-1.02*	2.826	*0.76*	3.180	*1.03*
LNSIZE	0.051***	*4.82*	-0.190***	*-4.63*	-0.185***	*-4.77*
LNAGE	0.057	*0.42*	0.494	*0.89*	0.428	*0.95*
HMARK	0.068*	*1.73*	0.092	*0.48*	-0.001	*-0.01*
IFEE	0.004	*1.18*	-0.001	*-0.08*	0.006	*0.37*
MFEE	-0.061**	*-2.05*	0.289**	*2.51*	0.244**	*2.38*
LEVERAGED	0.061*	*1.72*	0.361***	*2.66*	0.384***	*3.02*
MIN(Million$)	-0.001	*-0.18*	-0.004	*-0.15*	-0.030	*-1.47*
RESTRICTION	0.002***	*3.49*	-0.008***	*-3.93*	-0.007***	*-4.00*
LOCKUP	-0.001	*-0.40*	0.002	*0.27*	0.001	*0.15*
AUDIT	0.040	*1.00*	-0.150	*-1.10*	-0.205	*-1.42*
PERCAPITAL	0.059	*1.53*	0.226	*1.39*	0.212	*1.42*
OPEN	-0.071**	*-2.13*	-0.194	*-1.43*	-0.266**	*-2.19*
OPENENDED	0.029	*0.87*	0.204*	*1.74*	0.185	*1.65*
COMPLEXITY	-0.002	*-0.67*	-0.040***	*-3.48*	-0.032***	*-2.90*
Time Dummies	Yes		Yes		Yes	
Adjusted R-squared	0.172		0.277		0.274	
F-statistic	6.86		11.78		11.62	
Durbin-Watson stat.	1.90		1.97		1.89	

	SKEW		EXKURT		CF		VAR		MVAR	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-2.475	-	-	-	-	-	-7.511	-	-6.587	-
LNSIZE	-0.035	-	-	-	0.009	*0.37*	0.494***	*5.13*	0.713***	*5.36*
LNAGE	0.387*	*1.67*	1.311	*1.25*	0.038	*0.21*	-1.091	-	-1.833	-
HMARK	0.245**	*2.22*	0.124	*0.17*	0.282**	*2.55*	-0.147	-	0.869	*1.20*
IFEE	0.002	*0.25*	-	-	-0.006	-	0.007	*0.19*	-0.060	-
MFEE	0.064	*0.96*	-	-	0.153**	*2.38*	-	-	-0.337	-
LEVERAGED	0.002	*0.03*	-	-	0.059	*0.76*	-0.778**	-	-0.967**	-
MIN(Million$)	0.058*	*1.72*	0.000	*0.00*	0.058	*1.20*	0.009	*0.13*	0.349	*1.23*
RESTRICTION	0.000	-	0.001	*0.14*	-0.001	-	0.020***	*4.25*	0.014**	*2.42*
LOCKUP	0.009	*1.13*	-	-	0.014*	*1.65*	-0.006	-	0.054	*1.20*
AUDIT	0.037	*0.38*	-	-	0.067	*0.83*	0.387	*1.22*	0.720	*1.53*
PERCAPITAL	-0.024	-	0.344	*0.62*	0.082	*0.89*	-0.468	-	0.105	*0.17*
OPEN	0.247**	*2.20*	0.634	*0.98*	0.064	*0.59*	0.379	*1.20*	0.725	*1.17*
OPENENDED	-0.020	-	0.466	*0.89*	0.048	*0.48*	-0.447	-	-0.164	-
COMPLEXITY	-	-	0.037	*0.91*	-0.009	-	0.091***	*3.46*	0.072*	*1.84*
Time Dummies	Yes		Yes		Yes		Yes		Yes	
Adjusted R-squared	0.055		0.083		0.068		0.293		0.186	
F-statistic	2.65		3.55		3.07		12.69		7.45	
Durbin-Watson stat.	1.98		1.92		1.92		1.97		1.90	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

Table 24. Continued

	SSTDEV		SSKEW		SKURT		SCF	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	3.617	*1.27*	-2.131	*-1.97*	-4.420	*-1.30*	-2.730**	*-2.20*
LNSIZE	-0.118***	*-3.99*	-0.039**	*-2.36*	0.081	*1.47*	-0.047**	*-2.26*
LNAGE	0.122	*0.29*	0.369**	*2.29*	0.571	*1.15*	0.138	*0.77*
HMARK	0.111	*0.74*	0.119**	*2.19*	0.021	*0.11*	0.083	*1.20*
IFEE	-0.005	*-0.41*	0.004	*0.90*	-0.001	*-0.06*	0.003	*0.50*
MFEE	0.158**	*1.99*	0.077	*1.64*	0.050	*0.30*	0.045	*0.67*
LEVERAGED	0.245**	*2.44*	0.008	*0.19*	-0.005	*-0.04*	0.007	*0.13*
MIN(Million$)	-0.012	*-0.67*	0.009	*1.13*	-0.062**	*-2.08*	0.022**	*2.05*
RESTRICTION	-0.006***	*-3.67*	0.000	*-0.11*	0.001	*0.41*	0.000	*-0.33*
LOCKUP	0.005	*0.81*	0.001	*0.26*	0.009	*0.90*	-0.001	*-0.37*
AUDIT	-0.088	*-0.89*	-0.025	*-0.50*	-0.235	*-1.28*	0.037	*0.56*
PERCAPITAL	0.141	*1.20*	-0.033	*-0.68*	-0.064	*-0.40*	-0.010	*-0.16*
OPEN	-0.177*	*-1.89*	0.058	*1.10*	0.109	*0.68*	0.017	*0.29*
OPENENDED	0.119	*1.32*	-0.004	*-0.09*	0.217	*1.53*	-0.054	*-1.09*
COMPLEXITY	-0.032***	*-3.81*	0.004	*0.96*	-0.003	*-0.21*	0.003	*0.69*
Time Dummies	Yes		Yes		Yes		Yes	
Adjusted R^2	0.266		0.073		0.103		0.097	
F-statistic	11.22		3.22		4.22		4.02	
Durbin-Watson	1.93		1.91		1.98		1.99	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

The results in Table 24 also provide support for Hypothesis 5b as the complexity of derivative strategy has a statistically significant impact on the Cornish-Fischer expansion of residual returns of a fund of hedge funds. But the relation is statistically significant only at the 10 % level. In line with Hypothesis 5b, the results suggest that the complexity has a negative relation with the skewness of the distribution of residual returns of a fund of hedge funds. The result is different from hedge funds as the complexity of their derivative strategy is rather related to market-based returns while for funds of hedge funds it is related to idiosyncratic risk.

Table 24. Continued

	RSTDEV		RSSKEW		RKURT		ICF	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	0.022	*0.01*	0.614	*0.56*	-3.249	*-0.80*	-0.986	*-0.71*
LNSIZE	-0.145***	*-4.71*	-0.027	*-1.12*	-0.157	*-1.19*	0.017	*0.39*
LNAGE	0.604	*1.57*	-0.058	*-0.35*	0.937	*1.47*	-0.262	*-1.24*
HMARK	0.012	*0.09*	0.140	*1.54*	-0.098	*-0.17*	0.126	*0.76*
IFEE	0.003	*0.29*	-0.004	*-0.79*	0.020	*0.73*	-0.008	*-0.94*
MFEE	0.244***	*2.68*	0.117**	*2.38*	-0.654**	*-2.11*	0.239***	*2.72*
LEVERAGED	0.266***	*2.73*	0.018	*0.25*	0.121	*0.33*	-0.015	*-0.14*
MIN(Million$)	0.002	*0.06*	0.052*	*1.81*	0.112	*0.69*	0.012	*0.35*
RESTRICTION	-0.005***	*-3.83*	-0.001	*-0.53*	0.006	*1.15*	-0.002	*-1.08*
LOCKUP	-0.003	*-0.41*	0.007	*1.09*	-0.048	*-1.40*	0.016*	*1.81*
AUDIT	-0.114	*-1.13*	0.048	*0.60*	-0.474	*-1.13*	0.146	*1.07*
PERCAPITAL	0.163	*1.35*	0.032	*0.41*	0.524	*1.20*	-0.099	*-0.77*
OPEN	-0.103	*-0.96*	0.242***	*2.81*	0.559	*1.27*	0.047	*0.39*
OPENENDED	0.156	*1.85*	-0.010	*-0.13*	0.393	*0.92*	-0.099	*-0.87*
COMPLEXITY	-0.023***	*-2.78*	-0.020***	*-3.21*	0.013	*0.47*	-0.018*	*-1.85*
Time Dummies	Yes		Yes		Yes		Yes	
Adjusted R^2	0.260		0.029		0.056		0.041	
F-statistic	10.90		1.83		2.68		2.22	
Durbin-Watson	2.01		1.95		1.89		1.85	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

Table 25 presents the results for the sample of hedge funds analysed using Model 4. The results are denoted to test whether investing in other funds alters the relation between the complexity of the derivative strategy of a hedge fund and its performance and risk. The results suggest that investing in other funds is associated with weaker performance. This result is evinced by the Sharpe ratio, Sharpe ratio with downside volatility, and alpha. Investing in other funds results as -0.199 % lower monthly alpha. However, the result for the alpha is statistically significant only at the 10 % level.

Table 25. Complexity of Derivative Strategy and Investing in Other Funds

This table presents the parameter estimates of the cross-sectional analysis for the performance and risk estimates of hedge funds. The model for the cross-sectional analysis is the following (Model 4):

$$MEASURE_{ji} = \alpha_i + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \beta_1 COMPLEX_i,$$

$$+\beta_2 COMPLEX_i * OTHER_i + \beta_3 OTHER_i + e_i$$

where $MEASURE_{ji}$ defines a measure associated with higher moments *j* of fund *i*; $CONTROL_{ji}$ defines an additional control variable *j* of fund *i*; $COMPLEX_i$ defines the number of different derivatives used fund *i*, and $OTHER_i$ defines defines a dummy variable for investing in other funds by fund *i* (1 if the fund invests in other funds, and 0 otherwise). Asset dummies include controls for assets and primary assets in which hedge funds report investing. The sample includes 3,382 hedge funds. This table also presents the Durbin-Watson test for the first-order serial correlation. The standard errors are White (1980) heteroskedasticity robust. *t*-statistics are given in italic. See Table 1 for definitions of the variables.

	SHARPE		SHARPED		ALPHA		APPRAISAL	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
Fund Characteristics	Yes		Yes		Yes		Yes	
COMPLEXITY	-0.010***	*-3.65*	-0.013***	*-3.90*	-0.017	*-1.44*	-0.017***	*-2.77*
COMPLEXITY*OF	0.011**	*2.08*	0.014**	*2.30*	0.013	*0.65*	0.022**	*2.48*
OF	-0.057*	*-1.87*	-0.082**	*-2.16*	-0.199*	*-1.73*	-0.056	*-1.10*
Strategy Dummies	Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes	
Adjusted R²	0.227		0.197		0.068		0.118	
F-statistic	22.59		19.00		6.35		10.88	
Durbin-Watson	1.94		1.97		1.89		1.91	
	MEAN		STDEV		D		SKEW	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
Fund Characteristics	Yes		Yes		Yes		Yes	
COMPLEXITY	-0.018**	*-2.56*	0.027	*0.96*	0.030	*1.16*	-0.020*	*-1.66*
COMPLEXITY*OF	0.013	*0.93*	-0.101**	*-2.13*	-0.088*	*-1.69*	0.022	*0.94*
OF	-0.269***	*-3.74*	-0.270	*-1.04*	-0.074	*-0.30*	-	*-3.23*
Strategy Dummies	Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes	
Adjusted R²	0.173		0.280		0.305		0.117	
F-statistic	16.36		29.64		33.28		10.71	
Durbin-Watson	1.90		1.90		1.87		1.83	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

The results for the complexity of derivative strategy and hedge fund performance do not change significantly when Model 4 is used instead of Model 3. However, the coefficient on the joint effect of the complexity of the derivative strategy and investing in other funds is negative and statistically significant for the Sharpe ratio, Sharpe ratio with downside volatility and the appraisal ratio. Practically, the joint effect cancels out the negative relation between the complexity and hedge fund performance. For example, when a hedge fund invests in other funds, the use of 10 different derivatives affects the appraisal ratio positively by 0.050 (-0.017*10+0.022*10). The results compliments those presented for funds of hedge funds and hedge funds in Tables 15 and 24. In these tables, the complexity-performance relation is found to be negative and significant only for the sample of hedge funds. Accordingly, it is even more evident that the complexity of the derivative strategy of a hedge fund affects only those hedge funds which do not invest in other hedge funds.

The complexity-performance relation is not the only characteristic found in Table 25 complimenting the differences for funds of hedge funds and hedge funds. The complexity-risk relation is also altered by the consideration of funds investing in other funds. While the analyses presented earlier in this study suggests that there is no evidence for the complexity of the derivative strategy of a hedge fund to be consistent with risk management, the evidence clearly suggest that once a hedge fund invests in other funds the complexity is associated with lower risk. The joint coefficient of the complexity and investing in other funds is negative (positive) and statistically significant for the standard deviation and downside volatility (the VaR and MVaR measures). Moreover, the results suggest that the negative standard deviation-complexity relation is related to the residual return of a hedge fund. In conclusion, Hypothesis 3 is supported only when investing in other funds.

Investing in other funds also alters the relation between the left tail of the return distribution of a hedge fund and the complexity of its derivative strategy. While the complexity increases the left tail of the return distribution of market-based returns of a hedge fund, investing in other hedge funds mitigates the relation. In fact, the joint effect of the use of 10 different derivatives increases the value of the Cornish-Fischer expansion of market-based hedge fund returns by 0.120 (-0.033*10 + 0.045*10). Thus, the relation between complexity and the left tail of the return distribution of market-based returns is significantly different once a hedge fund invests in other hedge funds. Yet the evidence is different for funds of hedge funds for which the complexity seems to increase the left tail of the returns distributions of their residual returns, but not that of their ordinary returns.

Summarizing the results in Tables 24 and 25, derivatives use is more beneficial for investors when derivatives are used in the management of hedge fund portfolios. In relation to ordinary hedge funds, their use is also consistent with risk management by funds of hedge funds and funds which invest in other funds.

Table 25. Continued

	EXKURT		CF		VAR		MVAR	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
Fund Characteristics	Yes		Yes		Yes		Yes	
COMPLEXITY	0.114*	*1.69*	-0.023**	*-2.44*	-0.080	*-1.27*	-0.104	*-1.33*
COMPLEXITY*OF	0.019	*0.18*	0.023	*1.24*	0.248**	*2.28*	0.346**	*2.51*
OF	-0.456	*-0.80*	-	*-3.29*	0.359	*0.61*	-1.673**	*-2.19*
Strategy Dummies	Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes	
Adjusted R²	0.119		0.090		0.293		0.228	
F-statistic	10.92		8.25		31.41		22.67	
Durbin-Watson	1.82		1.90		1.89		1.86	
	RSTDEV		RSKEW		RKURT		ICF	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
Fund Characteristics	Yes		Yes		Yes		Yes	
COMPLEXITY	0.016	*0.73*	-0.001	*-0.18*	0.007	*0.17*	-0.003	*-0.23*
COMPLEXITY*OF	-0.081**	*-2.32*	0.014	*0.90*	0.076	*1.20*	-0.007	*-0.34*
OF	-0.098	*-0.48*	-0.245***	*-2.68*	-0.364	-	-0.095	*-0.68*
Strategy Dummies	Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes	
Adjusted R²	0.267		0.080		0.105		0.105	
F-statistic	27.80		7.40		1.79		9.64	
Durbin-Watson	1.89		1.85		9.58		1.76	
	SSTDEV		SSKEW		SKURT		SCF	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
Fund Characteristics	Yes		Yes		Yes		Yes	
COMPLEXITY	0.017	*0.87*	-0.001	*-0.18*	0.086**	*2.42*	-0.033***	*-2.61*
COMPLEXITY*OF	-0.054	*-1.56*	0.014	*0.90*	-0.124***	*-2.95*	0.045***	*2.84*
OF	-0.287	*-1.51*	-0.245***	*-2.68*	0.048	*0.18*	-0.101	*-0.99*
Strategy Dummies	Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes	
Adjusted R²	0.278		0.183		0.105		0.203	
F-statistic	29.26		17.42		9.58		19.70	
Durbin-Watson	1.89		1.89		1.79		1.90	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

7.9 Robustness, Validity and Relevance of the Findings of this Study

The results are also decidedly robust for time as the time-effect is controlled for using dummy variables that describe the annual listing of a hedge fund in the database. Thus, a financial crisis such the Russian debt crisis should not necessarily bias the results. The controls for the time-effect are especially important as systematically large losses across hedge funds at a certain time point could bias the estimates for skewness and excess kurtosis used in this study. Also, hedge fund strategies and the invested asset classes (also primary asset classes) reported by a hedge fund manager are controlled for.

Return smoothing and other reasons which may cause serial correlation in hedge fund returns may inflate the results. The results presented in Table 26 suggest that the variables in the cross-sectional analysis explain little of the persistence in hedge fund returns. Only for few variables the results suggest that the use of derivatives has an impact on the persistence of hedge fund returns. What is more, the complexity of derivatives use is not found to have an impact on persistence. In conclusion, the chances that the results are biased due to return smoothing and illiquid securities of hedge funds are very small.

Similar findings for the impact of the asset specialized use of options on the higher moments of the return distribution of a hedge fund across different subsamples also ensure the robustness of the results to some extent. In other words, the findings may not only be attributed to chance as they are similar for more than one sample. The results for the relation between the use of a more complex strategy by a hedge fund and the characteristics of a hedge fund examined are fairly similar for the samples of live and dead funds. As the result for the complexity is also robust for live and the "past" dead hedge funds, the results are replicable, and thus the conclusions based on them are more objective. Specifically, these characteristics are the nonlinear relation between complexity and hedge fund performance, and the linear relation between complexity and the left tails of the return distribution measured using the Cornish-Fischer expansion.

The univariate analysis for asset specialized options use and the correlation statistics for the complexity of derivative strategy also mainly yield evidence similar to the multivariate analyses in this study. This consistency further implies that the rejection of the null hypotheses related to derivatives use and the complexity of derivative strategies are not false. However, the correlation statistics for complexity and market-based versus the idiosyncratic risk characteristics of a hedge fund are slightly different from the multivariate tests. Also, the results for the use of equity index futures and hedge fund performance are different for the univariate and multivariate analysis of this study. As such, these results should be treated with greater caution. Admittedly, these characteristics can still be seen as the direction on which the use of complex derivative strategy has the greatest impact. However, hedge fund strategies are also considered in multivariate analysis which should be extremely relevant controls for the kind of risk of a hedge fund.

A potential problem related to the results of the study is endogeneity of the complexity of the derivative strategy of a hedge fund as previous records of fund information in the Lipper TASS database is overwritten when the database is updated. When the endogeneity problem is present, derivatives use may not be the cause of risk and performance, but, instead, it may be the result of performance and risk. Intuitively, hedge funds which have a good performance may decrease the complexity which may explain the negative relation between the complexity and hedge fund performance. Also, hedge funds which have heavy left tails of their return distributions may increase the complexity leading to a fault result that complexity is related to fat left tails of hedge fund return distributions. Fortunately, hedge funds do not change the status of their derivatives use much. Chen (2009) investigates potential endogeneity using the TASS database which is used in this study. He finds that only about 1.5 % of hedge funds changed their status of derivatives use between 2002 and 2006. Moreover, the above-mentioned biases are not very likely strong as the results are found for both live and dead hedge funds. Dead hedge funds usually have experienced poor performance before their liquidations, and therefore finding the result only for dead hedge funds would be a cause for serious caution. Liang (2000), for example, studies live and dead hedge funds and shows empirical evidence that poor performance is the main for hedge funds to be liquidated. The study by Getmansky et al. (2004) also suggests that dead hedge funds are performing poorly. As the results are robust for both live and dead hedge funds in the present study, the problem of endogeneity is very likely not serious.

To further address the problem of endogeneity hedge funds are divided into two subsamples according on whether their inception date is before the year 1999. The impact of the complexity of the derivative strategy of a hedge fund on its average return, performance measures and the Cornish-Fischer expansion of its return distribution is then examined using these samples. The year 1999 is chosen as a cut-point as the year of 1998 was dramatic for the hedge fund industry and caused some hedge funds to change their characteristics (see Liang 2001). Gupta et al. (2005) find a steep decline in the capitalization of hedge funds during the fall of 1998. As a result of the year many hedge funds may have changed their statuses and the more recent sample should be less exposed to the endogeneity problem.

Table 26. Derivatives Use and Return Persistence

This table presents the parameter estimates of the cross-sectional analysis for the mean return and risk estimates of hedge funds. The model for the cross-sectional analysis of entire sample (3,382) and funds of hedge funds (761) is the following (Model 3):

$$SLOPE_i = \alpha + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \beta_1 COMPLEX_i + e,$$

and the model for the cross-sectional analysis of subsamples is the following (Model 2):

$$SLOPE_i = \alpha + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \sum_{j=1}^{N} \beta_j DERIVATIVE_{ji} + e,$$

where $SLOPE_i$ defines the slope coefficient for persistence of fund *i*; $CONTROL_{ji}$ defines an additional control variable *j* of fund *i*, and $DERIVATIVE_{ji}$ defines a dummy variable for the use of a derivative *j* by fund *i* (1 if the derivative is used, otherwise 0). Asset dummies include controls for assets and primary assets in which hedge funds report investing. This table also presents the Durbin-Watson test for the first-order serial correlation. The standard errors are White (1980) heteroskedasticity robust. *t*-statistics are given in italics. See Table 1 for definitions of the variables.

	All		Equity		Fixed-Income		Commodity		Currency	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-	-	-0.175	*-1.18*	-	*-2.71*	0.169	*0.54*	0.006	*0.03*
LNSIZE	0.011***	*4.69*	0.006**	*2.06*	0.020***	*4.35*	0.000	*-0.01*	0.012**	*2.06*
LNAGE	0.037**	*2.16*	0.022	*1.06*	0.061**	*1.98*	-0.020	*-0.47*	-0.019	*-0.62*
HMARK	-0.002	-	0.016	*1.54*	0.029	*1.51*	-0.045	*-1.34*	-0.021	*-0.73*
IFEE	0.001	*0.85*	0.001	*1.34*	0.000	*0.23*	-0.003	*-1.37*	-0.002	*-0.89*
MFEE	0.005	*1.09*	0.006	*0.99*	0.001	*0.08*	-0.003	*-0.43*	-0.003	*-0.44*
LEVERAGED	0.002	*0.33*	0.009	*1.04*	0.002	*0.10*	0.035	*1.05*	-0.025	*-0.80*
LOCKUP	0.000	-	0.000	*0.24*	0.003**	*2.44*	0.006	*1.58*	0.004	*1.46*
MIN(Million$)	-0.004	*1.44*	0.000	*-0.14*	-0.011	*-1.58*	-0.003	*-0.18*	-	*-2.04*
RESTRICTION	0.001	*1.02*	0.000	*-0.42*	0.000	*0.61*	0.000	*0.53*	0.001	*1.14*
AUDIT	-0.003	-	-0.007	*-0.61*	-0.021	*-1.16*	0.040	*1.34*	0.029	*1.17*
PERCAPITAL	-0.004	-	-0.010	*-1.19*	-0.001	*-0.05*	-	*-1.84*	-0.001	*-0.04*
OPEN	-0.018**	-	0.000	*0.02*	-0.017	*-1.03*	-0.006	*-0.24*	-0.013	*-0.60*
OPENENDED	0.000	*0.01*	0.002	*0.21*	-0.007	*-0.42*	-0.017	*-0.64*	0.008	*0.36*
COMPLEXITY	0.001	*0.66*								
AE_OPTIONS			0.001	*0.09*	-0.004	*-0.19*	-0.013	*-0.41*	-0.057*	*-1.86*
AF_OPTIONS			0.025	*1.56*	-0.002	*-0.13*	0.013	*0.33*	0.019	*0.68*
AC_OPTIONS			0.014	*0.67*	0.022	*0.90*	-0.028	*-1.04*	0.013	*0.49*
ACUR_OPTIONS			-0.009	*-0.57*	0.012	*0.61*	0.062	*1.61*	0.040	*1.54*
AE_WARRANTS			0.018*	*1.79*	0.014	*0.68*	0.010	*0.12*	0.072*	*1.72*
AF_WARRANTS			0.007	*0.39*	-0.015	*-0.72*	0.043	*0.52*	-0.081	*-1.58*
AE_OTHER			-0.004	*-0.35*	0.029	*1.36*	0.020	*0.38*	-0.015	*-0.41*
AF_OTHER			-0.018	*-1.09*	-	*-2.76*	-0.074	*-1.20*	-0.016	*-0.45*
AC_OTHER			-0.017	*-0.64*	-0.021	*-0.67*	0.005	*0.11*	-	*-2.01*
ACUR_OTHER			-0.031*	*-1.93*	0.035	*1.30*	-0.049	*-0.95*	0.038	*1.03*
Strategy Dummies	Yes		Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes		Yes	
Adjusted R^2	0.203		0.178		0.329		0.032		0.118	
F-statistic	20.56		8.99		9.36		1.18		2.05	
Durbin-Watson	1.90		1.88		1.93		1.83		1.82	
N	3382		1841		838		245		363	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

Table 26. Continued

	All		Funds of Hedge Funds	
Variable	Coef.	*t*	Coef.	*t*
C	-0.312**	-2.57	0.336	1.36
LNSIZE	0.011***	4.79	-0.060	-1.63
LNAGE	0.033*	1.92	0.015***	3.41
HMARK	-0.001	-0.09	0.010	0.54
IFEE	0.001*	1.69	-0.001	-1.18
MFEE	0.005	1.14	0.000	0.02
LEVERAGED	0.003	0.39	0.021	1.51
LOCKUP	0.001	0.95	-0.001	-0.89
MINMillion$)	-0.004	-1.21	-0.012	-1.10
RESTRICTION	0.000	1.36	0.001**	2.46
AUDIT	-0.001	-0.07	-0.009	-0.57
PERCAPITAL	-0.004	-0.61	0.016	0.91
OPENTOPUBLIC	0.000	-0.02	-0.028	-1.39
OPENENDED	-0.019**	-2.30	-0.016	-0.81
COMPLEXITY	0.000	-0.13	-0.001	-1.26
OF	0.044**	2.00		
COMPLEXITY*OF	0.004	1.35		
Strategy Dummies	Yes		No	
Time Dummies	Yes		Yes	
Asset Dummies	Yes		No	
Adjusted R^2	0.21		0.04	
F-statistic	20.21		2.09	
Durbin-Watson	1.90		1.90	
N	3382		761	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

To evaluate the significance of endogeneity for the results two additional sub-samples are analysed. Table 27 presents the results for funds which have an inception date before the year 1999 and Table 28 presents the results for funds with inception after the year 1998. For funds which have inception time before 1999, the result for the relation between the complexity and performance measures are similar for the analysis of entire sample only for the Sharpe ratio and the Sharpe ratio with downside volatility. The impact of the complexity on the Cornish-Fischer expansion is not statistically significant for this period. For hedge funds with an inception date after the year 1998, the results are similar to the analysis using the full sample. In fact, the complexity is a relatively important factor in explaining the Cornish-Fischer expansion for the latter sample period as incentive fee is the only variable in addition to the complexity which has statistically significant impact on the expansion. Given that the more recent sample period confirms the results found in the previous analysis, it is very unlikely that the results presented in this study are solely biased due to endogeneity. Also, when compared to the relation between the lockup period and the alpha of a hedge fund, this relation is found to be significant only for the inception period after 1998 when endogeneity can be assumed to bias the results less.

Table 27. Analysis of Ex-1999 Incepted Funds

This table presents the parameter estimates of the cross-sectional analysis of average return and performance estimates of hedge funds. The model for the cross-sectional analysis is the following (Model 3):

$$MEASURE_{ji} = \alpha + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \beta_1 COMPLEX_i + e,$$

where $MEASURE_{ji}$ defines a measure associated with higher moments j of fund i; $CONTROL_{ji}$ defines an additional control variable j of fund i, and $COMPLEX_i$ defines the number of different derivatives used by fund i. Asset dummies include controls for assets and primary assets in which hedge funds report investing. The sample includes 1,554 hedge funds. This table also presents the Durbin-Watson test for the first-order serial correlation. The standard errors are White (1980) heteroskedasticity robust. t-statistics are given in italics. See Table 1 for definitions of the variables.

	SHARPE		SHARPED		APPRAISAL	
	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-0.368**	*-2.21*	-0.363**	*-2.02*	-0.926**	*-2.02*
LNSIZE	-0.003	*-0.15*	-0.006	*-0.24*	0.030	*0.54*
LNAGE	0.031***	*9.16*	0.032***	*7.83*	0.044***	*7.08*
HMARK	-0.009	*-0.51*	-0.026	*-1.10*	-0.003	*-0.14*
IFEE	0.001	*1.31*	0.002	*1.49*	0.005***	*2.92*
MFEE	0.002	*0.25*	0.001	*0.09*	0.007	*0.54*
LEVERAGED	0.018	*1.50*	0.019	*1.31*	0.031	*1.39*
MINIMUM(Million$)	0.002	*0.41*	0.004	*0.56*	0.002	*0.36*
RESTRICTION	0.001**	*2.35*	0.001***	*2.41*	0.001***	*2.59*
LOCKUP	0.001	*1.28*	0.001	*1.10*	0.000	*-0.19*
AUDIT	-0.020	*-1.28*	-0.020	*-1.22*	-0.045	*-1.33*
PERCAPITAL	-0.004	*-0.32*	-0.009	*-0.57*	-0.002	*-0.12*
OPEN	-0.055***	*-4.16*	-0.049***	*-3.22*	-0.068**	*-2.49*
OPENENDED	-0.002	*-0.12*	-0.001	*-0.07*	-0.027	*-1.10*
COMPLEXITY	-0.007**	*-2.30*	-0.008**	*-2.26*	-0.011	*-1.57*
Strategy Dummies	Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes	
Adjusted R^2	0.303		0.251		0.113	
F-statistic	16.35		12.80		5.49	
Durbin-Watson	2.09		2.11		2.10	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

When compared to the two recent studies by Aragon (2007) and Agarwal et al. (2009), the results of these studies are consistent with the statistics for the more recent sample used in this study. Restriction period and lockup period which are important determinants of hedge fund performance in these studies do not explain the alpha of a hedge fund in the earlier sample of this study. As such, the results for the earlier sample are not consistent with the other significant findings in the scholarly research on hedge funds.

In comparison to the complexity variable, a potential characteristic of endogeneity in Tables 27 and 26 is a positive association between incentive fee of a hedge fund and its performance (alpha and appraisal ratios) only for the earlier inception period. Hedge funds which demonstrated better performance through the 1997

Asian Crisis and the 1998 Russian Debt Crisis may have been able to sustain their high incentive fees while the other funds may have not been able to increase their incentive fees or they have been forced to reduce them to be more attractive for new capital. Indeed, Liang (2001) finds that relatively many hedge funds died in 1998. He also presents evidence that some funds lowered their incentive fees as a result of poor performance. In conclusion, the positive relation between incentive fee and the alpha of a hedge fund as indicated in Table 14 may be biased.

Table 27. Continued

	ALPHA		MEAN		CF	
	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-2.726*	*-1.77*	-0.984	*-1.36*	-2.132***	*-2.79*
LNSIZE	0.252	*1.18*	-0.002	*-0.02*	-0.060	*-0.54*
LNAGE	0.074**	*2.48*	0.081***	*5.02*	-0.006	*-0.33*
HMARK	0.120**	*1.99*	0.113**	*2.41*	-0.176**	*-2.20*
IFEE	0.016***	*2.78*	0.007*	*1.90*	0.008*	*1.77*
MFEE	0.053	*0.75*	0.052	*1.53*	0.069*	*1.80*
LEVERAGED	0.117	*1.62*	0.093**	*2.00*	-0.114	*-1.47*
MINIMUM(Million$)	-0.007	*-0.35*	-0.020	*-1.25*	0.028	*1.00*
RESTRICTION	0.001	*1.49*	0.002***	*2.99*	0.002**	*2.45*
LOCKUP	0.001	*0.28*	0.005	*1.37*	-0.004	*-0.62*
AUDIT	-0.061	*-0.42*	0.059	*0.75*	-0.012	*-0.16*
PERCAPITAL	0.019	*0.25*	0.055	*1.28*	-0.016	*-0.26*
OPEN	-0.058	*-0.58*	-0.085	*-1.29*	0.018	*0.23*
OPENENDED	-0.059	*-0.78*	-0.010	*-0.19*	-0.088	*-1.12*
COMPLEXITY	-0.018	*-1.07*	-0.025**	*-2.59*	-0.018	*-1.32*
Strategy Dummies	Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes	
Adjusted R-squared	0.064		0.175		0.125	
F-statistic	3.42		8.51		6.05	
Durbin-Watson stat.	2.17		2.04		1.74	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

Table 28. Analysis of Post-1998 Incepted Funds

This table presents the parameter estimates of the cross-sectional analysis of average return and performance estimates of hedge funds. The model for the cross-sectional analysis is the following (Model 3):

$$MEASURE_{ji} = \alpha + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \beta_1 COMPLEX_i + e,$$

where $MEASURE_{ji}$ defines a measure associated with higher moments *j* of fund *i*; $CONTROL_{ji}$ defines an additional control variable *j* of fund *i*, and $COMPLEX_i$ defines the number of different derivatives used by fund *i*. Asset dummies include controls for assets and primary assets in which hedge funds report investing. The sample includes 1,824 hedge funds. This table also presents the Durbin-Watson test for the first-order serial correlation. Time dummies start from 1999. The standard errors are White (1980) heteroskedasticity robust. *t*-statistics are given in italics. See Table 1 for definitions of the variables.

	SHARPE		SHARPED		APPRAISAL	
	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-1.206	*-1.25*	-1.338	*-1.26*	-1.715	*-0.99*
LNSIZE	0.159	*1.09*	0.192	*1.18*	0.202	*0.77*
LNAGE	0.035***	*8.17*	0.037***	*7.29*	0.049***	*4.77*
HMARK	-0.008	*-0.27*	-0.029	*-0.69*	0.004	*0.08*
IFEE	-0.003	*-0.91*	-0.002	*-0.47*	-0.004	*-0.66*
MFEE	-0.008	*-0.60*	-0.012	*-0.68*	0.044*	*1.68*
LEVERAGED	0.003	*0.16*	0.001	*0.02*	0.044	*1.24*
MINIMUM(Million$)	-0.008	*-1.49*	-0.007	*-0.94*	-0.002	*-0.13*
RESTRICTION	0.001***	*2.85*	0.002***	*2.99*	0.002**	*2.37*
LOCKUP	0.001	*1.20*	0.002	*1.37*	0.002	*0.65*
AUDIT	-0.002	*-0.07*	0.000	*0.00*	0.019	*0.43*
PERCAPITAL	0.021	*1.26*	0.012	*0.64*	0.046	*1.40*
OPEN	-0.052**	*-2.37*	-0.062**	*-2.52*	-0.156***	*-3.94*
OPENENDED	0.026	*1.24*	0.023	*0.93*	0.083**	*2.19*
COMPLEXITY	-0.010**	*-2.22*	-0.015***	*-2.69*	-0.017*	*-1.92*
Strategy Dummies	Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes	
Adjusted R^2	0.201		0.180		0.117	
F-statistic	12.73		11.24		7.18	
Durbin-Watson	1.99		1.88		1.95	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

It must also be noted that endogeneity may not just be a cause of false of rejection of the null hypothesis. It may also be a cause of accepting a false null hypothesis. For example, well performing funds may increase the complexity of their derivative strategies causing a positive bias in the complexity-performance relation. If fact, it is sensible to assume that hedge funds which existed during the 1997 Asian Crisis and the 1998 Russian Debt Crisis changed their risk management and derivatives use as a result from the lessons learned from the crises. If the complexity is likely to increase after good performance, the negative complexity-performance relation found in this study should not be biased.

Table 28. Continued

	ALPHA		CF		MEAN	
	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-7.972***	*-4.22*	-2.040	*-1.56*	-5.962***	*-4.71*
LNSIZE	1.043***	*3.59*	-0.004	*-0.02*	0.849***	*4.49*
LNAGE	0.054***	*2.63*	-0.003	*-0.23*	0.050***	*3.73*
HMARK	-0.028	*-0.24*	-0.150*	*-1.82*	-0.155**	*-2.15*
IFEE	0.010	*1.05*	0.007	*1.07*	0.008	*1.38*
MFEE	0.218***	*2.75*	0.038	*0.94*	0.061	*1.42*
LEVERAGED	0.071	*1.14*	-0.008	*-0.16*	0.050	*1.20*
MINIMUM(Million$)	-0.039**	*-2.36*	0.030	*1.52*	-0.040***	*-3.41*
RESTRICTION	0.002**	*2.17*	0.001	*0.67*	0.003***	*3.40*
LOCKUP	0.009*	*1.86*	0.004	*1.13*	0.012***	*3.54*
AUDIT	-0.033	*-0.44*	0.001	*0.03*	-0.041	*-0.85*
PERCAPITAL	0.077	*1.18*	-0.062	*-1.27*	0.090**	*2.24*
OPEN	-0.222***	*-3.31*	0.044	*0.70*	-0.057	*-1.15*
OPENENDED	0.074	*1.31*	-0.063	*-1.28*	0.004	*0.09*
COMPLEXITY	-0.022	*-1.54*	-0.035***	*-2.99*	-0.011	*-1.22*
Strategy Dummies	Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes	
Adjusted R^2	0.079		0.018		0.202	
F-statistic	5.02		1.84		12.81	
Durbin-Watson	1.71		1.74		1.88	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

The relevance of the variable for the complexity of the derivative strategy of a hedge fund is considered by analysing a binary variable indicating whether a hedge uses derivatives with the complexity variable. This analysis allows one to evaluate whether the present study provides relevant evidence after the earlier studies, particularly the study by Chen (2009). Table 29 presents the results of these analyses. The statistics include the adjusted R^2, and the AIC and SIC information criteria.

The results for hedge funds presented in Table 29 provide somewhat mixed results on the relevance of the complexity variable. The model without the binary variable has ultimately the best fit in explaining the alpha of a hedge fund suggesting that the variable is relevant. However, the fit of the model without complexity variable outperforms the model without the binary variable in explaining the Sharpe ratio and appraisal ratio in the terms of AIC and SIC. A reasonable conclusion is that a different result from the study by Chen (2009) for the complexity-performance relation is related to the exclusion of funds of hedge funds from the sample of hedge funds rather than the use of a new variable. For the analysis of standard deviation, both variables of derivatives use explain little this risk measure. Yet the complexity variable can still be considered as a relevant variable explaining hedge fund performance as there is a nonlinear relation between the complexity and the Sharpe ratio (see Table 21).

The relevance of the complexity variable is seemingly marked for the negative relation between the Cornish-Fischer expansion and the variable. This characteristic is suggested by two characteristics: first, only the coefficient for the complexity is statistically significant in explaining the expansion. Second, the model without the binary variable has the lowest AIC and SIC suggesting its fit outperforming that of the other models. The results indeed implies, in line with John et al. (2006), that it is the complexity of the derivative strategy of a hedge fund which matters in explaining the left tail in its return distribution.

The results for funds of hedge funds in Table 29 includes two surprising findings: first, the regression statistics suggest that the binary variable (the complexity variable) has a positive (negative) relation with the alpha and appraisal ratio of a hedge fund. The results suggests that the use of derivatives increases, which characterizes the binary variable used, the alpha of a fund of hedge funds by 0.137 % while the coefficient for the complexity variable is not statistically significant. As such, the use of derivatives is positively associated with the performance of a fund of hedge funds while the complexity of derivatives use has a negative and weak association with the performance. Second, the binary variable (the complexity variable) has a positive (negative) relation with the Cornish-Fischer expansion. This result actually presents evidence for Hypothesis 5b. This result is in fact found for both hedge funds and funds of hedge funds. Thus, the complexity of derivative strategy is associated with fatter left tails of the return distributions of funds of hedge funds as well. A difference to hedge funds is that funds of hedge funds seem to take this risk idiosyncratically while for hedge funds the risk is related to market-based factors of their returns (cf. Tables 23 and 24). Given this additional and different information in the binary and complexity variables of derivatives use, the relevance of the complexity variable is ample.

The complexity factor also has relevance in explaining the risk of a fund of hedge funds as the model without the binary variable of derivative has the best fit in the terms of the AIC and SIC information criteria. Thus, while the complexity increases the left tail of the return distribution of a hedge fund, it also decreases the value of conventional risk measures. In conclusion, the relevance of the complexity variable is considerable in explaining the standard deviation for funds of hedge funds as well.

Table 29. Relevance of the Complexity of Derivative Strategy

This table presents the Akaike Information Criterion (AIC), the Schwarz Information Criterion (SIC) and the parameter estimates of the cross-sectional analysis of hedge fund performance and risk on its derivatives use and complexity of derivative strategy. The model for the cross-sectional analysis is the following:

$$MEASURE_{ji} = \alpha_i + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \beta_1 COMPLEX_i + \beta_2 BINARY_i + e_i,$$

where $MEASURE_{ji}$ defines a measure associated with higher moments j of fund i; $CONTROL_{ji}$ defines an additional control variable j of fund i; $COMPLEX_i$ defines the number of different derivatives used by fund i, and $BINARY_i$ defines a dummy variable for the use of derivatives by fund i (1 if the fund invests in other funds, and 0 otherwise). The model also includes asset-, strategy-, and time dummies. Asset dummies include controls for assets and primary assets in which hedge funds report investing. The sample includes 3,382 hedge funds. The standard errors are White (1980) heteroskedasticity robust. *t*-statistics are given in italics. The highest (lowest) value for Adjusted R² (information criteria) is in boldface.

Panel A: Hedge Funds

					β_1		β_2	
		Adj. R²	SIC	AIC	Coef.	*t*	Coef.	*t*
ALPHA	Full model	0.06759	3.4786	3.3952	-0.016	*-1.32*	-0.014	*-0.24*
	No complex	0.06743	3.4766	3.3951			-0.046	*-0.85*
	No binary	**0.06785**	**3.4762**	**3.3946**	-0.017	*0.01*		
APPRAISAL	Full model	**0.11805**	1.8477	1.7644	-0.011*	*-1.78*	-0.029	*-0.90*
	No complex	0.11725	**1.7941**	**1.8465**			-0.052*	*-1.80*
	No binary	0.11803	1.8456	1.7641	-0.014**	*-2.45*		
SHARPE	Full model	**0.22833**	0.6248	**0.5414**	-0.005*	*-1.92*	-0.041**	-2.23
	No complex	0.22787	**0.6232**	0.5417			-0.052***	*-3.06*
	No binary	0.22687	0.6245	0.5430	-0.009***	*-3.41*		
STDEV	Full model	0.27860	5.1899	5.1066	0.000	*0.00*	0.071	*0.50*
	No complex	**0.27882**	**5.1875**	**5.1060**			0.072	*0.55*
	No binary	0.27877	5.1876	5.1061	0.006	*0.22*		
CF	Full model	0.08733	2.9803	2.8970	-0.021**	*-2.15*	-0.030	*-0.59*
	No complex	0.08644	2.9792	2.8977			-0.070	*-1.50*
	No binary	**0.08751**	**2.9780**	**2.8965**	-0.023**	*-2.56*		

Panel B: Funds of Hedge Funds

					β_1		β_2	
		Adj. R²	SIC	AIC	Coef.	*t*	Coef.	*t*
ALPHA	Full model	**0.1546**	2.1937	2.0171	-0.008	*-1.51*	0.137*	*1.83*
	No complex	0.1536	**2.1876**	**2.0170**			0.080	*1.36*
	No binary	0.1516	2.1899	2.0194	-0.002	*-0.39*		
APPRAISAL	Full model	**0.2624**	1.0061	**0.8295**	-0.007*	*-1.94*	0.079**	*2.00*
	No complex	0.2591	1.0032	0.8326			0.032	*1.01*
	No binary	0.2594	**1.0028**	0.8323	-0.003	*-1.06*		
SHARPE	Full model	0.3777	-0.3434	**-0.5200**	-0.001	*-0.42*	0.018	*0.88*
	No complex	**0.3784**	**-0.3519**	-0.5224			0.014	*0.84*
	No binary	0.3778	-0.3510	-0.5215	0.000	*0.15*		
STDEV	Full model	**0.2780**	4.2376	4.0610	-0.027**	*-1.98*	-0.283	*-1.12*
	No complex	0.2763	4.2326	4.0621			-0.472**	*-2.24*
	No binary	0.2770	**4.2317**	**4.0612**	-0.040***	*-3.48*		
CF	Full model	**0.0731**	3.0906	**2.9140**	-0.020**	*-2.47*	0.242**	*2.54*
	No complex	0.0681	3.0887	2.9182			0.097	*1.29*
	No binary	0.0685	**3.0883**	2.9177	-0.009	*-1.39*		

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

Leverage use is also a potential cause of bias in the results of this study. Therefore, it is sensible to extend the leverage variable use. The Lipper TASS database provides information for the average leverage use of a hedge fund which is self-reported by hedge fund managers. The problem using the variable is that it reduces the sample size to 2,996 funds. The results for the impact of the average leverage of a hedge fund used on its performance and risk measures are presented in Table 30. The results do not provide evidence that the inclusion of the variable alters the analysis of the complexity of the derivative strategy of a hedge fund and its performance and risk. Further, the average leverage explains relatively weakly hedge fund performance and risk when compared to the dummy variable of leverage use. Moreover, the average leverage variable does not have statistically significant impact on the dependent variables associated with the complexity of derivative strategy. For example, the dummy variable of leverage use has a statistically significant impact on the standard deviation of the returns of a hedge fund while the average leverage does not have an impact on this explanatory variable. As a result, it may be concluded that the bias in the results of this study arising from the leverage use is not severe although it cannot be ignored.

The earlier analysis of asset specialized derivatives use presented in Tables 12, 13, and 14 may be biased as a result of selectivity bias as explained in Section 5. To assess the effect of the sample selectivity bias on the results presented in Tables 12, 13, and 14, the Heckman's (1979) two-stage correction procedure is used. Table 31 presents the corrected results. The results do not change significantly after consideration of selectivity bias. The most considerable change is found for hedge funds which focussing on currency. In the analysis of this strategy, the coefficient for the asset specialized use of options is not statistically significant at the 10 % level after consideration of the selectivity bias. However, the change in t-statistics is only 0.04.

Table 30. Leverage Effect

This table presents the parameter estimates of the cross-sectional analysis of performance and risk estimates of hedge funds. The model for the cross-sectional analysis is the following:

$$MEASURE_{ji} = \alpha + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \beta_1 AVGL_i + \beta_2 COMPLEX_i + e,$$

where $MEASURE_{ji}$ defines a measure associated with higher moments *j* of fund *i*; $CONTROL_{ji}$ defines an additional control variable *j* of fund *i*: $AVGL_i$ defines the average leverage of fund *i* in percentages, and $COMPLEX_i$ defines the number of different derivatives used by fund *i*. Asset dummies include controls for assets and primary assets in which hedge funds report investing. The sample includes 2,996 hedge funds. This table also presents the Durbin-Watson test for the first-order serial correlation. The standard errors are White (1980) heteroskedasticity robust. *t*-statistics are given in italics. See Table 1 for definitions of the variables.

	SHARPE		SHARPED		APPRAISAL		ALPHA	
	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-0.496*	*-1.69*	-0.503	*-1.58*	-0.830	*-1.50*	-	*-3.36*
LNSIZE	0.034	*0.82*	0.040	*0.89*	0.033	*0.43*	0.371**	*2.29*
LNAGE	0.033***	*10.72*	0.034***	*9.72*	0.049***	*7.28*	0.074	*4.11*
HMARK	-0.006	*-0.34*	-0.026	*-1.09*	0.022	*0.74*	0.121*	*1.95*
IFEE	0.000	*0.05*	0.001	*0.28*	0.003	*1.10*	0.018***	*3.25*
MFEE	-0.004	*-0.58*	-0.005	*-0.68*	0.021*	*1.66*	0.108**	*2.01*
AVGLEVERAGE	0.000	*1.15*	0.000	*0.88*	0.000	*0.22*	0.000*	*1.83*
MINIMUM(Million$)	-0.001	*-0.15*	0.002	*0.41*	0.005	*0.60*	-0.027**	*-2.07*
RESTRICTION	0.001***	*4.00*	0.001***	*3.79*	0.001***	*3.70*	0.002**	*2.37*
LOCKUP	0.002**	*2.46*	0.003**	*2.24*	0.003	*1.51*	0.008**	*2.12*
AUDIT	-0.011	*-0.77*	-0.011	*-0.71*	-0.023	*-0.79*	-0.051	*-0.62*
PERCAPITAL	0.001	*0.05*	-0.005	*-0.39*	-0.004	*-0.23*	0.037	*0.72*
OPEN	-0.057***	*-4.74*	-	*-4.33*	-	*-4.39*	-0.157**	*-2.51*
OPENENDED	0.011	*0.73*	0.007	*0.40*	0.027	*1.07*	0.025	*0.49*
COMPLEXITY	-0.009***	*-3.71*	-	*-4.07*	-0.013**	*-2.39*	-0.013	*-1.09*
Strategy Dummies	Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes	
Adjusted R-squared	0.244		0.213		0.122		0.069	
F-statistic	22.92		19.37		10.48		6.03	
Durbin-Watson stat.	1.66		1.79		1.70		1.97	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

Table 31. Selectivity Bias and Derivatives Use

This table presents the parameter estimates of cross-sectional analysis for Value-at-Risk estimates of hedge funds. The model for the cross-sectional analysis is the following (Model 2):

$$MEASURE_{ji} = \alpha + \sum_{j=1}^{N} \lambda_j CONTROL_{ji} + \sum_{j=1}^{N} \beta_j DERIVATIVE_{ji} + e,$$

where $MEASURE_{ji}$ defines a risk or performance measure j of fund i; $CONTROL_{ji}$ defines an additional control variable j of fund i, and $DERIVATIVE_{ji}$ defines a dummy variable for the use of a derivative j by fund i (1 if the derivative is used, otherwise 0). The control variables include the inverse Mills ratio. Asset dummies include controls for assets and primary assets in which hedge funds report investing. This table also presents the Durbin-Watson test for the first-order serial correlation. The standard errors are White (1980) heteroskedasticity robust t-statistics are given in italics. t-statistics are given in italics. See Table 1 for definitions of the variables.

Asset focus: equity

	SHARPE		SHARPED		ALPHA		APPRAISAL		MEAN	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
AE_OPTIONS	0.023**	*1.96*	0.022	*1.62*	-0.026	-	0.006	*0.22*	0.011	*0.23*
AE_OTHER	-0.019	-	-0.017	-	-0.190**	-	-0.042*	-	-0.117**	-
IMILLS	-0.079	-	-0.073	-	-0.150	-	-0.164	-	-0.299	-
	STDEV		D		EXKURT		SKEW		CF	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
AE_OPTIONS	-0.428**	-	-0.298*	-	0.342	*1.14*	-0.153**	-	-0.093	-
AE_OTHER	-0.139	-	-0.200	-	0.054	*0.17*	0.125*	*1.92*	0.062	*0.98*
IMILLS	-0.560	-	-0.471	-	-0.465	-	-0.062	-	-0.088	-

Asset focus: fixed-income

	SHARPE		SHARPED		ALPHA		APPRAISAL		MEAN	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
AF_OPTIONS	-0.083	*-1.40*	-0.095	*-1.50*	0.005	*0.05*	-0.085	*-0.91*	-	*-1.98*
IMILLS	-0.899	*-0.76*	-0.728	*-0.49*	0.121	*0.03*	0.769	*0.35*	-1.225	*-0.36*
	STDEV		D		EXKURT		SKEW		CF	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
AF_OPTIONS	-0.157	*-0.55*	-0.204	*-0.56*	0.431	*0.37*	-0.231	*-1.45*	-	*-2.03*
IMILLS	-0.657	*-0.06*	1.593	*0.14*	-25.401	*-0.60*	5.925	*0.78*	-4.523	*-0.71*

Asset focus: currency

	SHARPE		SHARPED		ALPHA		APPRAISAL		MEAN	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
ACUR_OPTIONS	0.016	*0.48*	0.019	0.52	-0.011	*-0.05*	0.077	*1.03*	-0.052	*-0.41*
IMILLS	-0.004	*-0.01*	0.196	0.21	4.129	*0.67*	1.259	*0.42*	4.380	*1.59*
	STDEV		D		EXKURT		SKEW		CF	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
ACUR_OPTIONS	-0.880*	*-1.74*	-0.755*	*-1.67*	0.109	*0.14*	-0.202	*-1.16*	-0.256	*-1.63*
IMILLS	18.304*	*1.70*	8.283	*0.97*	24.717	*1.05*	7.395*	*1.69*	2.935	*0.85*

Asset focus: commodity

	SHARPE		SHARPED		ALPHA		APPRAISAL		MEAN	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
AC_OPTIONS	-0.018	*-0.45*	-0.059	*-1.01*	0.146	*0.25*	-0.115	*-1.40*	0.221	*0.93*
IMILLS	-2.267	*-0.75*	-2.870	*-0.71*	-45.335	*-1.19*	-11.824	*-1.25*	-15.462	*-1.07*
	STDEV		D		EXKURT		SKEW		CF	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
AC_OPTIONS	1.485	*0.97*	1.184	*1.17*	-0.210	*-0.33*	-0.389**	*-2.03*	-0.330**	*-2.03*
IMILLS	-83.717	*-0.93*	-50.825	*-0.87*	-5.646	*-0.12*	-8.028	*-0.62*	-10.022	*-0.89*

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.

In Table 31, the *t*-statistics the coefficients for the estimated coefficients for the inverse Mills ratio can be used to determine whether selectivity bias alters the results presented in Tables 12, 13, and 14.However, only couple of the coefficients for the inverse Mills ratio are statistically significant. The statistically significant ones are those for currency specialized funds in explaining skewess of return distribuitions and return standard devition. The result implies that selectivity bias alters only the analysis of derivatives use of currency specialized hedge funds. All in all, the results presented in Table 31 suggest that selectivity bias is not a market problem in the analysis of this study, yet albeit it cannot be ignored.

8 CONCLUSION OF THE STUDY

The conclusions and discussion of this study are categorized according to the motives for hedge funds to use derivatives, investors' benefits from derivative strategies, financial stability, and micro and market-based factors of hedge fund performance and risk. Finally, suggestions for future research are presented.

8.1 Motives for Hedge Funds to Use Derivatives

For mutual funds, the use of derivatives for cash flow management is strongly advocated by Deli et al. (2002), Marin et al. (2006), Frino et al. (2009). Hedge funds, instead, typically impose restrictions on investors' rights to withdraw their cash, and therefore cash management motivated use of derivatives may not be as important for hedge funds as for mutual funds. Nevertheless, the results presented in this study suggest that equity index futures are used as a substitute for share restrictions to manage cash flows given by two features: first, the use of these derivatives is negatively associated with lockup period and restriction period. The result implies that when the use of these restrictions is limited, these derivatives are the substitute. Second, the use of equity index futures is associated with lower alpha of a hedge fund which can be considered as a result of lower illiquidity risk premium. This makes sense as the share restrictions in turn are associated with higher alpha and illiquidity risk premium is a considerable component of hedge fund alphas (see Aragon 2007). Thus, as Frino et al. (2009) find that equity index futures are used for cash management, this study suggests that the same characteristic applies to hedge funds. But the use by hedge funds may be considered as inferior to the use of share restrictions.

The results of Chen (2009) imply that the derivatives of hedge funds are used consistently for risk management. Aragon et al. (2008) also present evidence that equity options are used for nondirectional hedging strategies. The results of this study provide contradictory evidence against Chen (2009) as the risk of a hedge fund is not reduced by the use of derivatives. In fact, the use of derivatives and the complexity of the derivative strategy of a hedge fund is rather related to "hidden risks" strategies which hedge fund managers may have incentives to take (see John et al. 2006). For the use of equity options, the results are partly consistent with the evidence of Aragon et al. (2008). But the use of these derivatives is also found to be associated with "hidden risks" strategies. These characteristics may also be related to other financial institutions similar to hedge funds. However, the results for funds of hedge funds and hedge funds investing in other funds suggest that the complexity is associated with lower risk. This finding also explains the different results for hedge funds by this study and Chen (2009), which includes funds of hedge funds in the same analysis with hedge funds. Seemingly, the use of derivatives by funds of hedge funds is more risk management motivated than that of hedge funds.

From Black's (1975) viewpoint, hedge funds may use options markets for speculative trading but the major concern is whether this speculative trading really utilizes information advantage. Aragon et al. (2007) find for a sample of 250 hedge fund advisors that their stock option holdings include predictive information. This study finds evidence that some characteristics which could be associated with informed trading: higher incentive fees, leverage use, and asset focus are associated with the use of equity options. It is also found that higher incentive fees and the use of leverage are associated with abnormal returns, but that the use of equity options is not found to exhibit such a characteristic. The use of equity options is also associated with higher Sharpe ratio but it is not associated with higher appraisal ratio, which accounts for the simplest buy and hold option strategies through its alpha component. As such, higher incentive fees awarded for asset specialized equity option users do not seem to be reasonable. The results for performance do not directly exclude the possibility that equity options are not used for informed trading. However, the ability of the factor model to account for the performance from the equity option strategies of hedge funds is associated with well known investment strategies rather than informed trading. Also, the association with lower skewness of returns and the use of equity options by funds with their primary focus on equity support this conclusion as Whaley (2002) suggests that such strategies involve lower skewness. Alternatively, the profits from informed trading may be captured by the other hedge fund characteristics used in this study.

As an additional implication, in contrast to those of Chen (2009), this study concludes that hedge funds behave like non-insurers rather than insurers in the equity options market (see Grossmann and Zhou 1996) due to the positive impact of use of equity options on performance (Sharpe ratio) and negative impact on skewness, which relates to limited upside potential.

8.2 Investors' Benefits from the Derivative Strategies

Options strategies and other derivative strategies may be popular even among individual investors. Also, the studies by Board et al. (2001), Isakov et al. (2001), Whaley (2002), McIntyre et al. (2007), and Kapadia et al. (2007) suggest that even the popular covered call strategy is profitable for investors. But the question relates whether these strategies are profitable at the fund management level. Hedge funds may also provide a laboratory to test the profitability of derivative strategies as they are free to perform them. For more conventional mutual funds, Marin et al. (2006) find in line with Koski et al. (1999), Johnson et al. (2004), and Fong et al. (2005) evince that the use of derivatives does not improve fund performance although Marin et al. (2006) present some contradictory evidence. In relation to these studies, the present study does not merely indicate that derivatives use may have a negative impact on the performance of a hedge fund but also that the marginal burden of performance is extremely high for the use of few derivatives when the performance is measured using the Sharpe ratio. The marginal cost of increasing the complexity of a derivative strategy decreases with the complexity. This characteristic implies that the implementation costs of the use of derivatives are high. This study also finds that the complexity of derivative strategy is negatively related to the appraisal ratio of a hedge fund but this relation is rather linear. For funds of hedge funds, no negative complexity-performance relation is found but the complexity is associated with lower risk. This result implies that investors may benefit from the risk management carried out by funds of hedge funds.

The use of complex derivative strategies by a hedge fund is also found to be clearly related to "hidden risk" as a heavier left tail of the return distribution of a hedge fund. The characteristic is also found for funds of hedge funds for which it is more difficult to detect the use of derivative has the opposite effect to that of the complexity. Thus, it is particularly the complexity and not just the use of derivative which is associated with hidden risk in the returns of funds of hedge funds. The difference in this hidden risk between hedge funds and funds of hedge funds is its origin. For hedge funds, the risk is hidden in their exposures to market-based factors while for funds of hedge funds the risk is hidden in idiosyncratic returns. Hedge funds may be motivated to take on the risk using market-based factors as the risk of a difference in their relative performance is mitigated. This type of herding behaviour may be a reasonable way for fund managers to manage reputational risk (see Scharfstein and Stein 1990) when extremely large losses occur. The systematic feature of hedge fund managers' risk characteristics may also be regarded as a behaviour which tilts hidden risks to explode contemporaneously. Therefore, these findings call for a marked attention and caution in the derivatives use by fund managers. Other potential explanations for the finding are correlated private information of fund managers (see Froot, Scharfstein and Stein 1992) and managers' cueing private information from the trades of other funds (see Bikhchandani, Hirsheifer, and Welch 1992). Funds of funds in turn are limited in their conventional hedge fund exposures as they primarily invest in other funds. Therefore, it is reasonable that their hidden risk strategies are related to their fund-specific risk as the present study suggests. In conclusion, as the research suggests that utility maximizing investors prefer lower kurtosis and higher skewness (see Arditti 1967; Kraus et al. 1976; Scott et al. 1980), the use of derivatives by a hedge fund has characteristics of higher moments not aligned with the preferences of the investors.

Given the evidence of this study on performance statistics and risk characteristics associated with the use of complex derivative strategies, it is a well founded conclusion that it is not beneficial for investors to invest in complex derivative strategies. Admittedly, the complexity is not found to be associated with the alpha of a hedge fund. This result implies that possibly by diversifying in hedge funds and reducing the impact of the denominators of the Sharpe and appraisal ratios, which are the volatilities of the returns and idiosyncratic returns, the problem can be mitigated.

In options trading, hedge funds do not seem to lead to poorer performance as found for individual investors according to the evidence of Bauer, Cosemans and Eichholtz (2008). Thus, it would be better that hedge funds as professional investors use options rather than individual investors. However, it would still be much more sensible just to invest in simple buy-and-hold option strategies. For example, Whaley (2002) suggests that these strategies can be profitable even after accounting for skewness and kurtosis of the returns.

A recent study by Frino et al. (2009) finds that the use of equity index futures by mutual fund managers may be beneficial for their investors as these derivatives may be used for cash management. This use may prevent significant fund inflows having a detrimental effect on the alpha of a fund as result of more efficient use of cash inflows. The results of this study present evidence that hedge funds using equity index futures show weaker abnormal performance. This association between the use of equity index futures and the performance is likely a result of the use of derivatives for uninformed trading and their substitute for efficient management of illiquid assets causing a loss in illiquidity risk premium. For hedge fund investors looking for alternative returns this characteristic may be undesirable.

8.3 Financial Stability

During the Russian financial crisis of 1998, the leveraged derivatives positions after extreme losses of the LTCM caused a need to control the bailout of this hedge fund, and the collapse of this hedge fund was a threat to financial stability.

Nine years later and in conjunction with the subprime mortgage crisis of 2007, derivatives use again played a considerable role through financial engineering. In this crisis, a significant number of structured products which were structured using derivatives and subprime loans produced enormous losses. Both these cases are in conjunction with the results of this study as the study relates the use of complex strategies to higher probability of suffering extreme losses.

Seemingly, the use of derivative strategies and asset specialized use of options by hedge fund-like institutions is “hidden risk” motivated and the last two financial crises, indeed, witness that derivative strategies can be a threat for financial stability. As a consideration, the role of financial intermediates and their strategies (see John et al. 2006) may also be important. For hedge funds, this “hidden risk” is also related to market-based risk factors which may imply that the type of risk is likely to be systematic for all hedge funds and more dangerous to financial stability as the risk may be realized contemporaneously. Due to this characteristic regulators should consider more effective monitoring for the use of complex derivative strategies by hedge funds. For funds of hedge funds, the association between the complexity and hidden risk is rather related to manager-specific risk.

Further, it could be that the asymmetry caused by the use of derivatives may not be seen when larger hedge fund portfolios are examined but history shows that even one hedge fund may undermine financial stability by its derivative strategies as in the case of LTCM. Therefore, special attention and regulation should be applied to large hedge funds employing complex derivative strategies. What is more, the complex derivative strategies do not seem to add value for investors. So why take risks by using complex derivative strategies if on average they are incapable of showing a profit?

In contrast to the use of complex derivative strategies, management fees, higher minimum investment, and restriction periods are associated with less “hidden risk” related to systematic exposure of hedge funds. Restriction periods, for example, may protect hedge funds from investor sentiment changes and fire fund liquidations, higher minimum investments and higher management fees may keep small investors from investing in hedge funds which may be more exposed to fire fund liquidations in financial market turmoil. Good advice for financial authorities would be to drive policies to encourage hedge funds to lengthen their redemption periods.

8.4. Micro and Macro Factors of Hedge Fund Performance and Risk

Several micro factors for hedge funds such as size and age may affect the performance and risk of hedge funds. The results of the study by Chen (2009) imply that the derivatives use of a hedge fund could be a micro factor of hedge fund risk. In this study, the results are also heterogeneous for different derivatives and asset specializations. The result for the heterogeneous implications of the use of options of hedge funds resembles the results for mutual funds by Johnson et al. (2004).

The results for the asset specialized use of options were the most significant for equity specialized funds. In general, the asset specialized use of options in general is found to be associated with negative skewness in the return distribution of a hedge fund. It also has a negative effect on the Sharpe ratio of equity specialized hedge funds but it is the only performance measure for which it has statistically significant association. In conclusion, the asset specialized use of options can be an important micro factor of performance and risk, especially for this type of hedge funds.

The most significant micro factor of hedge fund performance and risk found in this study is the complexity of the derivative strategy of a hedge fund. The complexity is capable of explaining the Sharpe ratio, the Sharpe ratio with downside volatility, and the appraisal ratio of a hedge fund. For funds of hedge funds, the complexity is capable in explaining their risk but not their performance.

This study suggests that the complexity is especially well able to explain some of the left tails of the return distributions of hedge funds and funds of hedge funds. The use of this factor is also theoretically well motivated (see John et al. 2006). The association found in this study for the left tail of the return distribution of a hedge fund is particularly related to market-based factors of hedge fund returns. Therefore, this study suggests that market-based factors are able to explain the special characteristics of hedge fund returns arising from the use of complex derivative strategies. Consequently, there seems to be an association between market-based factors of hedge fund performance and factors related to the derivatives use of hedge funds. Given these significant results, this study advocates the use of option- and derivatives-based micro factors for hedge funds in addition to option-like market factors of hedge funds (see, e.g., Fung et al. 1997, 2001; Mitchell et al. 2001; Agarwal et al. 2004).

This study also presents results for other hedge fund characteristics which are related to the left tail of the return distribution of a hedge fund. Other hedge fund characteristics than derivatives use associated with a heavier left tail of the distribution are lower minimum investment, openness to the public, shorter restriction period, lower management fees, and the use of high watermark provisions. Moreover, these results are mostly related to non-normality of market-based risk of a hedge fund. The study by Aragon (2007) argues that hedge funds benefit from share restrictions by managing illiquid assets better which is captured by illiquidity premium for investors. This study also reports that share restrictions may reduce the left tail of the return distribution of a hedge fund.

8.5 Suggestions for Further Research

In further studies, it would be interesting to ascertain what kind of hedge fund characteristics lead these funds to benefit from the use of options. It may well be that the sophistication of a hedge fund has an impact on its ability to benefit from the use of options. It may also well be that skilled managers can use options better than less skilled managers. The ability of hedge funds to engage in informed trading and its profitability should also be investigated. A viable way to study the problem further is to better classify those hedge funds that may have advantageous information. Also, the impact of the use of derivatives on hedge fund risk could be investigated using samples constructed on the strategy of a hedge fund.

A considerably further issue related to the complexity of the derivative strategy of a hedge fund may be herding behaviour associated with the complexity. For this potential research topic, the present study implies some directional evidence but it does not directly test whether the complexity is associated with herding behaviour.

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APPENDIX 1. The Classification and Definitions of Hedge Fund Strategies

- Convertible Arbitrage: The objective of this strategy is to invest in convertible securities of a company.

- Dedicated Short Bias: The objective of this strategy is to short overvalued equity securities and/or maintain a short exposure to the stock market.

- Emerging Markets: This strategy involves investing in emerging market securities.

- Equity Market Neutral: The objective of this strategy is to exploit market inefficiencies with minimum market exposure.

- Event-Driven: This strategy exploits market inefficiencies associated with special corporate events.

- Fixed-Income Arbitrage: The objective of this strategy is to exploit market inefficiencies in fixed-income markets.

- Global/Macro: The objective of this strategy is to exploit global profit opportunities across various asset classes.

- Long/Short Equity: This strategy involves investing in both long and short positions in equity markets using various investment strategies.

- Managed Futures: The objective of these funds, which are also known Commodity Trading Advisors (CTAs), is to invest in financial and commodity futures

- Multi-Strategy: The objective of this strategy is to allocate capital among different hedge fund strategies.

APPENDIX 2. The Relation Between the Use of Equity Index Futures and Hedge Fund Performance

This table presents the parameter estimates of the cross-sectional analysis for the performance and risk estimates of hedge funds. The model for the cross-sectional analysis is the following (Model 3):

$$MEASURE_{j\,i} = \alpha + \sum_{j=1}^{N} \lambda_j CONTROL_{j\,i} + \beta_1 (G1)_i + \beta_2 (G2)_i + e\,,$$

where $MEASURE_{j\,i}$ defines a measure associated with higher moments *j* of fund *i*; $CONTROL_{j\,i}$ defines an additional control variable *j* of fund *i*; $(G1)_i$ defines a dummy variable on whether a hedge fund uses equity index futures and belongs to strategy group 1 (1 if yes), and $(G2)_i$ defines a dummy variable on whether a hedge fund uses equity index futures and belongs to strategy group 2 (1 if yes). Strategy group 1 includes the dedicated short bias, event-driven, equity long/short, emerging market, and equity market neutral strategies. Strategy group 2 includes the managed futures, global macro, convertible arbitrage, and fixed-income arbitrage strategies. Asset dummies include controls for assets and primary assets in which hedge funds report investing. The sample includes 3,382 hedge funds. This table also presents the Durbin-Watson test for the first-order serial correlation. The standard errors are White (1980) heteroskedasticity robust. *t*-statistics are given in italic. See Table 1 for definitions of the variables.

	SHARPE		SHARPED		ALPHA		APPRAISAL	
Variable	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
C	-0.620**	*-2.18*	-0.565*	*-1.77*	-4.343***	*-4.07*	-0.915*	*-1.68*
LNSIZE	0.033***	*11.52*	0.035***	*10.23*	0.068***	*3.98*	0.048***	*7.29*
LNAGE	0.052	*1.29*	0.050	*1.13*	0.435***	*2.86*	0.046	*0.60*
HMARK	-0.001	*-0.05*	-0.022	*-0.98*	0.042	*0.70*	0.015	*0.54*
IFEE	0.000	*-0.02*	0.000	*0.25*	0.016***	*3.22*	0.002	*0.84*
MFEE	-0.001	*-0.19*	-0.003	*-0.35*	0.120**	*2.33*	0.027**	*2.05*
LEVERAGED	0.002	*0.15*	-0.002	*-0.13*	0.106**	*2.22*	0.026	*1.12*
MINIMUM(Million$)	-0.005	*-1.30*	-0.004	*-0.67*	-0.025**	*-2.05*	-0.002	*-0.17*
RESTRICTION	0.001***	*3.89*	0.002***	*3.97*	0.002**	*2.31*	0.002***	*3.37*
LOCKUP	0.002**	*2.24*	0.003**	*2.37*	0.007**	*1.99*	0.002	*1.22*
AUDIT	-0.011	*-0.74*	-0.010	*-0.58*	-0.060	*-0.83*	-0.011	*-0.36*
PERCAPITAL	0.006	*0.61*	0.000	*0.00*	0.039	*0.81*	0.011	*0.54*
OPEN	-	*-3.55*	-	*-3.34*	-0.151***	*-2.58*	-0.111***	*-4.34*
OPENENDED	0.014	*0.93*	0.011	*0.59*	0.052	*1.13*	0.041	*1.55*
G1	-0.013	*-1.23*	-0.010	*-0.80*	-0.173**	*-2.54*	-0.033	*-1.42*
G2	0.023	*0.86*	0.026	*0.77*	-0.145	*-1.07*	0.036	*0.75*
Strategy Dummies	Yes		Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes		Yes	
Asset Dummies	Yes		Yes		Yes		Yes	
Adjusted R-squared	0.225		0.194		0.069		0.116	
F-statistic	22.79		19.07		6.58		10.90	
Durbin-Watson stat.	1.94		1.97		1.90		1.91	

* refers to a statistical significance at the 10% level; ** refers to a statistical significance at the 5% level; *** refers to a statistical significance at the 1% level.