Hedge Funds: Performance Analysis, Strategy Classification, and Portfolio Construction

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ABSTRACT

Supported by the perception of superior risk-return characteristics compared to traditional asset classes, hedge funds are enjoying increasing popularity in the investment community. The term "Hedge Fund" is used to describe private investment vehicles with few investment restrictions. Hedge funds can apply a large variety of different investment strategies and often use different investment instruments at the same time to express a certain trading idea.

The objective of the thesis is to contribute in various areas of hedge fund research, particularly with respect to capacity issues in the industry, performance evaluation, construction of portfolios with hedge funds and the evaluation of funds of hedge funds. Each topic is supported with comprehensive empirical analysis based on a very large set of hedge fund data.

The research results suggest that investor concerns of capacity issues in the hedge fund industry are justified. Cross-sectional regressions indicate a decrease in returns, Sharpe ratios, standard deviations and alphas of hedge funds with increasing fund sizes.

A further key subject of the thesis is the evaluation of long-term performance persistence based on a broad range of traditional and alternative performance measures. The finding of performance persistence confirms the frequently debated added value of quantitative hedge fund selection. The result is supported by a comprehensive relative efficiency measure developed with the relatively new technique of data envelopment analysis.

The results of quantitative cluster-based hedge fund classification techniques partially correspond with the qualitative self-classification of hedge fund managers. The cluster-based classification is used for the development of weighting schemes for the construction of hedge fund portfolios. The assessment focuses on the ability of cluster-based weighting schemes to improve the risk-return characteristics of hedge fund portfolios.

ABSTRACT IN GERMAN

Hedge-Fonds erfreuen sich steigender Beliebtheit in der Vermögensanlage, nicht zuletzt augrund der Sichtweise von hohen Risiko-Rendite Charakteristika im Vergleich zu traditionellen Anlageklassen. Der Begriff „Hedge-Fonds“ wird verwendet um private Anlagevehikel mit wenigen Investmentrestriktionen zu beschreiben. Hedge-Fonds können eine Vielfalt von unterschiedlichen Investmentstrategien einsetzen und verwenden oft unterschiedliche Investmentinstrumente um eine bestimmte Investmentidee auszudrücken.

Die Dissertation verfolgt die Zielsetzung einen Beitrag in verschiedenen Bereichen der Hedge-Fonds Forschung zu leisten und beschäftigt sich insbesondere mit der Frage von Kapazitätsgrenzen, der Performancebewertung, der Konstruktion von Portfolios mit Hedge-Fonds und der Bewertung von Dachfonds. In jedem Teilbereich wird die Diskussion des Themas durch umfangreiche empirische Analysen anhand eines grossen Hedge-Fonds Datensatzes unterstützt.

Die Analysen bestätigen die Bedenken von Investoren in Bezug auf Kapazitätsgrenzen von Hedge-Fonds. Renditen, Standardabweichungen, Sharpe Ratios und Alphas von Hedge-Fonds sinken mit zunehmenden Fondsgrössen.

Ein weiteres Schlüsselthema ist die Untersuchung von langfristiger Performancepersistenz basierend auf verschiedenen traditionellen und alternativen Performancemassen. Die Existenz von Performancepersistenz bestätigt den oft umstrittenen Mehrwert eines quantitativen Ansatzes für die Hedge-Fonds Selektion. Das Resultat wird von einem umfassenden relativen Effizienzmass anhand der relativ neuen Technik der Data Envelopment Analyse unterstützt.

Die Resultate von quantitativen Methoden zur Klassifikation von Hedge-Fonds basierend auf einer Clusteranalyse stimmen zum Teil mit der qualitativen Selbstklassifikation der Hedge-Fonds Manager überein. Die quantitative Klassifikation wird zur Entwicklung von Gewichtungsschemata für die Konstruktion von Hedge-Fonds Portfolios verwendet. Die Untersuchung fokussiert auf die Eignung der quantitativ hergeleiteten Gewichtungsschemata zur Verbesserung der Risiko-Rendite Charakteristika von Hedge-Fonds Portfolios.

I INTRODUCTION

Since the late nineties, hedge funds have gained widespread acceptance due to the perception of high risk-return characteristics and distinct correlation properties compared to traditional asset classes. Many studies have tried to answer the question of whether hedge fund managers are able to consistently add value. The difficulty in answering this question lies in the fact that the returns of the hedge fund universe are not directly observable. Unlike mutual funds, hedge funds are private investment vehicles that are not required to publish performance data. Therefore, there exists no database in the hedge fund industry that covers the entire hedge fund universe.

A THE HEDGE FUND INDUSTRY

Recent attempts to increase the transparency of the hedge fund industry are still in an early stage. No common legal or administrative standards exist for the setup of a hedge fund. With the increased popularity of hedge funds, the clientele of the industry is transitioning from predominantly high net worth individuals to a more diversified client base, resulting in the majority of inflows coming from institutional investors such as funds of hedge funds or pension funds.

The hedge fund industry has almost 13,675 single manager hedge funds, 1,400 managed futures and 6,100 funds of hedge funds at the end of 2006[1]. The diversification benefits of hedge funds in a portfolio with traditional asset classes have been extensively discussed in the industry. Alternative investments in general and hedge funds in particular have become the third pillar alongside equities and bonds in any diversified portfolio for both institutional as well as private investors. With the enhanced transparency requirements of institutional investors, significant efforts are made to enlighten the somewhat mysterious asset class of hedge funds.

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[1] According to the 2006 hedge fund database study of Strategic Financial Solutions

B OBJECTIVE OF THE THESIS

The objective of the thesis is to contribute to the discussion of key research questions in the hedge fund industry. Generally, two broad areas of applied hedge fund research can be differentiated, namely hedge fund selection and portfolio construction. The thesis aims to contribute to the discussion of hedge fund selection by assessing quantitative selection methodologies such as data envelopment analysis. The portfolio construction of hedge fund portfolios is investigated with modern quantitative portfolio construction methodologies such as cluster analysis.

Within the scope of analyzing benefits in quantitative hedge fund selection, an overview is given about the extensive literature concerning performance measurement with hedge funds. Most performance studies with hedge fund data have a descriptive character and therefore differ from the objective of the performance analysis in this thesis that focuses on the assessment of performance persistence with regard to its benefits for hedge fund selection.

Studies about performance measurement with hedge funds have been published since the late nineties. Ackermann, McEnally and Ravenscraft (1999) and Liang (2000, 2001) give an overview of hedge fund returns and focus on the various biases inherent in hedge fund databases. Liang (2000) estimates an annual survivorship bias[2] of 2.24% and 2.43% in two different studies. Fung and Hsieh (2000) find an annual bias of 3% for hedge funds and 1.4% for funds of hedge funds. These findings are also in line with the estimates of Brown, Goetzmann and Ibbotson (1999). Large differences are found in the estimates of the attrition rate[3] of hedge funds. While Agarwal and Naik (2000a) report an attrition rate of 2.17% in the HFR database, Brown, Goetzmann and Ibbotson (1999) estimate an attrition rate of 20% in the U.S. Offshore Fund directory. Liang (2003a) gives insight into the accuracy of hedge fund returns in hedge fund databases by comparing the data

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[2] Following Malkiel's method (1995), the survivorship bias is evaluated as the difference in the performance of the "observable" portfolio containing each fund in the database from the beginning of the sample period and the portfolio of surviving funds.

[3] The attrition rate in the hedge fund industry refers to the percentage of funds that drops from the data source within a certain time period. The average attrition rate is typically calculated retrospectively on an annual basis by going back in time to find all funds that existed at a given point in time and determining how many had not survived one year later. Biases associated with this method are discussed in Fung and Hsieh (1997a).

quality of the TASS database with the HFR database, two of the largest commercial hedge fund data providers. The various biases associated with hedge fund data are motivated in Chapter II. Hedge fund databases typically exhibit low overlap among each other leading to a high data dependency of the results on the data source chosen for empirical analysis. To avoid biases from the choice of a database provider, several of the largest commercial hedge fund databases are combined for empirical analysis. The thesis is structured into four research topics.

1 RESEARCH TOPIC I

The first research topic is dedicated to capacity issues of hedge funds. The strong growth of the hedge fund industry raises the question of a potential dilution of hedge fund returns. Various hedge fund strategies are exploiting a limited number of opportunities in the market and many hedge fund managers claim to face capacity limits within their specific hedge fund strategy. On one hand, the decreasing barriers to enter the hedge fund industry are leading to a surge of hedge fund start-ups and, on the other hand, large hedge fund groups are institutionalizing their business to meet the high due diligence standards of a rapidly growing investor base.

Despite of the growing capacity concerns in the hedge fund industry, little research has been dedicated to that issue with mixed results. Herzberg and Mozes (2003) and Hedges (2003) argue that smaller funds outperform larger funds. Gregoriou and Rouah (2003) and Kazemi and Schneeweis (2003) find no evidence for an impact of fund sizes on hedge fund returns. Liang (1999) finds a positive relationship between fund sizes and returns. Edwards and Caglayan (2001) suggests that hedge fund performance increases at a declining rate with increasing fund sizes and Amenc and Martellini (2003) argue that large funds have higher alphas than small funds. Getmansky (2004) suggests the idea of life cycles of hedge funds with outperforming funds attracting more fund inflows.

Chapter III contributes to the literature with an in-depth analysis of the impact of fund sizes and fund flows on hedge fund and CTA performance. A percentiles-based approach is used that allows a more accurate assessment whether larger hedge funds underperform smaller hedge funds, as is often conjectured in the hedge fund industry. The impact of fund sizes is analyzed with respect to fund returns, standard deviations, Sharpe ratios and alphas derived from a multi asset class factor model. The second order effect of assets on hedge fund performance is analyzed by investigating the impact of fund flows. Hedge fund managers often need a certain time period to invest large asset inflows that can have a diluting effect on performance. Large outflows require liquidations of positions that could be expensive and to the disadvantage of remaining investors.

2 RESEARCH TOPIC II

In the second research topic the quantitative selection of hedge funds is approached by analyzing the persistence in hedge fund returns. A range of studies such as Agarwal and Naik (2000a), Brown, Goetzmann and Ibbotson (1999) and Kat and Menexe (2003) provide a detailed discussion of the subject. Most studies find little or no evidence for performance persistence in hedge fund performance. Many studies dedicated to the measurement of performance persistence are investigating the subject by focusing on short term performance persistence of one to twelve month horizons such as Agarwal, Daniel and Naik (2005), Amenc, Bied and Martellini (2003), Barès, Gibson and Gyger (2003), Boyson and Cooper (2004), Brown and Goetzmann (2003), Capocci and Hubner (2004), Capocci, Corhay and Hubner (2005), Gregoriou and Rouah (2001), Herzberg and Mozes (2003), Koh, Koh and Teo (2003), Kosowski, Naik and Teo (2007), Malkiel and Saha (2005) and Park and Staum (1998).

The lack of liquidity in hedge fund investments due to hedge fund-specific features such as long lock-up periods, quarterly redemptions and redemption notices of several months suggests a hedge fund investment horizon of at least three to five years. Very few studies assess medium-term performance persistence with twelve to 36-month horizons such as De Souza and Gokcan (2004), Edwards and Caglayan (2001), Jagannathan, Malakhov and Novikov (2006) and Kouwenberg (2003).

Chapter IV contributes to the literature with an analysis of long-term performance persistence of up to 60 months. In addition to that a larger variety of traditional and alternative performance measures is used to test performance persistence accounting for the specific return distribution properties of hedge funds.

A unique relative efficiency score is derived that considers a variety of performance measures simultaneously.

Fung and Hsieh (1997a) show the limits of simple linear statistical measures such as standard deviations, Sharpe ratios and correlations. New performance measures such as the Sortino ratio, omega or the upside potential ratio have been developed to account for higher moments of hedge fund return distributions. Several alternative performance measures are motivated and discussed with regards to their benefits for hedge fund selection.

The relative efficiency measure is based on the technique of data envelopment analysis discussed by Gregoriou (2003), Gregoriou, Sedzro and Zhu (2005), Nguyen-Thi-Thanh (2006) and Eling (2006). Data envelopment analysis is used to derive multi-dimensional efficient frontiers for the assessment of hedge fund performance. A particularly large data set based on a combination of several of the largest commercial database providers is used for the analysis.

3 RESEARCH TOPIC III

The third research topic contributes in the area of portfolio construction with hedge funds. Empirical evidence and the nature of the various hedge fund strategies indicate that hedge funds build a heterogeneous group compared to traditional asset classes such as bonds and equities.

Several authors propose factor models to explain hedge fund returns. Fung and Hsieh (1997a) employ Sharpe's (1992) model and use a principal component analysis to explain hedge fund returns. Agarwal and Naik (2000b) develop a factor model and point out the non-linear option-like exposures of various hedge fund strategies. An interesting approach overcoming the short history of hedge fund returns has been proposed by Agarwal and Naik (2004). The authors use the underlying risk factors estimated with a multi-factor model to simulate the effects of the major stock market crises of 1929 and 1987 on hedge fund returns. Schneeweis, Kazemi and Martin (2003) investigate the differences between a single-factor and a multi-factor model to explain hedge fund strategy returns. Brealey and Kaplanis (2001) investigate changes in factor exposures to explain hedge fund returns over time.

Amenc and Martellini (2003) provide a comprehensive study on the performance of various hedge fund indices. In their search for the true, unobserved, fully representative and unbiased index of the various hedge fund strategies, they use Kalman filter techniques, principal component analysis and minimum variance analysis to extract the best one-dimensional summary of a “pure” hedge fund index from the data of a number of various hedge fund index providers. Various recent studies such as Agarwal and Naik (2004), Jaeger (2005), Kat and Palaro (2007) and Diez de los Rios and Garcia (2007) are discussing the issue of benchmarking and replicating hedge funds returns.

In Chapter V a different approach is discussed. In order to investigate the structure of hedge fund returns, a principal component analysis and a cluster analysis are applied to a large sample of hedge funds. The principal component analysis quantifies the degree of heterogeneity of the hedge fund industry and individual hedge fund strategies. Main factors influencing hedge fund returns are identified. The cluster analysis is used to derive a quantitative classification of hedge funds based on their past returns.

Previous studies about cluster analysis with hedge funds are provided by Brown and Goetzmann (2003), Das (2003), Maillet and Rousset (2003), Baghai-Wadji et al. (2005), Martin (2000), Das and Das (2005) and Bianchia et al. (2005).

In this thesis the qualitative self-reported classification of hedge fund managers is compared with the results of the cluster-based classification. One major contribution to the existing literature is the assessment of the stability of clusters and persistence of cluster characteristics over time. The study also goes one step further than previous studies by deriving concepts for portfolio construction based on the results of the cluster analysis. Portfolio weighting schemes are assessed with respect to their ability to improve the risk-return characteristics of hedge fund portfolios.

4 RESEARCH TOPIC IV

The fourth research topic is dedicated to funds of hedge funds. A variety of studies has been conducted in that space. Fung and Hsieh (2000), Liang (2003b) and Brown, Goetzmann and Liang (2004) provide performance studies with fund of hedge funds returns. Agarwal and Kale (2007) compare funds of hedge funds to multi-strategy hedge funds and Kat and Palaro (2006) compare funds of hedge funds to a generic futures trading strategy. Kat (2002) and Ineichen (2002a) provide insights in portfolio construction with funds of hedge funds. Davies, Kat and Lu (2005) and Gregoriou (2003a) are discussing funds of hedge funds selection under consideration of specific return distribution properties of funds of hedge funds.

Chapter VI contributes to the existing literature with a detailed performance analysis containing methods for the selection of funds of hedge funds based on data envelopment analysis and an assessment of the impact of fund sizes on the performance of funds of hedge funds. Fund of hedge funds performance is compared to hedge fund performance under consideration of the additional fee load of funds of hedge funds. A survivorship analysis is conducted and multi asset class factor models are used to explain fund of hedge funds alphas.

Further related literature is discussed in the specific chapters. Literature concerning the capacity issue in the hedge fund industry is described in Chapter III C. Literature about performance persistence and data envelopment analysis is discussed in Chapter IV B. The research area about strategy classification of hedge fund returns is described in Chapter V B. Literature about funds of hedge funds is analyzed in Chapter VI B.

II HEDGE FUND DATA

Due to the opaque nature of the hedge fund industry, the availability of high quality data is crucial for research purposes with hedge fund data. Substantial improvements in the efforts of various data providers in capturing a larger and more representative sample of the hedge fund industry is opening an extensive field for research opportunities in a still relatively young research arena. Due to the lack of a comprehensive database containing the track records of all hedge funds and the nature of the data collection process in the past, hedge fund data is subject to a number of biases.[4]

A DATABASE BIASES AND INFORMATION CONTENT

In this section a brief overview of the biases inherent in commercial hedge fund databases is given. The academic literature basically knows three major biases in hedge fund databases: Survivorship bias, instant history bias and selection bias.

Survivorship bias occurs when a sample of hedge funds includes only funds that are operating at the end of the sampling period and excludes funds that have stopped reporting performance data during the period. Funds that stop reporting have not necessarily ceased operations. On one hand, funds may voluntarily stop reporting because they do not want to publish bad performance and harm their reputation. On the other hand, they may stop reporting because they have reached the optimal size for their trading style and therefore no longer seek investors.

For the survivorship analysis in this thesis a common definition of survivorship bias is used. The return difference between two data samples is calculated. In the first sample both, “living” funds that are still reporting returns on a regular basis and “dead” funds that have stopped reporting their returns to the data provider are included. The second sample consists of funds that are still reporting at the end of

[4] Fung and Hsieh (2000) provide a detailed discussion of natural versus spurious biases in the hedge fund industry.

the data period. The difference in the returns between the two samples is defined as the survivorship bias.

Instant history bias occurs if database vendors are backfilling the performance of hedge funds when they add new funds to their database. Hedge fund managers often try to develop a certain track record before they start publishing the performance to commercial databases. Funds that fail to develop a good track record in the first months may have an interest in avoiding showing their track record to the public. Only those funds that want to market their track record in order to attract new investors will report their performance to commercial databases. Therefore, hedge fund data that is backfilled into the databases is generally subject to the instant history bias.

Selection bias occurs if the hedge funds in the database are not representative of the universe of hedge funds due to the selection criteria of the database vendors. Some databases may require annual audit reports, a minimum asset size or other criteria to take funds into their database.

Hedge fund databases often started collecting data in the nineties and therefore most studies only cover a relatively short time horizon. Research studies that deal with data that goes back to earlier than 1994 usually inherit the various measurement biases.

The literature on hedge fund returns shows a large variety of different results due to different data samples. The choice of a representative data set is therefore crucial in order to draw meaningful conclusions from empirical results.

B EMPIRICAL DATA

In the empirical analysis different data sets are used for different purposes. Unlike most studies with hedge fund returns, the studies in this thesis are primarily based on a broad data set using a combination of various commercial data sources. Relatively low overlap between various data sources in the hedge fund industry suggests the combination of several databases to extend the available data set. Two different hedge fund data sets with different qualities are used in this thesis depending on the purpose of the study.

1 HEDGE FUND DATA SET I

Data set I is used in Chapter III when asset and return data is required. Four databases from TASS, one of today's largest commercial hedge fund data providers, are combined with the CISDM database. Many empirical studies are based on the TASS or CISDM database. Liang (2000, 2003a) compares the data quality of the TASS database with the HFR database and concludes that TASS has a high data quality. TASS maintains four separate databases, a hedge fund database with "living" hedge funds, and one "hedge fund graveyard" database with funds that have stopped reporting, one CTA database with "living" funds and one "CTA graveyard" database. The combination of the four databases containing "living" and "dead" funds allows deriving the survivorship bias. The average annual survivorship bias in the TASS database over the time period from January 1994 to May 2005 is 3.54%. This finding is in line with Fung and Hsieh (2000) who state a survivorship bias of 3%. TASS started to build their databases in 1993/1994. Data prior to 1994 is backfilled by hedge fund managers starting to report in 1994 or later. Therefore, data prior to 1994 contains a number of biases and has not been used for the analysis.[5]

Funds may voluntarily stop reporting any time. It can be assumed that the primary reason for stopping the reporting of data to commercial data sources is a lack of willingness to publish bad performance data and consequently harm the reputation of the fund. Funds that drop from the database do therefore not necessarily cease their operation. TASS classifies exiting funds in seven categories. A summary can be found in Table 2.1. More than 50% of the exiting funds have been liquidated and 3.3% of the funds merged with other funds. Other reasons for exiting are more difficult to interpret. 2.65% of the funds indicated that they are

[5] Malkiel and Saha (2005) argue that in the years 1994 to 1997 the vast majority of the reported returns in the TASS databases were backfilled, while only in the later years, from 2001 or later, does the number of non-backfilled returns exceed the number that was backfilled.

closing for new investments, but the number might be much higher since almost 44% of the funds refused to state any reason for exiting or were unreachable.

TABLE II-1: TASS graveyard database – reasons for exiting

Reasons for exiting	Number of funds	Percentage
Funds liquidated	1,135	50.1%
Funds no longer reporting to TASS	661	29.2%
TASS has been unable to contact the manager	197	8.7%
Unknown	133	5.9%
Funds merged into another entity	74	3.3%
Funds closed to new investment	60	2.7%
Funds dormant	4	0.2%
Total number of funds	2,264	100.0%

Hedge funds in the TASS graveyard databases are classified according to their reasons for exiting. The table illustrates the classification taking data until April 2005 into account.

All four TASS databases combined contain a total of 7,588 funds: 3,619 funds in the hedge fund database, 2,123 funds in the hedge fund graveyard database, 493 funds in the CTA database and 1,353 funds in the CTA graveyard database. The CISDM database contains 4,287 hedge funds and 2,187 CTAs reporting performance data prior to April 2005. An overview about the various hedge fund and CTA databases is given in Table 2.2 and Table 2.3.

TABLE II-2: Hedge fund data in the TASS and CISDM databases

Hedge fund database	Number of funds	Percentage
TASS hedge fund database	3,619	36.1%
TASS graveyard database	2,123	21.2%
CISDM hedge funds	4,287	42.7%
Total number of hedge funds	10,029	100.0%

The table presents the number of hedge funds in the TASS and CISDM databases. The time period until April 2005 is taken into account.

TABLE II-3: CTA data in the TASS and CISDM databases

CTA database	Number of funds	Percentage
TASS CTA database	493	12.2%
TASS graveyard CTA database	1,353	33.5%
CISDM CTAs	2,187	54.2%
Total number of CTAs	4,033	100.0%

The table presents the number of CTAs in the TASS and CISDM databases. The time period until April 2005 is taken into account.

From the combined hedge fund data sample based on the TASS and the CISDM databases 1,315 funds are classified as funds of hedge funds and are eliminated from the sample. Funds of hedge funds are treated in a separate analysis. The remaining 8,714 hedge funds are evaluated with regard to their data quality. The analysis conducted with this data set requires two time series for each fund, one for return data and one for the development of the individual fund sizes. Especially the time series of fund sizes are often incomplete.

The inconsistencies in the asset data can partly be explained by the fact that some hedge funds have been reporting their fund sizes only on a quarterly, semi-annual or annual basis, particularly in their early years of reporting, while the data quality improved substantially in the later years of the data collection period.

On one hand, hedge funds with incomplete data should be eliminated in order to avoid any additional biases in the data sample, but, on the other hand, the size of the sample is important since the elimination of many funds would result in a sample that is less representative for the hedge fund universe. A compromise needs to be found between data quality and data quantity. The decision is made that all funds with more than 10% missing data points in return data or more than 20% missing data points in asset data are eliminated.[6] Table 2.4 gives a brief overview about the data cleaning process for the combined data set containing the TASS and CISDM

[6] 890 hedge funds are eliminated for reporting no return or asset data in the time period from January 1994 to April 2005, 17 funds are eliminated with more than 10% missing return data and 1,339 hedge funds are eliminated with more than 20% missing asset data resulting in a total number of 2,246 hedge funds with insufficient data quality.

databases. The data sample contains 8,714 hedge funds excluding funds of hedge funds. With the adjustment, 2,246 hedge funds are excluded because of insufficient data quality. Missing data points in assets under management are the main restriction. In addition to that, further 1,769 hedge funds have been eliminated to avoid double counting of funds. Finally, a sample of 4,699 hedge funds with assets of 436 billion USD is used for the analysis.

TABLE II-4: Hedge fund and CTA data cleaning process

	Hedge funds	CTAs
Funds in the TASS and CISDM databases	10,029	4,033
Funds of hedge funds	1,315	
Funds with insufficient data quality	2,246	709
Funds eliminated to avoid double counting	1,769	606
Funds used for further analysis	4,699	2,718

The table describes the data cleaning process for the hedge fund and CTA data samples. The data set combines data from the TASS database with the CISDM database. 4,699 hedge funds and 2,718 CTAs are used for further empirical analysis.

Since CTAs generally exhibit performance characteristics that are often considered distinct from other hedge fund strategies, a separate analysis is conducted with a sample of CTAs[7]. The TASS and CISDM databases combined contain a total of 4,033 CTAs. After eliminating funds that are double counted and funds with poor data quality, a sample of 2,718 CTAs with assets of 157 billions USD is left for further analysis. The results of the analysis with CTAs are then compared with the results of the analysis with hedge funds.

[7] Edwards and Liew (1999) investigate the properties of hedge funds and CTAs and suggest treating them as separate asset classes.

2 HEDGE FUND DATA SET II

Data set II combines data from three of the largest commercial database providers: TASS, HFR and Hedgefund.net. Data set II is used whenever the study is focusing on the analysis of return data. This is the case in Chapter IV and V.

For this purpose a clean data sample with a minimum track record for each hedge fund over the same time period is required. There is a tradeoff between maximizing the number of funds and maximizing the time horizon used for the analysis. On one hand, a time horizon that is too short might be affected by temporary cycles and is not representative in the long term. On the other hand, one of the shortcomings in most existing studies is the use of a small data sample. In order to maximize the size of the data sample, an enlarged data sample is used that contains data from six different hedge fund databases: TASS hedge fund, TASS CTA, TASS hedge fund graveyard, TASS CTA graveyard, HFR and Hedgefund.net. The objective of the analysis based on data set II is to identify the influencing factors of hedge fund returns. Biases in the data sample are therefore not relevant.

The analysis of the data on a strategy level requires a unique strategy classification scheme. The different classification schemes of various data sources indicate that no consensus exists in the hedge fund industry. Chapter V C discusses the challenges in deriving a unique classification scheme for hedge funds.

A minimum of 60 data points is used for the analysis and all funds with an insufficient track record are excluded. The 60-month sample period from May 2000 to April 2005 contains the largest data sample. All funds with more than three missing data points in that period are excluded. Hedge funds that appear in several data sources are kept only once. From hedge fund managers with onshore and offshore funds or several vehicles for the same strategy, the one with the longest track record is kept and the others are eliminated. From the 3,049 funds with a 60-month track record 1,748 funds are eliminated, and the remaining 1,349 funds are used for the analysis. Details about the data set are illustrated in Table 2.5.

In some parts of the study, a longer time period of 120 months, from May 1995 to April 2005, is used for the analysis. Due to the lengthening of the time horizon, the number of hedge funds with returns over the entire time period further decreases. Across all databases 480 hedge funds have a track record for the 120-month time period. The sample of 480 hedge funds is primarily used to analyze the long-term performance persistence of hedge funds.

TABLE II-5: Data quality of hedge fund data set II with 1,349 hedge funds

Databases	Funds (initially)	Funds with 60 months track record	Funds with "clean" data used for the study
All TASS databases	7,588	1,165	850
HFR database	4,690	970	228
Hedgefund.net database	4,623	962	271
Total number of funds	16,901	3,097	1,349

The data set combines six different commercial databases including TASS hedge fund, TASS CTA, TASS hedge fund graveyard, TASS CTA graveyard, HFR and Hedgefund.net. In the data cleaning process funds with more than three missing data points in the time period from May 2000 to April 2005 are not counted in the fourth column. In case of several investment vehicles for the same fund, only the vehicle with the longest track record is counted, while the others are excluded from the sample.

3 FUND OF HEDGE FUNDS DATA SET

Chapter VI is dedicated to the analysis of funds of hedge funds. The TASS databases are used as a basis for the analysis due to the relatively high quality of asset data reported by TASS.

The TASS databases contain 1,315 funds of hedge funds per June 2005 including funds that ceased reporting to TASS. The data quality is documented in Table 2.6. For the empirical analysis four funds of hedge funds with more than 10% missing return data and 479 funds of hedge funds with more than 20% missing asset data are eliminated. The missing asset data of funds is the main restricting criteria in the data cleaning process. A further 170 funds of hedge funds are eliminated to avoid double counting. The remaining sample of 662 funds of hedge funds is used in the analysis. The study covers the time period from January 1994 to April 2005.

For the data envelopment analysis the sample is reduced to funds with at least a 60-month track record from May 2000 to April 2005. 167 funds of hedge funds meet the criteria. A second sample with 55 funds that exhibit at least 120 months track record over the time period from May 1995 to April 2005 is used to test the persistence of the results.

TABLE II-6: Data quality of funds of hedge funds in the TASS database

Missing returns	Number of funds	Percentage
At least 1 datapoint missing	175	13.31%
More than 1%	146	11.10%
More than 3%	52	3.95%
More than 5%	19	1.44%
More than 10%	4	0.30%

Missing fund sizes	Number of funds	Percentage
At least 1 datapoint missing	820	62.36%
More than 1%	810	61.60%
More than 3%	742	56.43%
More than 5%	686	52.17%
More than 10%	583	44.33%
More than 20%	479	36.43%

The table is based on data from the TASS database per June 2005. The total sample contains 1,315 funds of hedge funds. The time period from January 1994 to April 2005 is used for the analysis.

III IMPACT OF FUND SIZES AND FUND FLOWS ON HEDGE FUND PERFORMANCE

Capacity issues based on large inflows in well-performing hedge funds are among the most frequently discussed concerns in the hedge fund industry. In this section the impact of fund flows and fund sizes on hedge fund and CTA performance is investigated. The findings confirm the legitimacy of investor concerns regarding capacity issues in the hedge fund industry. The results of the empirical study suggest a strong negative relationship between fund sizes and hedge fund returns, standard deviations, Sharpe ratios and alphas derived from an asset class multi-factor model.

A GROWTH OF THE HEDGE FUND INDUSTRY

A large number of different hedge fund strategies have been developed over time and the number of hedge funds is increasing at record rates. Nearly 13,675 single manager hedge funds, 1,400 managed futures and 6,100 funds of hedge funds have been counted in the 2006 hedge fund database study of Strategic Financial Solutions[8]. These numbers show an increase of 5,575 single manager hedge funds and 1,950 funds of hedge funds from the 2005 hedge fund database study. Although it remains difficult to quantify the actual size of the hedge fund industry due to the lack of regulation, the asset base in single manager hedge funds is estimated to be around USD 1.41 trillion in 2006[9], an impressive growth compared to USD 400 billion in 1995.[10] Projected growth rates for the coming years remain high as institutional investors intend to increase their allocation to hedge funds. Industry specialists estimate the size of the hedge fund industry in 2010 at USD 2 trillion or more.[11] Many large hedge funds are already closed for new investments due to

[8] The annual hedge fund database study of Strategic Financial Solutions examines the hedge fund listings from twelve of the major hedge fund databases. The numbers are adjusted for duplicate records.

[9] According to the 2006 database study of Strategic Financial Solutions.

[10] See, for example, "Hedge Fund Growth: Good News or Bad?", www.forbes.com, June 20, 2005.

[11] According to Sprecher P., "Is Two Trillion Dollars too Little", *AIMA Journal*, June 2004.

limited capacities in their strategies. Hedge fund investors conjecture that further asset inflows into the hedge fund industry go hand in hand with decreasing performance due to limited investment opportunities for various hedge fund strategies.

B RESEARCH TOPIC I

Capacity is becoming a serious issue not only for large hedge fund investors that are looking for investment opportunities to employ large amounts of capital, but also for hedge fund investors that are looking for good hedge funds that are open for investment. Increasing efficiency of financial markets results in decreasing arbitrage opportunities that are the primary source of returns of some hedge fund strategies. In this thesis, it is investigated whether an increasing asset base in hedge funds is diluting performance.

The impact of fund sizes on hedge fund performance is non-trivial. On one hand, it can be conjectured that small hedge funds are underperforming larger hedge funds due to a higher expense ratio. In the assessment of expected net returns, operational costs need to be taken into account. In that respect smaller funds are at a disadvantage due to a higher cost ratio based on relatively high fixed operating costs. On the other hand, many investment professionals argue that smaller funds may be willing to take more risk resulting in higher expected gross returns. Smaller funds also benefit from an enhanced flexibility to concentrate their capital under management on their best investment ideas. The ten best investment ideas of a hedge fund manager are generally better than the 100 best ideas. Smaller hedge funds are also more nimble and their portfolio therefore tends to be more liquid due to smaller position sizes. Large funds may face difficulties in liquidating their positions in difficult market environments. Large funds also tend to have a diversified client base, more resources and often a more rigorous risk management approach compared to smaller funds.

Many studies have been published about factors impacting hedge fund returns such as Fung and Hsieh (1997a), Agarwal and Naik (2000b), Schneeweis, Kazemi and Martin (2003), Ammann and Moerth (2005) and Brealy and Kaplanis (2003).

Generally, it can be differentiated between return-based factors investigated among others with techniques such as factor models, principal component analysis and cluster analysis and qualitative factors such as fund sizes, fund flows, lengths of track record, fee structure and many others.

While the effect of fund size on performance is one of the largest concerns in the hedge fund industry, it has received little research attention from studies exclusively focusing on this subject. This section attempts to fill this gap by focusing exclusively on two factors namely fund sizes and fund flows.

The relationship between fund sizes, fund flows and performance is evaluated from different angles. Hedge fund returns, standard deviations, Sharpe ratios and alphas derived from an asset class multi-factor model[12] are investigated with respect to fund sizes and fund flows. The study is supported by empirical evidence based on a large data sample of hedge fund returns and fund sizes.

The analysis suggests that on average large funds cannot take advantage of their economies of scale. On the contrary, a significant negative relationship between fund sizes and hedge fund performance is revealed. In a closer investigation of fund flows, it is investigated whether funds can cope with increased inflows and invest new capital efficiently. The analysis shows that periods with high asset inflows in individual funds are typically followed by periods of below average returns.

The structure of this section is the following: A discussion of related literature in section C is followed by a description of the data set used for the analyses in section D. Next, the methodology is introduced in section E and the results of an empirical analysis concerning the impact of fund sizes on hedge fund returns, standard deviations, Sharpe ratios and alphas of hedge funds and CTAs is presented in section F. Section G concludes.

[12] In contrast to the standard asset-class factor model of Sharpe (1992) excess returns are used to derive alphas from the factor models to investigate the impact of fund sizes.

C RELATED LITERATURE

The impact of fund sizes on returns for mutual funds has been investigated by Clark (2003). The study investigates several holding periods and concludes that no significant return differences can be found between small and large mutual funds. With respect to hedge fund research, some studies are touching the relationship between hedge fund sizes and returns with varying results.

Herzberg and Mozes (2003) investigate the impact of several factors on hedge fund performance and conclude that smaller hedge funds tend to outperform larger funds in absolute terms and in particular in risk-adjusted terms. Hedges (2003) confirms the results that smaller funds outperform larger funds, but also concludes that mid-sized funds perform the worst. This phenomenon is explained with the concept of mid-life crises for hedge funds.

Gregoriou and Rouah (2003) find no evidence for a relationship between fund sizes and hedge fund returns, Sharpe ratios or Treynor ratios in the time period from January 1994 to December 1999. The sample used for the study contains 204 hedge funds and 72 funds of hedge funds and is therefore significantly smaller than in this study and not necessarily representative for the hedge fund industry today.

Edwards and Caglayan (2001) argue that hedge fund performance increases at a declining rate as fund sizes increase. The authors derive six-factor alphas from a similar framework than that of Fama and French (1993, 1996). The six-factor alphas are then regressed on five variables: size, the reciprocal of size to capture nonlinearity in the size-performance relationship, age, and both management and incentive fees. Both size variables are statistically significant for all hedge funds and for all investment styles except “global macro” and “global”. A positive coefficient on the size variable together with a negative coefficient on the size reciprocal variable indicates that hedge fund performance increases at a declining rate as fund sizes increase.

Liang (1999) investigates the impact of fund characteristics with a cross-sectional regression and finds a significant positive relationship between fund assets and performance. The assets of the funds are taken only from one point in time at the end of the period. Therefore, the result may simply suggest that successful funds attract more money over time and therefore have a positive correlation to past performance. The study does therefore not necessarily measure the impact of fund sizes on performance, but the impact of performance on fund sizes. The data set used contains only 385 funds investigated over a three years time horizon from January 1994 to December 1996.

Amenc and Martellini (2003) support the view by investigating two equally sized groups with large and small funds. For each group, the average alpha is computed based on a number of different models, such as the standard CAPM, an adjusted CAPM for the presence of stale prices and an implicit factor model extracted from a principal component analysis. For all models the mean alpha for large funds exceeds the mean alpha for small funds. The separation of the data in small and large funds is simplistic and not sufficient to measure the relationship between fund sizes and performance.

A similar approach has been chosen by Kazemi and Schneeweis (2003). At the beginning of each year funds within each style are either assigned a large or a small subgroup depending on the size of assets under management. The authors find that large or small funds do not uniformly outperform the other group. The study contains only 15 to 30 hedge funds in each subgroup.

Getmansky (2004) investigates life cycles of hedge funds and finds that outperforming funds are attracting more fund inflows suggesting that hedge fund investors are chasing hedge fund returns. The study also analyzes the relationship between hedge fund returns and fund sizes with quadratic cross-sectional regressions. The results suggest a concave relationship for various hedge fund strategies in particular for strategies investing in less liquid instruments such as Convertible Arbitrage, Event Driven and Emerging Markets. The study is investigating individual hedge fund strategies separately despite of the limited number of funds per strategy. The study also contains an analysis of the relationship between fund flows and returns and reveals that large flows into bigger hedge funds are associated with poor future performance.

Goetzmann, Ingersoll and Ross (2003) examine the relationship between fund flows and past performance for hedge funds by regressing net fund growth on lagged returns in cross section. The differential response of new money to past returns is examined via a piecewise linear regression. The authors find that new money responds by flowing out of the poorest performers.

This chapter enlightens the discussion of capacity issues in the hedge fund industry and contributes to the existing literature with a detailed analysis of the impact of fund sizes and fund flows on hedge fund performance. In contrast to previous studies a percentiles-based methodology is used that allows deriving a more precise assessment of the size-performance relationship. Hedge funds and CTAs are classified in percentiles according to their fund sizes in order to test the relationship of fund sizes with a range of performance and risk measures such as fund returns, standard deviations, Sharpe ratios and alphas based on a multi-factor model. The relationships are investigated with linear and quadratic cross-sectional regressions. The analysis is supported with a large data set. An extensive discussion of the topic can also be found in Ammann and Moerth (2005) and Ammann and Moerth (2006b).

D DATA SET

Hedge fund data set I as described in Chapter II is used for the analysis in this section. The analysis is conducted with two samples, one containing 4,699 hedge funds and the other one 2,718 CTAs. The time period from January 1994 to April 2005 is used for the analysis. The empirical results concerning factor models and cross-sectional regression analysis are illustrated for both samples. Differences between the results of the data set with hedge funds and the data set with CTAs are discussed in the relevant context.

E METHODOLOGY

In a first step the difference between asset-weighted and equally weighted returns is analyzed. In a second step an asset class factor model is used to explain excess returns.[13] Therefore, eleven asset class factors representing all traditional asset classes are defined.[14] The asset class factors are the MSCI World Index, the NASDAQ Composite Index, the Russell 2000 Index, the Wilshire Micro Cap Index, the Lehman Aggregate Bond Index, the Lehman High Yield Credit Bond Index, the JP Morgan Government Bond Index, the Goldman Sachs Commodity Index, crude oil, the London Gold Bullion USD Index and the Chicago Board Options Exchange SPX Volatility Index.

The factor model is similar to the Sharpe's (1992) "style regression" with the difference that the risk-free rate is distracted and the excess return is used as the dependent variable. The equation

$$r_t - r_f = Alpha + \sum_{k=1}^{n} \beta_k x_{kt} + \varepsilon_t \qquad (3.1)$$

with k factors and the factor loadings β_k specifies the factor model.[15] In order to avoid multicollinearity and to facilitate the interpretations of the results, a model with fewer factors is derived. Therefore, the eleven factors are divided in four asset classes representing equities, bonds, commodities and volatility. The optimal combination of factors is tested given the constraint that one factor of each asset class is included in the factor model. The resulting four-factor model is then used for further analysis.

In the next step the funds are ranked according to their fund sizes and the sample is broken into 100 percentiles. The average fund size and the average returns are calculated for each percentile i. Monthly data is used to conduct the analysis. The average annualized returns are then regressed on the natural logarithms of the average fund sizes for the 100 percentiles. A linear regression of the form

$$r_i = \alpha_i + \beta \ \log(Assets_i) + \varepsilon_i \qquad (3.2)$$

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[13] The 90-day T-Bill rate is deducted from hedge funds returns to derive excess returns.

[14] Schneeweis, Kazemi and Martin (2003) investigate three different methods to explain excess returns: (a) single-factor approach using a small capitalization equity index (b) a multi-factor linear unconditional model and (c) a SDF/GMM approach. The authors find that in most cases the alphas are rather similar regardless of the empirical methodology applied.

[15] The risk free interest rate is discounted from all asset class factors with the exception of the CBOE SPX Volatility Index, since the volatility index is the only index that is not representing an asset class in a traditional sense.

is specified and a quadratic regression of the form

$$r_i = \alpha_i + \beta_1 \log(Assets_i) + \beta_2 (\log(Assets_i))^2 + \varepsilon_i . \qquad (3.3)$$

Newey-West covariance matrix estimators are used to account for heteroskedasticity and serial correlation in each regression analysis.[16]

Further, annualized standard deviations and annualized risk-adjusted returns are then regressed on fund sizes using the following linear and quadratic specifications.

$$\sigma_i = \alpha_i + \beta \ \log(Assets_i) + \varepsilon_i \qquad (3.4)$$

$$\sigma_i = \alpha_i + \beta_1 \log(Assets_i) + \beta_2 (\log(Assets_i))^2 + \varepsilon_i \qquad (3.5)$$

$$SR_i = \alpha_i + \beta \ \log(Assets_i) + \varepsilon_i \qquad (3.6)$$

$$SR_i = \alpha_i + \beta_1 \log(Assets_i) + \beta_2 (\log(Assets_i))^2 + \varepsilon_i \qquad (3.7)$$

The standard deviations and Sharpe ratios are referring to percentiles and not to individual funds. Each percentile can be considered as a portfolio of funds with similar fund sizes. For the calculation of the Sharpe ratios 90-day T-Bill rates are used as risk free rate.

Alphas are calculated for each individual percentile based on the previously derived four-factor model and therefore the model described in equation 3.1 is applied 100 times to derive equation 3.8.

$$r_{it} - r_{ft} = Alpha_i + \sum_{k=1}^{n} \beta_{ik} x_{kt} + \varepsilon_{it} \qquad (3.8)$$

The relationship between the alphas derived from the 100 factor models and the average fund sizes for the 100 percentiles is then further investigated with the following linear and quadratic regressions.

$$Alpha_i = \alpha_i + \beta \ \log(Assets_i) + \varepsilon_i \qquad (3.9)$$

$$Alpha_i = \alpha_i + \beta_1 \log(Assets_i) + \beta_2 \log(Assets_i)^2 + \varepsilon_i \qquad (3.10)$$

[16] According to Newey and West (1987).

The robustness of the results of the regression analysis is tested with two common approaches. First, each regression analysis is repeated over two 68-month sub-periods from January 1994 to August 1999 and from September 1999 to April 2005. Second, the relationship between fund sizes and alphas is repeated with four three-factor models in addition to the original four-factor model. The three-factor models are derived by separately dropping one factor from the original four-factor model each time.

The relationship between fund flows in rolling 12-month periods and returns in the following 12-month period is also investigated. Hedge funds are therefore ranked according to their fund flows in each month and percentiles are built. Annual fund flows are then regressed on the annual returns of the following 12-month period as specified in equation 3.11. Since fund flows can be positive as well as negative, it is not possible to take the logarithm of fund flows. Equation 3.11 therefore differs from equation 3.2, where the logarithms of fund sizes are used to facilitate a graphical presentation of the results.

$$\prod_{t=1}^{12}(1+r_{it}) = \alpha_i + \beta\ Flows_i + \varepsilon_i \qquad (3.11)$$

The returns of the deciles are evaluated based on fund flows and fund sizes. An F-Test is conducted to find out whether the average returns of the deciles are different from each other.

$$F = \frac{s_2^2}{s_1^2} = \frac{\sum_{j=1}^{K} 10(x_{.j} - x_{..})^2}{\sum_{j=1}^{K}\sum_{i=1}^{n}(x_{ij} - x_{.j})^2}$$ follows the F-distribution with (K-1, N-K) degrees of freedom. K = 10 represents the number of deciles and n_j = 10 represents the number of percentiles in each decile j while $N = \sum_{i=1}^{K} n_j = 100$ represents the total number of percentiles across all deciles. The numerator s_2^2 describes the variation of returns $x_{.j}$ of the ten deciles with respect to the average return $x_{..} = \frac{1}{100}\sum_i \sum_j x_{ij}$ across all 100 percentiles. The denominator s_1^2 describes the aggregate variation of

returns x_{ij} of the ten percentiles within each of the ten deciles j and $x_{\cdot j} = \frac{\sum_{i=1}^{10} x_{ij}}{10}$ expresses the returns of each decile j. A one tailed test is carried out as it is necessary to ascertain whether s_2^2 is larger than s_1^2.

F EMPIRICAL RESULTS

In this section the empirical analysis is conducted with the hedge fund and CTA samples of data set I discussed in Chapter II.

1 EQUALLY VERSUS ASSET WEIGHTED RETURNS

Most existing studies about the performance of hedge funds are using equally weighted returns in order to estimate returns of the unobservable hedge fund universe. One reason why most studies have focused on equally weighted hedge fund returns is the poor data quality of hedge funds' assets under management. Since the quality of available data improved significantly in the last years, it is now feasible to calculate asset weighted returns using the TASS and CISDM databases. Asset weighted returns are suitable to derive average returns of hedge fund investors while equally weighted returns measure the returns of the average hedge fund.

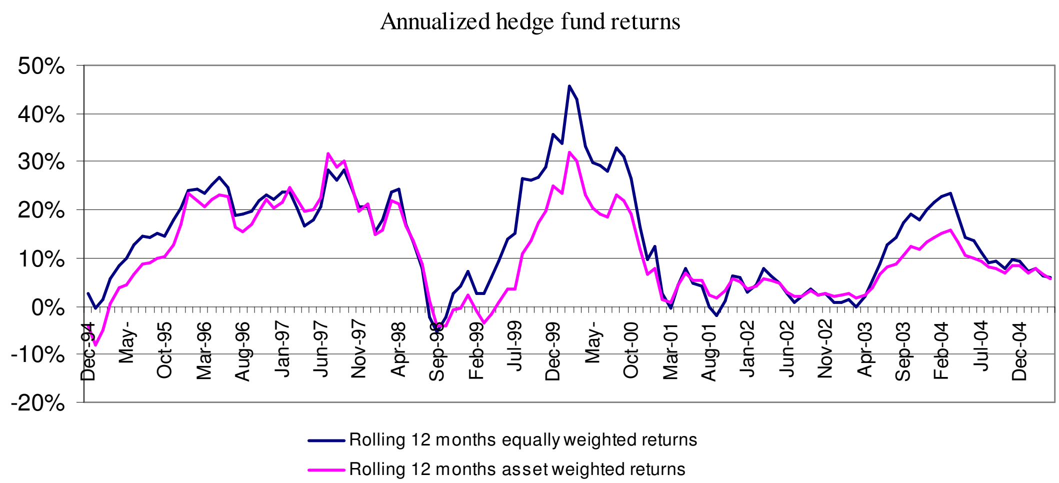
A number of index providers developed different methodologies to benchmark hedge fund returns. Most hedge fund indices are equally weighted. Examples for exceptions are the CSFB-Tremont hedge fund indices[17] and some of the MSCI hedge fund indices.

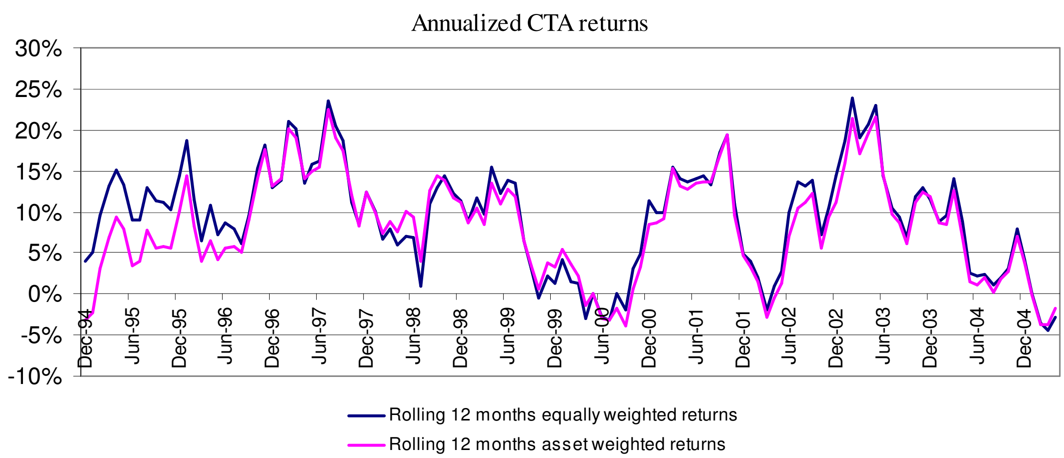
Both equally weighted and asset weighted returns are calculated for rolling 12-month periods from January 1994 to April 2005. Figure 3.1 shows a comparison between rolling 12-month equally weighted and rolling 12-month asset weighted

[17] The CSFB-Tremont hedge fund indices contain approximately 400 hedge funds representing 160 billion USD in assets. The indices focus on large hedge funds. Hedge funds require a minimum of 50 million USD assets under management, a minimum track record of one year and audited financial statements in order to become part of the index.

returns for hedge funds and CTAs. Temporary differences between equally weighted and asset weighted hedge fund returns are obvious in the period of the internet bubble in 1999 and at the beginning of 2000. Figure 3.1 suggests that in periods with high returns equally weighted returns are higher than asset weighted returns indicating a higher risk appetite of smaller funds. The difference between equally and asset weighted returns is less pronounced for CTAs.

FIGURE III-1: Equally versus asset weighted rolling 12-month returns





Rolling 12-month equally weighted and rolling 12-month asset weighted returns are illustrated over a 136-month time period from January 1994 to April 2005. The samples contain 4,699 hedge funds and 2,718 CTAs from the TASS and CISDM databases.

The survivorship bias is mitigated since both “dead” and “living” funds are included in the analysis. Biases like the instant history bias and the selection bias are hard to avoid and are therefore affecting the results. Some of the largest hedge funds do not report to any database. Hence the results of this study might be different had those funds been included in the database.

The annualized return difference between equally and asset weighted hedge fund returns is 2.90% over the 136-month period. The difference is statistically significant at the 1% significance level. The findings based on asset weighted returns are useful from a macro perspective in order to get a general view on hedge fund returns, while the individual investor who is building equally weighted or risk weighted hedge fund portfolios may be more interested in looking at equally weighted returns.

The annualized return difference between equally and asset weighted CTA[18] returns is 1.30% over the 136-month period. The difference is statistically significant at the 5% significance level.

2 ASSET CLASS FACTOR MODELS

Asset class factor models are used in order to derive hedge fund alphas. Table 3.1 represents the results of a multiple regression analysis of the eleven asset class factors described in the methodology section on the returns of the samples with 4,699 hedge funds and 2,718 CTAs based on equation 3.1.

Almost 85% of the excess hedge fund returns can be explained with the eleven-factor model. The high explanatory power of the result compared to previous studies can partially be explained by the increased dependency of hedge fund returns on equities in the last years of the sample period. The factors with the strongest explanatory power in the model are the MSCI World Index and the Wilshire Micro Cap Index.

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[18] The hurdles to start a CTA are smaller compared to most other hedge fund strategies. Therefore, a large number of small CTAs exists that may influence the result of the analysis.

TABLE III-1: Asset class factor models with eleven factors

Hedge funds			
Factors	Coefficient	Standard error	P-value
ALPHA	0.002	0.001	0.62%
MSCI WORLD	0.224	0.037	0.00%
WILSHIRE MICRO CAP IND.	0.170	0.030	0.00%
VIX	0.012	0.006	3.95%
JPM GL. GOV. BOND INDEX	0.312	0.199	11.86%
LEHMAN HIGH YIELD INDEX	0.007	0.006	24.87%
RUSSELL 2000	0.045	0.040	26.17%
LEHMAN BOND INDEX	-0.208	0.204	30.98%
GSCI	0.021	0.027	43.54%
GOLD INDEX	0.012	0.022	58.83%
CRUDE OIL	0.005	0.017	75.53%
NASDAQ	0.002	0.021	93.46%
R-squared	0.849	Adjusted R-squared	0.835
CTAs			
Factors	Coefficient	Standard error	P-value
ALPHA	0.002	0.002	43.22%
JPM GL. GOV. BOND INDEX	1.109	0.529	3.81%
GSCI	0.143	0.072	5.07%
NASDAQ	-0.082	0.057	14.81%
GOLD INDEX	0.083	0.059	15.89%
VIX	0.020	0.015	18.86%
CRUDE OIL	-0.047	0.044	28.56%
LEHMAN BOND INDEX	-0.568	0.542	29.65%
WILSHIRE MICRO CAP IND.	0.081	0.080	31.15%
MSCI WORLD	0.092	0.100	35.95%
LEHMAN HIGH YIELD INDEX	-0.011	0.016	50.90%
RUSSELL 2000	-0.010	0.107	92.31%
R-squared	0.241	Adjusted R-squared	0.174

Asset class factor models with eleven factors are used to explain excess returns of hedge funds and CTAs. Standard errors and p-values are calculated for each factor. The time period from January 1994 to April 2005 is used for the regression analysis.

Only 24.1% of the excess CTA returns can be explained with the eleven-factor model. CTAs have very distinct characteristics from other hedge fund strategies that make them less dependent on asset class factors. The objective of most CTAs is to time the markets by taking long and short directional bets on a large variety of futures on equity indices, interest rates, currencies and commodities at any point in time. Due to the varying long and short exposures and the diversification across many markets, the correlation of CTAs to traditional markets is generally low therefore leading to a lower explanatory power of a linear factor model. The result is therefore in line with expectations.

Single-factor models are calculated for each of the eleven asset class factors to get more insight into the dependencies of hedge fund and CTA returns on individual factors. The results are illustrated in Table 3.2. For hedge funds all four equity indices as well as the volatility index are highly significant on a stand-alone basis. The three bond indices and gold are not statistically significant, while the Goldman Sachs Commodity Index and crude oil are both statistically significant at the 10% significance level.

It is interesting to see that small cap equity indices such as the Wilshire Micro Cap Index and the Russell 2000 have a higher explanatory power than the MSCI World and the NASDAQ. This result is in line with the findings of Schneeweis and Kazemi (2003) and suggests that hedge fund managers see more opportunities in small cap stocks that have typically less research coverage from investment banks.

The single-factor models applied to CTAs indicate that the coefficients of the JP Morgan Global Government Bond Index and the Lehman Aggregate Bond Index are significant at the 1% significance level. The Goldman Sachs Commodity Index and Gold are significant at the 5% significance level. None of the equity indices is statistically significant on a stand-alone basis. The result supports the assumption that CTAs are generally taking exposures in a larger variety of markets.

TABLE III-2: Single-factor models for eleven asset class factors

Asset classes	Factors	Factor beta	Stand. error	P-value	R-squared	Monthly alpha
		Hedge funds				
EQUITIES						
	MSCI WORLD	0.391	0.029	0.00%	0.5698	0.46%
	WILSHIRE MICRO CAP IND.	0.270	0.014	0.00%	0.7384	0.34%
	NASDAQ	0.216	0.013	0.00%	0.6660	0.50%
	RUSSELL 2000	0.325	0.017	0.00%	0.7396	0.47%
BONDS						
	JPM GL. GOV. BOND IND.	-0.135	0.129	29.64%	0.0081	0.72%
	LEHMAN HIGH YIELD IND.	0.021	0.014	13.75%	0.0164	0.70%
	LEHMAN BOND INDEX	0.042	0.136	75.54%	0.0007	0.72%
COMMODITIES						
	GSCI	0.056	0.032	7.73%	0.0231	0.68%
	GOLD INDEX	0.060	0.050	23.16%	0.0107	0.71%
	CRUDE OIL	0.032	0.019	10.23%	0.0198	0.67%
VOLATILITY						
	VIX	-0.057	0.009	0.00%	0.2386	0.81%
		CTAs				
EQUITIES						
	MSCI WORLD	-0.089	0.053	9.35%	0.0209	0.45%
	WILSHIRE MICRO CAP IND.	-0.023	0.032	48.31%	0.0037	0.42%
	NASDAQ	-0.045	0.027	9.79%	0.0203	0.43%
	RUSSEL 2000	-0.033	0.039	39.45%	0.0054	0.41%
BONDS						
	JPM GL. GOV. BOND IND.	0.671	0.143	0.00%	0.1412	0.36%
	LEHMAN HIGH YIELD IND.	-0.016	0.017	34.98%	0.0065	0.41%
	LEHMAN BOND INDEX	0.585	0.153	0.02%	0.0982	0.40%
COMMODITIES						
	GSCI	0.093	0.037	1.35%	0.0447	0.32%
	GOLD INDEX	0.135	0.059	2.39%	0.0375	0.37%
	CRUDE OIL	0.030	0.023	20.14%	0.0122	0.35%
VOLATILITY						
	VIX	0.021	0.012	7.32%	0.0238	0.35%

Single-factor models for all eleven asset class factors are used to explain excess returns of hedge funds and CTAs. Monthly alphas and R-squares are calculated for each model. Newey-West covariance matrix estimators are used to account for heteroskedasticity and serial correlation. The time period from January 1994 to April 2005 is used for the regression analysis.

A second multi-factor model is derived with fewer factors in order to better interpret the result. For each of the four asset classes the single-factor model with the highest explanatory power is taken and the four factors are combined in a factor model with four asset class factors. In a second step for each asset class all potential factors are tested with the objective to find the four-factor model with the highest adjusted R-Squared that is representing all four asset classes. An overview is given in Table 3.3.

TABLE III-3: R-Squares of factor models based on four asset classes

Equities	Bonds	Commodities	Volatility	Adjusted R-squared
		Hedge funds		
RUSSELL 2000	LEHMAN BOND	GSCI	VIX	0.7384
MSCI WORLD	LEHMAN BOND	GSCI	VIX	0.5761
NASDAQ	LEHMAN BOND	GSCI	VIX	0.6672
WILSHIRE MICRO	LEHMAN BOND	GSCI	VIX	0.7489
WILSHIRE MICRO	LEHMAN HY	GSCI	VIX	0.7467
WILSHIRE MICRO	JPM GOV BOND	GSCI	VIX	0.7480
WILSHIRE MICRO	LEHMAN BOND	GOLD	VIX	0.7438
WILSHIRE MICRO	LEHMAN BOND	CRUDE OIL	VIX	0.7455
		CTAs		
RUSSELL 2000	JPM GOV BOND	GSCI	VIX	0.1711
MSCI WORLD	JPM GOV BOND	GSCI	VIX	0.1685
NASDAQ	JPM GOV BOND	GSCI	VIX	0.1698
WILSHIRE MICRO	JPM GOV BOND	GSCI	VIX	0.1704
RUSSELL 2000	LEHMAN HY	GSCI	VIX	0.0506
RUSSELL 2000	LEHMAN BOND	GSCI	VIX	0.1464
RUSSELL 2000	JPM GOV BOND	GOLD	VIX	0.1546
RUSSELL 2000	JPM GOV BOND	CRUDE OIL	VIX	0.1468

Asset class factor models with four factors representing each asset class are used to explain excess hedge fund and excess CTA returns. For each asset class all asset class factors are tested given the asset class factors of the other asset classes. A selection of the possible combinations is presented above. Adjusted R-squares are calculated for each model. Newey-West covariance matrix estimators are used to account for heteroskedasticity and serial correlation. The time period from January 1994 to April 2005 is used for the regression analysis.

For hedge funds the resulting four-factor model representing equities, bonds, commodities and volatility contains the Wilshire Micro Cap Index, the Lehman High Yield Credit Bond Index, the Goldman Sachs Commodity Index and the CBOE Volatility Index and is illustrated in Table 3.4. The constant, indicating the alpha of hedge funds, is positive and statistically significant at the 1% significance level. The annualized alpha of the model is 4.49%. The asset class factor model with four factors is explaining more than 75% of the hedge fund returns.

For CTAs the resulting four-factor model representing all four asset classes contains the Russell 2000, the JP Morgan Global Government Bond Index, the Goldman Sachs Commodity Index and the CBOE Volatility Index. The annualized alpha is 2.91%, but is not statistically significant.

TABLE III-4: Asset class factor model with four factors

Hedge funds			
Variable	Coefficient	Standard error	P-value
ALPHA	0.004	0.001	0.02%
WILSHIRE MICRO CAP	0.253	0.015	0.00%
LEHMAN BOND INDEX	0.074	0.068	27.72%
GSCI	0.027	0.016	9.90%
VIX	-0.012	0.006	3.26%
R-squared	0.756	Adjusted R-squared	0.749
CTAs			
Variable	Coefficient	Standard error	P-value
ALPHA	0.002	0.002	23.83%
RUSSELL 2000	0.028	0.044	51.66%
JPM GL. GOV. BOND INDEX	0.632	0.143	0.00%
GSCI	0.085	0.035	1.65%
VIX	0.024	0.013	7.30%
R-squared	0.196	Adjusted R-squared	0.171

Asset class factor models with four factors are used to explain excess hedge fund and excess CTA returns. Standard errors and p-values are calculated for each factor. Newey-West covariance matrix estimators are used to account for heteroskedasticity and serial correlation. The time period from January 1994 to April 2005 is used for the regression analysis.

Table 3.5 shows deciles of fund sizes and annualized average returns of the hedge funds in each decile. The result suggests that smaller hedge funds are outperforming larger funds. Many institutional investors are focusing on hedge funds with a larger asset base and are therefore eliminating funds with the highest return potential based on the indication of fund sizes. Institutional investors who are looking for funds with a minimum of USD 100 million under management will only focus on funds in the top two deciles. Many of the largest funds are closed for investment and many investors are therefore left with a relatively small universe of potential investment candidates. An F-Test is conducted in order to test whether the average performance numbers in the deciles are statistically different from each other. The calculated F-value is higher than the critical value at the 5% significance level. The variance between the deciles is therefore significantly larger than the variance of the percentiles within the deciles.

For CTAs the relationship between fund sizes and returns is less obvious. CTAs in the smallest decile exhibit a significantly higher performance on average. The higher average is distorted by a small number of extreme outliers with very high returns sometimes exceeding 100% in individual months at the expense of substantially higher volatility. The F-statistic fails to indicate that the variance between the deciles is larger than the variance of the percentiles within the deciles.

TABLE III-5: Hedge fund and CTA fund sizes and returns

Hedge fund sizes and returns			
Percentile	Average fund sizes		Average returns p.a.
91st-100th	616,002,761		8.82%
81st-90th	142,827,528		9.30%
71st-80th	75,858,653		10.75%
61st-70th	46,368,962		12.00%
51st-60th	29,944,735		11.79%
41st-50th	19,575,482		13.59%
31st-40th	12,380,328		14.75%
21st-30th	7,270,043		15.22%
11th-20th	3,628,454		15.26%
1st-10th	1,157,310		16.71%
Average	95,501,426		12.82%
F-statistic	2.2505	P-value	2.55%
CTA fund sizes and returns			
Percentile	Average fund sizes		Average returns p.a.
91st-100th	454,532,888		5.97%
81st-90th	80,365,225		6.27%
71st-80th	35,487,127		7.72%
61st-70th	19,089,444		8.49%
51st-60th	10,753,454		7.60%
41st-50th	6,261,303		8.50%
31st-40th	3,551,528		9.24%
21st-30th	1,897,097		7.85%
11th-20th	861,825		7.44%
1st-10th	225,630		14.12%
Average	61,302,552		8.32%
F-statistic	0.6546	P-value	74.74%

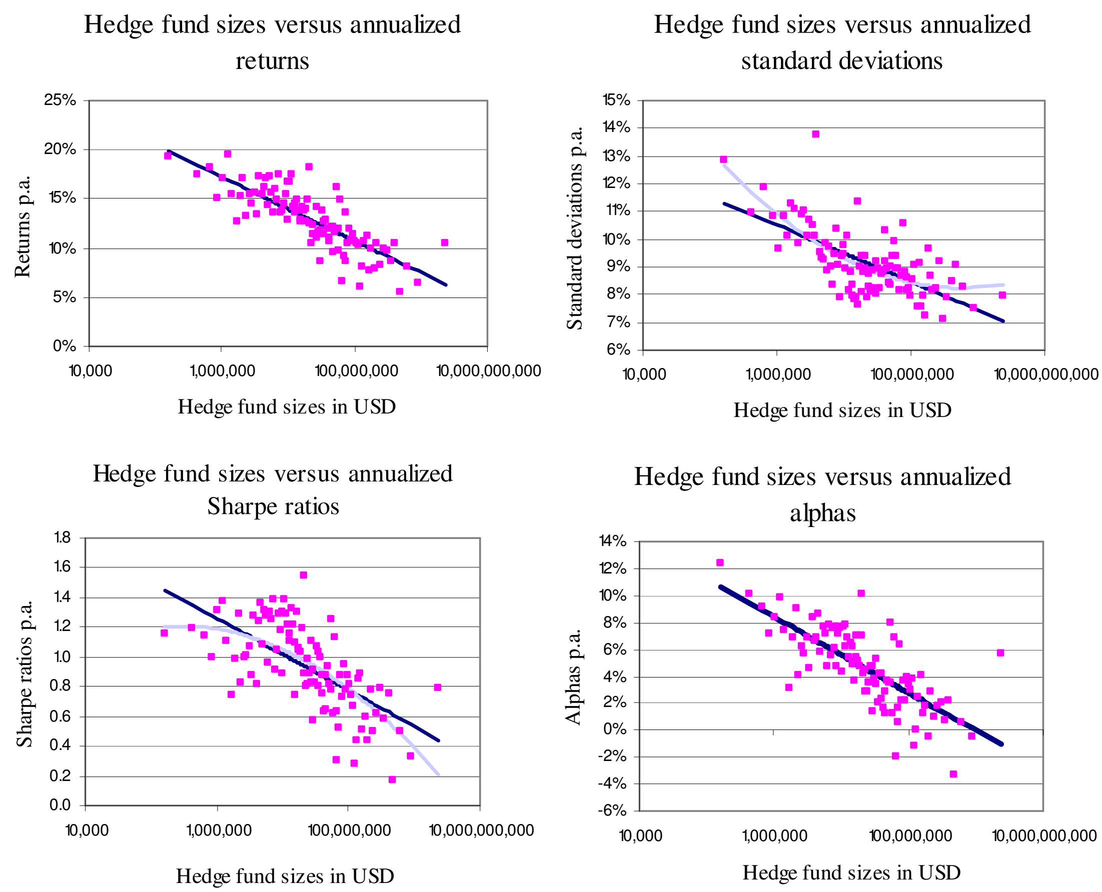
The samples of 4,699 hedge funds and 2,718 CTAs are classified in percentiles and deciles according to their fund sizes. The second column illustrates the average fund sizes of each decile. The third column shows the average returns for each decile. The F-Test is conducted to find out whether the average returns of the deciles are different from each other. A one tailed F-distribution is used. The time period from January 1994 to April 2005 is used for the analysis.

3 CROSS-SECTIONAL REGRESSIONS

Cross-sectional regressions are applied to further investigate the subject. The hedge fund and CTA sample data is broken into 100 percentiles according to their fund sizes. Each percentile represents a sub-sample that contains funds with similar fund sizes. The constitution of the sub-samples changes in each month as the assets under management are changing and funds with increasing assets relative to their peer group fall into a higher percentile.

In the first regression analysis the average excess returns of the 100 sub-samples are regressed on the logarithms of the average fund sizes of the sub-samples according to equation 3.2. The results of the regression analysis are presented in Figure 3.2 and Table 3.6. Each data point in Figure 3.2 represents an average annualized return for one asset percentile in the data sample. The coefficient of the size variable is statistically significant at the 1% significance level and indicates that larger hedge funds are underperforming. This result is in line with the findings of Liang (1999) and Amenc and Martellini (2003). The robustness of the results is confirmed in the regression analysis based on the two 68-month sub-periods. The quadratic term in the quadratic regression according to equation 3.3 is not statistically significant.

FIGURE III-2: Hedge fund sizes versus performance criteria



4,699 hedge funds of the TASS and CISDM databases are ranked according to their fund sizes and 100 asset percentiles are built in each month. The average fund sizes of the percentiles are plotted versus annualized returns, standard deviations, Sharpe ratios and alphas. The alphas are derived from excess hedge fund returns and an asset class factor model with four factors. The factors are the Goldman Sachs Commodity Index, the Wilshire Microcap Index, the CBOE Volatility Index and the Lehman Aggregate Bond Index. Linear and quadratic regression analyses are performed. The quadratic relationships are illustrated if the quadratic terms are statistically significant. The time period from January 1994 to April 2005 is used for the analysis.

TABLE III-6: Regression results of fund sizes versus returns

	Hedge funds			CTAs		
Dependent variable	Returns p.a.					
Independent variable	Logarithms of fund sizes					
Linear regression						
	Coefficient	Std. error	P-value	Coefficient	Std. error	P-value
C	0.3676	0.0177	0.0000	0.2141	0.0221	0.0000
Log of fund sizes	-0.0141	0.0010	0.0000	-0.0082	0.0014	0.0000
R-squared	0.6530			0.2665		
Adj. R-squared	0.6495			0.2590		
Quadratic regresson						
C	0.3221	0.1196	0.0084	0.6923	0.1113	0.0000
Log of fund sizes	-0.0087	0.0143	0.5449	-0.0698	0.0141	0.0000
(Log of fund sizes)^2	-0.0002	0.0004	0.7011	0.0019	0.0004	0.0000
R-squared	0.6536			0.3872		
Adj. R-squared	0.6464			0.3746		

For the regression analysis 4,699 hedge funds and 2,718 CTAs are ranked according to their fund sizes and 100 asset percentiles are built in each month. The average annualized returns of each of the 100 percentiles are regressed on the logarithms of the average fund sizes of the percentiles. Linear and quadratic regression analyses are performed. Newey-West covariance matrix estimators are used to account for heteroskedasticity and serial correlation. The time period from January 1994 to April 2005 is used for the analysis.

The impact of hedge fund sizes on standard deviations is explored in a linear regression analysis specified in equation 3.4. The standard deviations refer to percentiles and therefore portfolios of funds, rather than individual funds. The standard deviation of portfolios of funds is generally lower than the standard deviation of individual funds due to diversification benefits. The analysis suggests that larger funds have on average a lower standard deviation. The relationship is significant at the 1% significance level. The results can be found in Figure 3.2 and Table 3.7. The regression analysis in both sub-periods also confirms statistically significant relationships. The relationship between fund sizes and standard deviations is intuitive since large funds generally benefit from a broader diversification and therefore a reduction of the standard deviation. Larger funds have often attracted assets based on a proven track record and might therefore shift their focus on capital preservation. Highly aggressive strategies with concentrated bets are sometimes more difficult to implement with a large asset base due to capacity constraints. Larger funds are in a better position to impose less favorable liquidity conditions on investors to control their asset flows. Common tools to keep investors in the fund are lockup periods, redemption gates or redemption fees for early withdrawal of investments. A stable asset base allows for better planning of investments. The manager can therefore more consistently apply the strategy or also invest in illiquid securities that are not priced on a daily basis and diminish the volatility of the fund. The relationship between fund sizes and standard deviations is also tested for convexity. The quadratic term of the quadratic regression specified in equation 3.5 is statistically significant at the 1% significance level. Figure 3.2 shows the convex shape of the quadratic relationship.

TABLE III-7: Regression results of fund sizes versus standard deviations

Dependent variable	Standard deviations p.a.					
Independent variable	Logarithms of fund sizes					
Linear regression						
	Coefficient	Std. error	P-value	Coefficient	Std. error	P-value
C	0.1662	0.0086	0.0000	0.1830	0.0097	0.0000
Log of fund sizes	-0.0044	0.0005	0.0000	-0.0043	0.0006	0.0000
R-squared	0.4410			0.3419		
Adj. R-squared	0.4353			0.3352		
Quadratic regresson						
C	0.3537	0.0546	0.0000	0.3292	0.0509	0.0000
Log of fund sizes	-0.0270	0.0065	0.0001	-0.0231	0.0065	0.0005
(Log of fund sizes)^2	0.0007	0.0002	0.0008	0.0006	0.0002	0.0043
R-squared	0.5029			0.3952		
Adj. R-squared	0.4927			0.3827		

For the regression analysis 4,699 hedge funds and 2,718 CTAs are ranked according to their fund sizes and 100 asset percentiles are built in each month. The average annualized standard deviations of each of the 100 percentiles are regressed on the logarithms of the average fund sizes of the percentiles. Linear and quadratic regression analyses are performed. Newey-West covariance matrix estimators are used to account for heteroskedasticity and serial correlation. The time period from January 1994 to April 2005 is used for the analysis.

Next, the relationship between hedge fund sizes and Sharpe ratios is explored based on equation 3.6. Similar to the standard deviations, the Sharpe ratios are referring to asset percentiles that are representing portfolios of hedge funds with similar size. Due to the diversification benefits of portfolios, Sharpe ratios of individual hedge funds are typically lower than Sharpe ratios of portfolios. The findings of the regression analysis are illustrated in Figure 3.2 and Table 3.8. Large hedge funds have on average a lower Sharpe ratio. The relationship is significant at the 1% significance level. The result is also robust in both 68-month sub-periods. This result is in line with the findings of Herzberg and Mozes (2003). The quadratic regression analysis according to equation 3.7 indicates a concave relationship between fund sizes and Sharpe ratios. The quadratic term in the quadratic regression analysis is statistically significant at the 10% significance level.

TABLE III-8: Regression results of fund sizes versus Sharpe ratios

	Hedge funds			CTAs		
Dependent variable	Sharpe ratios p.a.					
Independent variable	Logarithms of fund sizes					
Linear regression						
	Coefficient	Std. error	P-value	Coefficient	Std. error	P-value
C	2.7225	0.2116	0.0000	1.1435	0.1590	0.0000
Log of fund sizes	-0.1055	0.0124	0.0000	-0.0488	0.0099	0.0000
R-squared	0.4239			0.1984		
Adj. R-squared	0.4180			0.1902		
Quadratic regresson						
C	-0.7118	1.3849	0.6085	3.5106	0.8392	0.0001
Log of fund sizes	0.3072	0.1650	0.0657	-0.3536	0.1066	0.0013
(Log of fund sizes)^2	-0.0123	0.0049	0.0138	0.0096	0.0034	0.0051
R-squared	0.4590			0.2611		
Adj. R-squared	0.4478			0.2459		

For the regression analysis 4,699 hedge funds and 2,718 CTAs are ranked according to their fund sizes and 100 asset percentiles are built in each month. The average annualized Sharpe ratios are regressed on the logarithms of the average fund sizes of the percentiles. Newey-West covariance matrix estimators are used to account for heteroskedasticity and serial correlation. The time period from January 1994 to April 2005 is used for the analysis.

In the next step the relationship between hedge fund sizes and alphas derived from the asset class factor model with four factors is discussed. The regression analysis used to derive the alphas for the 100 percentiles is specified in equation 3.8 and the cross-sectional regression to test the relationship between the alphas and fund sizes is based on equation 3.9. The alphas in the four-factor model account for risk exposures to commodities, small-cap stocks, bonds and volatility. Figure 3.2 and Table 3.9 illustrate the results of the regression analysis. The coefficient of the linear regression analysis is statistically significant at the 1% significance level and indicates lower alphas for larger hedge funds.

TABLE III-9: Regression results of fund sizes versus annualized alphas

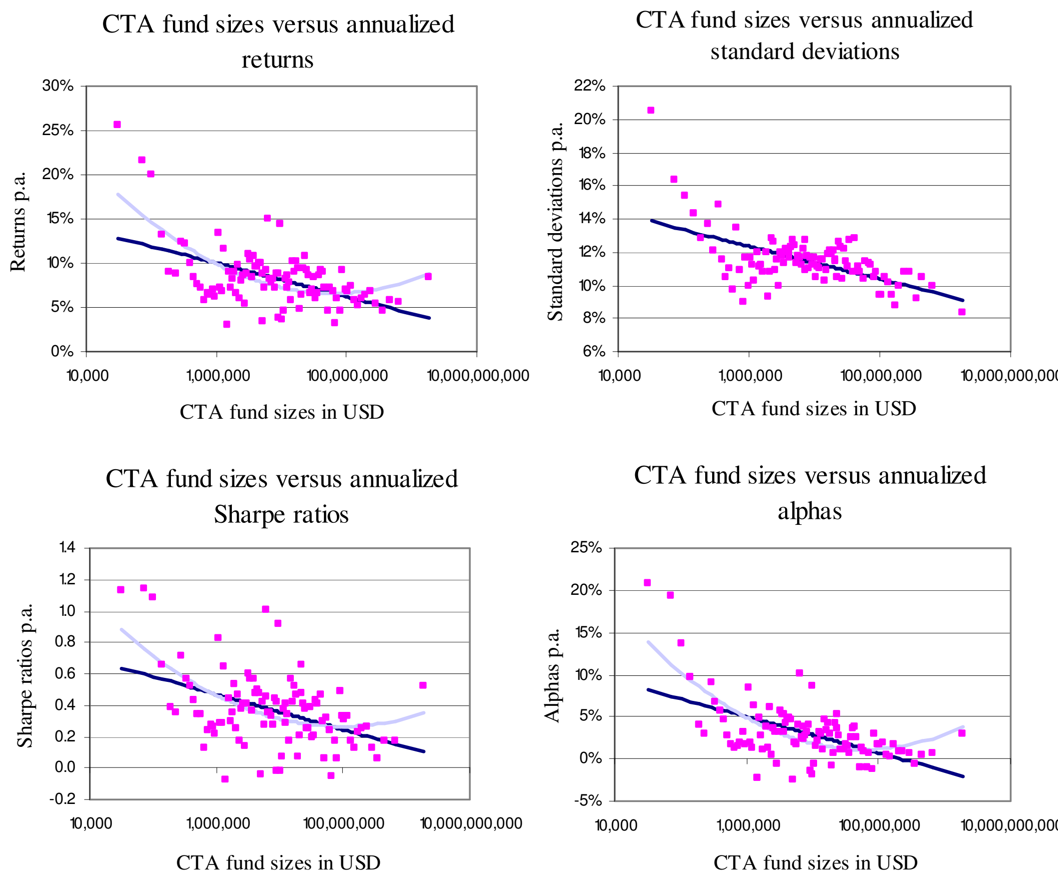
	Hedge funds			**CTAs**		
Dependent variable	Alphas p.a.					
Independent variable	Logarithms of fund sizes					
Linear regression						
	Coefficient	Std. error	P-value	Coefficient	Std. error	P-value
C	0.2531	0.0186	0.0000	0.1786	0.0227	0.0000
Log of fund sizes	-0.0122	0.0011	0.0000	-0.0093	0.0014	0.0000
R-squared	0.5623			0.3050		
Adj. R-squared	0.5579			0.2979		
Quadratic regresson						
C	0.3892	0.1246	0.0023	0.7315	0.1113	0.0000
Log of fund sizes	-0.0286	0.0148	0.0571	-0.0805	0.0141	0.0000
(Log of fund sizes)^2	0.0005	0.0004	0.2719	0.0022	0.0004	0.0000
R-squared	0.5678			0.4498		
Adj. R-squared	0.5589			0.4385		

For the regression analysis 4,699 hedge funds and 2,718 CTAs are ranked according to their fund sizes and 100 asset percentiles are built in each month. The annualized alphas of each of the 100 percentiles are regressed on the logarithms of the average fund sizes of the percentiles. The alphas are derived from excess hedge fund and excess CTA returns based on an asset class factor model with four factors. The factors used for the hedge fund sample are the Wilshire Micro Cap Index, the Lehman Aggregate Bond Index, the Goldmans Sachs Commodity Index and the CBOE Volatility Index. The factors used for CTA sample are the Russell 2000, the JP Morgan Government Bond Index, the Goldman Sachs Commodity Index and the CBOE Volatility Index. Linear and quadratic regression analyses are performed. Newey-West covariance matrix estimators are used to account for heteroskedasticity and serial correlation. The time period from January 1994 to April 2005 is used for the analysis.

The result is confirmed in the analysis with both 68-month sub-periods. In the analysis with four three-factor models the relationship between fund sizes and alphas is also robust at the 1% significance level. The four three-factor models are derived by separately dropping one factor of the original four-factor model each time. The quadratic term of the quadratic regression analysis according to equation 3.10 is not statistically significant.

The cross-sectional regression analysis for CTAs indicates a statistically significant negative relationship between fund sizes and returns, standard deviations, Sharpe ratios and alphas. The results are illustrated in Figure 3.3 as well as Table 3.6, Table 3.7, Table 3.8 and Table 3.9. The linear relationship between fund sizes and returns is statistically significant at the 5% significance level. The linear relationships for standard deviations, Sharpe ratios and alphas are statistically significant at the 1% significance level. It can be observed that very small funds exhibit extreme characteristics with substantially higher returns and standard deviations. The analysis over the two 68-month sub-periods confirms the robustness of most of the results. The only exception is a lack of statistical significance in the relationship between fund sizes and standard deviations in the second sub-period. The quadratic terms in the quadratic regression analyses are statistically significant at the 5% significance level for returns, Sharpe ratios and alphas. The robustness of the results with regard to alphas is confirmed in the analysis with the four three-factor models. The quadratic term is not significant for standard deviations. For returns, Sharpe ratios and alphas a convex relationship can be observed. The nonlinearity tends to be driven by very small funds. The impact of a small number of outliers on the results of the quadratic relationships limits the interpretation of the results.

FIGURE III-3: CTA fund sizes versus performance criteria



2,718 CTAs of the TASS and CISDM databases are ranked according to their fund sizes and 100 asset percentiles are built in each month. CTA fund sizes are plotted versus annualized returns, standard deviations, Sharpe ratios and alphas. The alphas are derived from excess CTA returns and an asset class factor model with four factors. The factors are the Russell 2000, the JP Morgan Government Bond Index, the Goldman Sachs Commodity Index and the CBOE Volatility Index. Linear and quadratic regression analyses are performed. The time period from January 1994 to April 2005 is used for the analysis.

The impact of fund flows on the performance of hedge funds and CTAs is also investigated. Therefore hedge funds and CTAs are ranked according to their fund flows in each month and percentiles as well as deciles are built similar than with fund sizes. Table 3.10 gives a general overview about hedge fund and CTA returns in combination with fund flows for each decile.

TABLE III-10: Hedge fund and CTA fund flows and returns

Hedge fund flows and returns			
Percentile	Average annual fund flows		Average returns p.a.
91st-100th	165,607,388		8.96%
81st-90th	32,946,344		12.03%
71st-80th	14,225,238		13.77%
61st-70th	6,445,941		14.80%
51st-60th	2,619,224		17.34%
41st-50th	730,398		16.75%
31st-40th	-344,694		16.46%
21st-30th	-2,724,833		14.91%
11th-20th	-10,558,021		14.94%
1st-10th	-95,956,576		14.39%
Average	11,299,041		14.43%
F-statistic	2.6339	P-value	0.94%
CTA fund flows and returns			
Percentile	Average annual fund flows		Average returns p.a.
91st-100th	114,464,936		7.31%
81st-90th	16,110,818		8.50%
71st-80th	4,810,743		9.87%
61st-70th	1,521,792		10.67%
51st-60th	399,513		11.83%
41st-50th	-64,592		9.59%
31st-40th	-647,988		9.57%
21st-30th	-2,114,173		8.85%
11th-20th	-6,730,848		9.80%
1st-10th	-58,450,594		10.75%
Average	6,929,961		9.67%
F-statistic	0.5056	P-value	86.69%

The samples of 4,699 hedge funds and 2,718 CTAs are classified in percentiles and deciles according to their fund flows. The second column illustrates the average annual fund flows of each decile. The third column shows the average annual returns in the following year for each decile. The average annual fund flows are based on the period from January 1994 to April 2004 while the average annual returns are based on the period from January 1995 to April 2005. Rolling 12-month data is used. The F-Test is conducted to find out whether the average returns of the deciles are different from each other. A one tailed F-distribution is used.

The result suggests that large inflows reduce the performance in the following 12-month period. Hedge funds with weaker inflows or even outflows are generally outperforming in the following 12-month period. The F-Test indicates a significant relationship between annual hedge fund flows and annualized returns in the following 12-month period based on a 1% significance level. For CTAs the relationship between fund flows and CTA returns is less obvious.

The subject is further investigated with cross-sectional regression analysis by regressing returns on fund flows according to equation 3.11. The results are illustrated in Table 3.11. The analysis indicates a strong relationship between hedge fund flows and 12-month lagged annual returns. The result suggests that strong asset growth has a negative impact on fund performance. Hedge funds with weaker inflows or even outflows are generally outperforming in the following 12-month period. The relationship between fund flows and hedge funds returns is statistically significant at the 1% significance level for the 136-month period and for both 68-month sub-periods. The result is in line with the findings of Getmanksy (2004).

TABLE III-11: Regression results of fund flows versus lagged annual returns

	Hedge funds			CTAs		
Dependent variable	12-months lagged rolling 12-months CTA returns					
Independent variable	Fund flows					
Linear regression						
	Coefficient	Std. error	P-value	Coefficient	Std. error	P-value
C	0.1462	0.0024	0.0000	0.0980	0.0018	0.0000
Fund flows	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R-squared	0.6530			0.2918		
Adj. R-squared	0.6495			0.2846		

For the regression analysis 4,699 hedge funds and 2,718 CTAs are ranked according to their fund flows and 100 fund flow percentiles are built in each month. In the regression analysis average 12-month lagged returns for each of the 100 percentiles are regressed on the average fund flows of the percentiles. Newey-West covariance matrix estimators are used to account for heteroskedasticity and serial correlation. The time period from January 1994 to April 2005 is used for the analysis.

A similar result is obtained in the analysis with CTAs. The relationship between fund flows and CTA returns is statistically significant at the 5% significance level over the 136-month period and the first 68-month sub-period. The result is not statistically significant over the second 68-month sub-period.

G SUMMARY OF FINDINGS

This chapter contributes to existing literature about hedge fund and CTA performance with a detailed analysis of the impact of fund sizes and fund flows on performance. Fund sizes are investigated with regard to their influence on returns, standard deviations, Sharpe ratios and alphas derived from an asset class factor model. The analysis is conducted separately for a sample of hedge funds containing 4,699 hedge funds and a sample of CTAs based on 2,718 CTAs. In both cases empirical evidence is revealed for a negative relationship between fund sizes and returns suggesting that larger hedge funds are generally underperforming smaller hedge funds.

The analysis based on cross-sectional regression techniques supports the hypothesis that hedge fund managers and CTAs are increasing their fund size beyond the optimal size. The observed relationship between standard deviations and fund sizes is also negative. The lower returns of large funds go therefore hand in hand with lower standard deviations. The analysis with risk-adjusted returns reveals that larger funds tend to have lower Sharpe ratios. The lower standard deviations of large funds are therefore not sufficiently compensating for lower returns.

The average alphas generated by hedge funds derived from a simple asset class factor model are statistically significant over the period from January 1994 to April 2005. The negative relationship between fund sizes and returns also holds after adjusting the returns for the risk free rate and factor exposures to commodities, small-cap stocks, bonds and equity volatility. Alphas for smaller funds therefore tend to be higher than alphas for larger funds.

The relationships between CTA fund sizes and returns, standard deviations, Sharpe ratios and alphas are also negative. Large CTAs are therefore underperforming smaller CTAs with lower standard deviations, lower Sharpe ratios and lower alphas.

The analysis of fund flows and returns suggests that funds with strong inflows are generally underperforming in the following 12-month period. Hedge fund managers are primarily remunerated with a performance fee. In absolute terms the performance fee can be increased by higher returns, but also by a larger asset base. A hedge fund manager who is maximizing personal income may therefore be willing to grow a fund above its optimal size from a pure performance perspective. In the long-term a good performance is instrumental in attracting assets and also enhances the reputation of the manager. Therefore, the manager faces a trade-off between optimizing the performance of the fund and optimizing revenues of the company. Although many large hedge fund managers are closing their funds, there seems to be a temptation to accept more asset inflows than optimal from a performance perspective. The same fund flows-performance relationship can be observed for CTAs. The empirical evidence for managers increasing their fund size beyond the optimal point is limited by the relatively small number of very large funds compared to the total number of hedge funds.

Different hedge fund strategies have different capacity limits. The strategy-specific characteristics of the asset-return and flow-return relationship open opportunities for further research projects. For the percentiles based approach, the number of hedge funds available for each hedge fund strategy is not sufficient to break the strategy-specific samples further down into 100 sub-samples over a 136-month period. The results of strategy-specific analysis are therefore limited by the data available.

In general it can be concluded that the discussion about capacity issues in the hedge fund industry is justified. Large inflows as well as large fund sizes tend to have a negative impact on the performance of hedge funds and CTAs. Hedge fund investors that are focusing on the selection of large hedge funds may receive lower returns on average. The relationship between fund sizes and fund of hedge funds performance is investigated in Chapter VI.

IV A RELATIVE EFFICIENCY MEASURE TO EVALUATE HEDGE FUNDS

The selection of hedge funds can be approached from a qualitative and a quantitative perspective. The quantitative evaluation of hedge funds is a challenge for hedge fund investors because of non-normal return distributions observed in the hedge fund industry. In particular, the question of benchmarking hedge funds is non-trivial due to a large variety of different hedge fund strategies. The motivation for this chapter is the objective to evaluate the benefits of a relative efficiency measure as a tool for the quantitative selection of hedge funds. A precondition for the selection of hedge funds based on quantitative criteria is the existence of performance persistence. Statistically significant performance persistence is revealed based on a relative efficiency measure that captures multiple risk-return attributes in one single performance score. A variety of traditional and alternative performance and risk measures, commonly applied in the field of performance analysis with hedge funds, is used in an approach based on data envelopment analysis.

A RESEARCH TOPIC II

The objective of this chapter is the derivation of a relative efficiency measure for hedge funds based on a chosen set of evaluation criteria that account for investor goals and the specific properties of hedge funds.

Unlike traditional fund managers that are evaluating their performance relative to a benchmark, hedge fund managers are striving to achieve high absolute returns with controlled risk. The absolute return approach implies the objective of maximizing returns that can be attributed to the investment skills of the manager as opposed to returns depending on observable market factors. In other words the manager is striving to maximize alpha and minimize beta. The consequence is a large variety of different hedge fund strategies with different return profiles. The objection of hedge fund managers to accept benchmarks based on observable market factors is sufficient to reject any attempt to assess hedge fund performance based on market indices.

One alternative is the construction of strategy specific hedge fund indices as benchmarks for individual hedge funds. This approach raises various challenges. A key question of constructing hedge fund indices is the strategy classification of hedge funds, a subject that is further discussed in chapter V. Given the large variety of hedge fund strategies it is also questionable if aggregated hedge fund indices can accurately reflect the strategy of individual hedge funds. In addition to that, strategy specific hedge fund indices generally fail to meet the properties of valid benchmarks such as investability, measurability on a frequent basis and transparency concerning the constituents of the indices. Further, hedge fund indices often exhibit a number of biases such as survivorship bias and selection bias.

Given the difficulties in measuring hedge fund performance relative to observable market factors or hedge fund specific indices, the focus of performance evaluation in the hedge fund industry is often associated with the assessment of risk-adjusted returns and the development of alternative performance and risk measures.

Investors are generally interested in selecting the best managers out of a limited set of hedge funds open for investment. The direct comparison of hedge funds relative to each other based on a variety of performance criteria is therefore a more natural approach. The criteria used for the evaluation of hedge funds should also reflect the individual preferences of investors.

Given the variety of different risk and return profiles in the hedge fund industry on one hand and varying preferences of investors on the other hand, a flexible framework for performance assessment needs to be derived. The framework developed in this chapter allows the individual investor to choose a set of available evaluation criteria that account for different risk and return aspects. A general approach that takes these aspects into account is the methodology of data envelopment analysis.

Data envelopment analysis is a powerful quantitative tool to assess relative efficiencies and is applied in a wide range of different disciplines from engineering, public administration to commerce and finance. The application of data envelopment analysis to a set of hedge funds provides a useful tool to assess the risks and the performance of hedge fund investment opportunities.

In contrast to traditional risk-return optimization introduced by Markowitz (1959), data envelopment analysis is not limited to the two dimensions of returns and standard deviations. Data envelopment analysis supports the evaluation of a range of hedge funds with respect to multiple evaluation criteria such as returns, maximum drawdowns, skewness, positive/negative months etc. Data envelopment analysis can therefore be targeted to individual preferences concerning the selection of evaluation criteria for hedge funds. The approach compares each hedge fund relative to its peers based on each of the selected evaluation criteria.

In addition to that, performance persistence of the various evaluation criteria and the efficiency scores resulting from the data envelopment analysis is investigated. The assessment of performance persistence is essential for quantitative hedge fund selection. Any performance study without assessment of performance persistence reduces performance analysis to a pure descriptive character with little use in the selection of hedge funds. This chapter therefore discusses the evaluation of long-term performance persistence and reveals evidence for the persistence of relative efficiencies over time.

The structure of the chapter is the following: Initially related literature is discussed in section B, followed by a description of the data set used for the empirical analysis in section C. The methodology of data envelopment analysis and various alternative performance measures used in the analysis are described in section D. Furthermore, the empirical results are presented in section E and finally the major findings are summarized in section F.

B RELATED LITERATURE

Several studies evaluate the persistence of hedge fund returns, Sharpe ratios and appraisal ratios[19]. Agarwal and Naik (2000a) find little persistence in Sharpe ratios and appraisal ratios of hedge funds. Brown, Goetzmann and Ibbotson (1999) and Malkiel and Saha (2005) find no evidence of performance persistence in raw returns or risk-adjusted returns of hedge funds. Capocci and Hubner (2004) find weak evidence for performance persistence in middle performance deciles, but no performance persistence of the funds in the highest and lowest deciles. Capocci, Corhay and Hubner (2005) extend the analysis with results of performance persistence of mid-performance deciles in bull markets. A further study on performance persistence of hedge fund returns has been contributed by Kat and Menexe (2003). They find little evidence in the persistence of mean returns, but reveal evidence in hedge fund returns' higher moments. In an attempt to measure alphas with a variety of models, Amenc, Curtis and Martellini (2004) find that different models disagree on the absolute risk-adjusted performance of hedge funds, but largely agree on their relative performance with respect to similar rank orders.

Herzberg and Mozes (2003) find no persistence in hedge fund performance, but high persistence in standard deviations and correlations to underlying markets. The study introduces a multi-factor hedge fund selection model based on returns, maximum drawdowns, standard deviations, assets under management, changes in assets under management, Sharpe ratios, Sortino ratios, Calmar ratios and Sterling ratios. The findings suggest that the construction of a portfolio based on several factors exhibit higher returns and Sharpe ratios than portfolios constructed based on returns or Sharpe ratios only.

This chapter contributes to the literature by assessing long-term performance persistence. The time horizon of hedge fund investments typically exceeds the horizon used for the analysis of performance persistence in most existing studies.

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[19] The appraisal ratio is defined as alpha divided by the residual standard deviation resulting from a regression of the hedge fund return on the average return of all the hedge funds following the strategy. The appraisal ratio accounts for the difference in the volatility of returns and is leverage-invariant.

Given the illiquid nature of hedge fund investments and the variety of available protective measures for hedge fund managers such as long lock-up periods, quarterly or semi-annual redemption frequencies and long notice periods for redemptions of 90 days or longer suggest a typical investment horizon of several years. Surprisingly, only a limited number of studies is approaching the measurement of performance persistence over more than a 12-month period. Baquero, Horst and Verbeek (2005) find some evidence of performance persistence for the quarterly and annual horizon, but fail to find statistical significance at the two-year horizon. De Souza and Gokcan (2004) analyze performance persistence for a 24-month and 36-month horizon and find no persistence in returns, but strong persistence in volatility. Edwards and Caglayan (2001) investigate performance persistence for 12-month and 24-month periods and find significant persistence for both winners and losers. Harri and Brorsen (2004) find significance performance persistence for one-month to 24-month horizons. The study also shows that the persistence varies by strategy and is the strongest for Market Neutral hedge funds as well as for funds of hedge funds. Evidence of performance persistence on a 36-month horizon has been found by Jagannathan, Malakhov and Novikov (2006) and Kouwenberg (2003).

Eling (2007) compares various studies about performance persistence of hedge funds and explains the varying results primarily based on different methodologies applied in the studies. The study also reveals evidence for performance persistence for shorter horizons of up to six months, but no evidence for long-term performance persistence.

The methodology of data envelopment analysis (DEA) has first been introduced by Gregoriou (2003b) and Gregoriou, Sedzro and Zhu (2005) to the evaluation of hedge funds. Both studies use the first three partial moments of the upper (lower) side of return distributions as input (output) criteria. Gregoriou, Sedzro and Zhu (2005) apply three DEA models to data of Zurich Capital Markets over a five year time period from 1997 to 2001.

Nguyen-Thi-Thanh (2006) discusses the evaluation of hedge funds based on traditional moments of return distributions in a study based on 38 hedge funds. Additional constraints are added with regard to the first four lower and upper partial moments and quantile-based metrics are investigated. The study also applied a sensitivity analysis to appraise the robustness of efficient funds. Eling (2006) discusses different DEA models and conducts an analysis based on 30 hedge funds.

This chapter enlightens the discussion of data envelopment analysis as a relative efficiency measure in the selection of hedge funds and contributes to the existing literature with a detailed analysis of the persistence of relative efficiencies derived from a data envelopment analysis approach that separates between in- and out-of-sample periods. Compared to existing studies this chapter uses a richer set of evaluation criteria over a longer time period based on an extensive data sample allowing to focus on the performance persistence of relative efficiencies. In contrast to previous studies based on different methodologies, strong evidence of performance persistence is found based on data envelopment analysis with various sets of evaluation criteria.

C DATA SET

The data used in the empirical analysis is based on data set II as described in Chapter II B. A combination of three different data sources, TASS, HFR and Hedgefund.net is used.

A 120-month time period, from May 1995 to April 2005, is used for the analysis.[20] All funds with insufficient track record are eliminated from the data sample. 480 hedge funds meet the criteria. Alternative risk measures based on lower partial moments and drawdowns are used in the data envelopment analysis. Some of these measures can only be calculated if the hedge funds have at least one negative month. Three funds in the sample are outliers with no negative month in the 120-month time period and are therefore dropped from the sample, resulting in a total

[20] The requirement of a 120-month track record for hedge funds restricts the sample substantially. The resulting sample of 480 hedge funds is therefore subject to various biases and can only be considered representative for hedge funds with a long-standing track record rather than the entire hedge fund industry.

number of 477 hedge funds used for the analysis. Two of the three funds excluded follow a fixed income arbitrage strategy while the third fund applies an equity market neutral approach.[21]

To test the persistence of the results, the time period is divided into two sub-periods of 60 months, from May 1995 to April 2000 and from May 2000 to April 2005. Again the data is screened for outliers with no negative months in the two sub-periods. Four funds, three equity market neutral funds and one convertible arbitrage fund, have no negative months in at least one of the sub-periods and are therefore dropped from the sample. The persistence of the data envelopment analysis is therefore investigated with a sample of 473 hedge funds.

Fung and Hsieh (2004) and Fung et al. (2007) argue that the collapse of Long-Term Capital Management in September 1998 and the peak of the technology bubble in March 2000 can be interpreted as structural breaks in hedge fund returns. To avoid the time-dependence of the results, the analysis in this chapter is repeated with different breakpoints for the two sub-periods. The 120-months time period is also divided in April 2001 resulting in a 72-month in-sample period combined with a 48-month out-of-sample time period as well as in April 2002 resulting in an 84-month in-sample period in combination with a 36-month out-of-sample period. The selection of sub-periods with different breakpoints serves to test the stability of the results.

D METHODOLOGY

Cooper, Seiford and Zhu (2004) describe data envelopment analysis as a methodology directed to frontiers rather than central tendencies. Instead of trying to fit a regression plane through the center of the data as in a linear regression, a piecewise linear surface is floated to rest on the top of the observations,

[21] The elimination of funds with no negative months introduces a bias to the data set. In this chapter the funds are compared relative to each other based on various evaluation criteria and the ranking of the funds is not influenced by the bias in the data set.

representing an efficient frontier. The efficiency of *n* different hedge funds is then a set of *n* linear programming problems.

The key strength of the data envelopment analysis is the ability to handle multiple inputs and multiple outputs simultaneously independently of the units of inputs and outputs. Inputs and outputs can have very different units. For example, input one can be a standard deviation while output one can be a percentage of positive months without requiring an a priori tradeoff between the two. Data envelopment analysis does not require an assumption of a functional form relating inputs to outputs. Any hedge fund can be directly measured against all other hedge funds in the sample.

The objective of data envelopment analysis is to facilitate the relative comparison with peers as opposed to providing a measure of absolute efficiency. A hedge fund is considered to be relative-efficient if and only if it improves the performance of any existing hedge fund portfolio in at least one of the relevant evaluation criteria. In other words, a hedge fund is relative-efficient if no portfolio of other hedge funds can be created that exhibits superior characteristics in all of the selected evaluation criteria. Each fund has therefore its own weighting system based on its input and output characteristics relative to its peers.

In contrast to regression-based methods, data envelopment analysis is not only limited to one dependent variable. The relationship between input and output variables in any data envelopment analysis approach can be expressed with

$$\sum_{r=1}^{s} u_r y_r = \alpha + \sum_{i=1}^{m} v_i x_i \,, \tag{4.1}$$

where u_r and v_i are unknown weights representing importance or tradeoffs among outputs y_r and inputs x_i.

The ratio of outputs to inputs is used to measure the relative efficiency of hedge funds. This ratio is to be maximized and can be written as

$$\max h_o(u,v) = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \,. \tag{4.2}$$

A set of normalizing constraints for each hedge fund reflects the condition that the virtual output to virtual input ratio of every hedge fund must be less than or equal to unity. The mathematical programming problem may thus contain the following conditions:

$$\frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \le 1 \tag{4.3}$$

for $j = 1,\dots,n$ hedge funds, and

$u_r, v_i \ge 0$ for all i and r.

In order to limit the optimization to a representative solution, the constraint

$$\sum_{i=1}^{m} v_i x_{io} = 1 \tag{4.4}$$

is added.

The change of variables from (u, v) to (μ, v) is a result of the Charnes-Cooper transformation,

$$\max z = \sum_{r=1}^{s} \mu_r y_{ro} \tag{4.5}$$

subject to

$$\sum_{r=1}^{s} \mu_r y_{ro} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \tag{4.6}$$

$$\sum_{i=1}^{m} v_i x_{io} = 1 \tag{4.7}$$

$$u_r, v_i \ge 0$$

for which the linear programming dual problem is

$$\theta^* = \min \theta$$

subject to

$$\sum_{j=1}^{n} x_{ij}\lambda_j \le \theta x_{io} \qquad \text{for } i = 1,...,m \tag{4.8}$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j \ge y_{ro} \qquad \text{for } r = 1,...,s \tag{4.9}$$

$$\lambda_j \ge 0 \qquad \text{for } j = 1,...,n\,. \tag{4.10}$$

A number of different methods exists for data envelopment analysis. The input-oriented variable returns-to-scale concept that is used in this chapter requires the specification of the additional constraint

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{4.11}$$

to make sure that any convex combinations of hedge funds are either on or enveloped by the efficient frontier.

One requirement in the specified data envelopment model is that values of x_{ij} and y_{rj} must not be negative.[22] To account for possible negative values of some hedge funds, the translation invariance property of the variable returns-to-scale approach allows the following adjustment of input and output variables:

$$\hat{x}_{ij} = x_{ij} + \beta_i \tag{4.12}$$

$$\hat{y}_{rj} = y_{rj} + \pi_r \tag{4.13}$$

The efficient frontier remains the same if x_{ij} and y_{rj} are replaced with $\hat{x}_{ij}$ and $\hat{y}_{rj}$, respectively. The translation values β_i and π_r are set to turn possible negative values x_{ij} and y_{rj} into positive values $\hat{x}_{ij}$ and $\hat{y}_{rj}$.

One weakness of data envelopment analysis is the computational intensity since a separate linear program needs to be solved for each hedge fund in the analysis.

[22] Nguyen-Thi-Thanh (2006) shows that input-oriented (output-oriented) DEA models can still be used when negative values are only present in outputs (inputs).

Data envelopment analysis is an extreme point technique and is therefore also affected by outliers in the data set. The existence of positive outliers decreases the average efficiency score since the relative efficiency scores of all hedge funds are benchmarked to the characteristics of the best performing hedge funds in the sample. The larger the sample, the higher the probability of having positive outliers is and the lower the expected average efficiency score is. The efficiency scores of the in-sample period can therefore not be directly compared to the efficiency scores of the out-of-sample period. It is a nonparametric technique and statistical hypothesis tests are therefore difficult.

Data envelopment analysis provides a general framework that allows the user to choose the evaluation criteria according to personal preferences. In this chapter a broad range of traditional and alternative performance and risk measures is used for the assessment of hedge funds. The advantage in choosing a large set of criteria is the opportunity to capture a large number of dimensions in the risk-return framework. A disadvantage occurs if certain criteria are redundant due to interdependencies, but actually have more impact in the analysis than they should. The flexibility of data envelopment analysis also allows assigning different weightings to various criteria to capture individual preferences. In this study equal importance of all criteria is assumed.

This chapter uses different sets of common criteria in hedge fund evaluation as input and output variables for the data envelopment analysis. The selection of the evaluation criteria intends to reflect the preferences of investors that can differ from investor to investor. The use of a variety of different criteria reflects the assumption that different investors have different objectives and therefore different utility functions. A variety of utility functions can be taken into account by using a general framework that does not rely on the assumption that all investors follow an aggregated utility function derived by the behavior of the idealized perfectly rational investor in a highly constrained environment. Even for one individual investor the utility function is changing during the various stages of the investors' life based on changing goals, changing tax situations and changing risk aversion. Therefore a multitude of utility functions is required to describe the behavior of an individual. Traditional risk measures such as standard deviations and beta represent only one utility function and are therefore not sufficient.

Plantinga and de Groot (2001) show in a study with mutual funds that different risk-adjusted performance measures can be associated with different levels of risk aversion suggesting that investors with low risk aversion should use for instance the Sharpe ratio, while investors with intermediate or high levels of risk aversion are better off in using the Sortino ratio or the upside potential ratio. One general path to avoid biases through the selection of criteria is the use of a broad range of criteria simultaneously. This approach assumes that investors want to take a variety of different evaluation dimensions into account reflected by a broad set of evaluation criteria.

The foundation of the alternative performance measures considered in the data envelopment analysis is motivated prior to the selection of the criteria. Various criteria are based on lower partial moments (LPM).

LPM provide a general concept for measuring return variability to an absolute benchmark. Since variance is not a complete measure of risk in the case of asymmetric return distributions, LPM are a useful alternative with regard to hedge fund returns. LPM consider only negative deviations of returns from a threshold or target return. Measuring risk relative to a target return is a more straightforward approach that requires less unrealistic assumptions underlying the traditional risk-return framework of modern portfolio theory. The threshold or target return is also often referred to as minimum acceptable return. Various investor groups such as pension funds are defining their goals in terms of a target return. Any goal-oriented performance analysis needs to take the goal of investors in the performance measure into account.

According to Nawrocki (1991), LPM as measures of downside risk are consistent with stochastic dominance criteria. Stochastic dominance does not make any distributional assumptions and assumes a very general set of utility functions.

Nawrocki (1999) is arguing that an individual has different financial compartments, with different goals and different utility functions. Risk measures such as LPM provide a multitude of utility functions that capture the whole range of human behavior from risk seeking to risk averse. A unique lower partial moment efficient frontier exists for each compartment of an individual investor. Downside risk measures can therefore be considered a closer match to how investors actually behave in investment situations rather than how investors are supposed to behave in traditional portfolio theory.

In standard statistical moments investors prefer higher values of odd moments such as skewness and prefer lower values of even moments such as variance or kurtosis. A higher degree of the LPM measure indicates a higher weight for the negative deviation from the target return reflecting a higher aversion to below target returns. The LPM of order zero expresses the shortfall probability, the LPM of order one expected shortfall and the LPM of order two semi-variance if the threshold return is chosen equal to the average return. The degree of risk aversion of individuals can be as high as four according to Nawrocki (1999).

The use of LPM of higher order has the advantage of penalizing negative returns at an exponential rate, accounting for the actual behavior of individuals in the decision-making process under uncertainty. The LPM measure also exhibits a relationship with skewness since a higher LPM value is in line with a greater degree of negative skewness and therefore a higher risk for the investor.

According to Fishburn (1977) the n-degree LPM is defined as

$$LPM_n(\tau, F) = \int_{-i}^{h} (\tau - r) df(r) \tag{4.14}$$

This definition can be expressed with the computational formula for LPM

$$LPM_{in} = \frac{1}{m} \sum_{t=1}^{m} \left[Max(0, \tau - r_{it}) \right]^n \tag{4.15}$$

where τ is the target return, m is the number of observations, n is the LPM degree, and r_{it} is the periodic return for security i during period t.

Various downside risk measures have been developed based on LPM. Omega, a performance measure introduced by Keating and Shadwick (2002), is based on the first order LPM. The Omega metric has the advantage over traditional measures that it captures all information of the return distribution of an investment. A further advantage is the fact that its value depends on the risk appetite based on the choice of the minimum acceptable return. Omega is defined as the probability-weighted ratio of gains to losses subject to a given loss threshold τ. The portfolio with the higher Omega has a greater probability of delivering returns that match or exceed the return threshold τ. The return threshold can be tailored to individual investor preferences. For the purpose of this study the threshold is set equal to the risk free rate, expressed by the 90-day T-bill rate. Omega is defined as

$$\Omega_i(\tau) = \frac{\mu - \tau}{LPM_{1i}(\tau)} + 1 , \qquad (4.16)$$

where μ_i stands for the average return of fund *i* and LPM_{1i} expresses the first order lower partial moment for fund *i*.

In a second step the Sortino ratio is introduced as a representative ratio based on the second order LPM. The Sortino ratio has been introduced by Sortino and van der Meer (1991) and can be written in the form

$$SortinoRatio = \frac{\mu - \tau}{\sqrt{LPM_{2i}(\tau)}} . \qquad (4.17)$$

Despite of the criticism of the inventor[23], the Sortino ratio gained quick popularity in the hedge fund industry and is widely recognized as a risk measure. The focus on downside volatility guarantees that investments with substantial upside volatility and limited downside volatility are not considered risky. This is in line with the general understanding about risk in the investment industry. Investors are generally more concerned about losses than about positive outliers in returns. The assumption of normal distributions is therefore a major shortcoming of performance measures based on the standard deviation. Especially in the alternative investment industries various hedge fund strategies are known to exhibit non-normal return distributions based on the extensive use of derivatives therefore making the case for risk measures accounting for downside volatility.

Kaplan and Knowles (2004) introduced Kappa as a generalized downside risk-adjusted performance measure and discuss the conceptual link between omega and

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[23] See Sortino, Kordonsky and Forsey (2006)

the Sortino ratio. Kappa can be used to derive omega, the Sortino ratio or another risk-adjusted performance ratio by only changing one parameter

$$Kappa_n = \frac{\mu - \tau}{\sqrt[n]{LPM_{ni}(\tau)}}. \quad (4.18)$$

A third order kappa is used in this chapter based on the third order lower partial moment

$$Kappa_3 = \frac{\mu - \tau}{\sqrt[3]{LPM_{3i}(\tau)}}. \quad (4.19)$$

The third order lower partial moment is relevant for investors with higher risk aversion. The degree of risk aversion depends on the shape of the utility function of individual investors. Kappa is also sensitive to skewness and kurtosis if the threshold return τ is substantially below the mean return. Risk measures based on higher degrees of lower partial moments can be derived depending on the risk aversion of investors. Kaplan and Knowles (2004) show that the ranking of various hedge fund indices based on downside risk measures using the first three orders of LPM can depend on the degree of the LPM used.

From the downside risk measures, the Sortino ratio is the most popular measure in the hedge fund industry. A large amount of literature has also been published about the newer Omega. Kappa based on the third LPM can be considered for individuals with a higher risk aversion. LPM of the fourth or higher degrees are typically not used in hedge fund industry.

A further performance measure based on partial moments is the upside potential ratio introduced by Sortino, van der Meer and Plantinga (1999)

$$UpsidePotentialRatio_i(\tau) = \frac{HPM_{1i}(\tau)}{\sqrt{LPM_{2i}(\tau)}}, \quad (4.20)$$

where $HPM_{1i}(\tau)$ stands for the higher partial moment of hedge fund *i*, given the return threshold τ. Higher partial moments measure the positive return variation above the threshold return.

The numerator of the upside potential ratio can be interpreted as the potential for success and the denominator as the risk of failure. The upside potential ratio therefore accounts for asymmetric return profiles by rewarding not only investments with limited downside potential, but also investments that can achieve high positive returns. Given two investments with similar downside risk, the upside potential ratio will favor the investment with higher positive return variation. Behavioral finance theory often describes observed investor behavior of taking profits too early and letting losses run. This kind of behavior can be avoided by using the upside potential ratio. The upside potential ratio is appropriate for investors seeking upside potential with downside protection as opposed to maximizing expected returns.

One further dimension to evaluate the performance of hedge funds is the investigation of drawdowns, a measure of the magnitude of the loss of a hedge fund in percentage terms. Maximum drawdown in a predefined time period is one of the most popular risk measure used in the hedge fund industry due to its straightforward and intuitive character. Investors are generally concerned about the maximum loss of a particular investment and maximum drawdown gives a direct answer to that question based on the actual track record of the investment. One shortcoming for the measure is that the largest historical drawdown is very time-sensitive and requires the measurement over long time horizons to gain relevance. Investments therefore need to be compared over the same time horizon. The typical choice for the time horizon is three years. A further shortcoming is that the predictability of historical drawdowns for potential future drawdowns is limited in the case of skewed or kurtotic return distributions.

A performance measure based on the maximum drawdown introduced by Young (1991) is the Calmar ratio

$$CalmarRatio_i = \frac{\mu_{annualized}}{\left|MaximumDrawdown_{i1}\right|}. \tag{4.21}$$

The Calmar ratio relates the maximum drawdown to annualized returns. Similar to the Sharpe ratio and the upside potential ratio, the Calmar ratio takes the opportunity gain and the opportunity loss into account. In contrast to other performance measures, the Calmar ratio explicitly takes the maximum loss in the denominator into account.

Another risk measure frequently used in the evaluation of hedge funds is the modified value-at-risk discussed by Favre and Galeano (2002) with regard to hedge funds. The modified value-at-risk is based on the Cornish-Fisher expansion and has the advantage of taking asymmetric and kurtotic features of returns into account.

$$ModifiedVaR = -\mu - \left[z_c + \frac{1}{6}(z_c^2 - 1)S + \frac{1}{24}(z_c^3 - 3z_c)K - \frac{1}{36}(2z_c^3 - 5z_c)S^2 \right]\sigma , \quad (4.22)$$

where μ is the return mean, σ is the standard deviation, S is the skewness, K is the excess kurtosis and z_c is the critical value for probability $(1-\alpha)$. For a 95% probability $z_c = -1.96$.

Different sets of evaluation criteria are selected for the data envelopment analysis considering several of the performance measures presented above. The selection of the criteria is intended to avoid overlap between the various criteria without losing relevant dimensions in the performance measurement. In practice the key decision element in selecting the set of criteria should be the preference of the individual investor. A large set of criteria intends to account for different utility functions of different investors.

In a first approach eight evaluation criteria, three input and five output criteria, are used simultaneously. The input criteria that are minimized contain standard deviation, maximum drawdown and kurtosis. The output criteria to be maximized contain return, skewness, proportion of positive months, omega and alpha derived from a four asset class factor model.[24] The set of criteria contains commonly used alternative performance measures in addition to the four traditional moments of the return distribution. The alternative performance measures, proportion of positive months, omega and maximum drawdown, are each capturing a distinct performance dimension that is different from the information captured by traditional performance measures. Alpha is used as the only benchmark-oriented risk adjusted performance measure taking factors representing all traditional asset classes into account.

[24] The alphas are derived from excess returns and an asset class factor model with four factors. The factors are the Goldman Sachs Commodity Index, the Wilshire Micro Cap Index, the CBOE Volatility Index and the Lehman Aggregate Bond Index.

In a second approach the set of criteria is increased to 13 criteria to account for further alternative performance measures. The approach particularly emphasizes downside risk measures often discussed in the literature with regard to hedge funds. The additional criteria are modified value at risk, Sortino ratio, kappa, upside potential ratio and Calmar ratio. The use of additional criteria can also be criticized since redundant information is kept in the DEA approach.[25] Omega, Sortino ratio, kappa, and upside potential ratio are based on LPM and are therefore capturing a similar performance dimension, but different degrees of risk aversion. Due to the similarity of various criteria it is assumed that the approach with 13 criteria does not lead to substantially different results compared to the approach based on eight evaluation criteria.

In a third approach the initial set of eight evaluation criteria is reduced to six criteria by dropping skewness and kurtosis. Skewness and kurtosis capture information that is not covered by the remaining six criteria. The rationale of the DEA approach without skewness and kurtosis is based on the difficulties of estimating criteria of the third and fourth order for sub-periods containing 60 data points or less.

Various methods exist to assess the persistence of the results. Agarwal and Naik (2000a) differentiate between regression-based parametric and contingency-table non-parametric methods for testing performance persistence. The non-parametric methods are based on contingency tables for winners and losers where a fund is defined as a winner when the performance of that fund is greater than the median, while otherwise it is defined as a loser. A Chi-square statistic is used to test the observed frequency distributions to what extent winners (losers) in the first period continue to fall into the winners (losers) group in the second period. This method can be extended over multiple time periods. A Kolmogrov-Smirnov test can then be applied to test the relationship between winners and losers. For the purpose of this study the differentiation between two groups, winners and losers, is oversimplified

[25] Modified value at risk captures information contained in skewness and kurtosis. Modified value at risk is used as an input variable, while skewness is used as an output variable. Skewness is therefore implicitly used on both sides of the equations and can be considered as redundant. A similar argument can be made for the Calmar ratio that contains maximum drawdowns. Maximum drawdown is used separately as an input variable and implicitly in the Calmar ratio that is used as an output variable.

and does not capture sufficient information required with regard to hedge fund selection. The typical investor wants to use more precise performance information to select a fund other than the probability that a winning fund continues to perform better than the median in the second time period.

Parametric regression-based methods have the advantage of capturing the degree of out- or underperformance of hedge funds in a two-period setup. The disadvantage of regression-based methods in testing performance persistence is the assumption of normally distributed values. The distribution of values of alternative performance measures is often highly skewed. Parametric regression-based methods are therefore not considered in this study.

In order to assess the persistence of the results in the data envelopment analysis, rank correlations between in-sample and out-of-sample periods are calculated. The Spearman rank correlation test is used to test for the significance of the correlations.[26] For each pair of observations, the difference in the ranks, d_i, can be determined. The quantity

$$R = \sum_{i=1}^{n} d_i^2 \tag{4.23}$$

is then calculated.

The test statistic is

$$Z = \frac{6R - n(n^2 - 1)}{n(n+1)\sqrt{(n-1)}}\,. \tag{4.24}$$

The advantages of rank correlations is the lack of an assumption on the distribution of the various performance measures without having to oversimplify by classifying each fund as a winner or loser in each time period.

[26] See Kanji (1999), p. 93

E EMPIRICAL RESULTS

The empirical analysis is conducted with the data described in section IV C. The efficient frontier is calculated based on the optimizations explained in section IV D. 477 hedge funds and a set of eight evaluation criteria described in the methodology section is used in the data envelopment analysis. Additional performance criteria are exhibited for illustration purposes only and are not used in the DEA optimization process. The characteristics of the data are illustrated in Table 4.1. Median values are exhibited instead of mean values in order to avoid the distorting impact of outliers on the statistic. The median values of the various performance measures are presented separately for efficient funds and non-efficient funds.

The minimum and maximum values indicate the presence of outliers in particular with regard to the downside risk measures omega, Sortino ratio, kappa and Calmar ratio. The data envelopment analysis over the 120-month time period indicates that 34 hedge funds exhibit a relative efficiency score of one and therefore span the efficiency frontier. The remaining 443 hedge funds have an efficiency score between zero and one and are enveloped by the plane of the efficiency frontier. The number of efficient hedge funds and the efficiency scores depend on the number of evaluation criteria chosen for the analysis, the number of hedge funds in the sample and the time period for the analysis. The relative efficiency scores can therefore only be interpreted relative to other hedge funds in the sample and do not have any meaning on an absolute basis.

The group of efficient funds exhibits higher median values across all five output evaluation criteria, return, skewness, proportion of positive months, alpha and omega. The group also exhibits lower median input values, standard deviation, maximum drawdown and excess kurtosis compared to the group of non-efficient funds.

The analysis is repeated based on 13 evaluation criteria using the additional performance measures, Sortino ratio, kappa, upside potential ratio and Calmar ratio as additional output criteria and modified value-at-risk as additional input criteria. The results indicate that one further fund is classified as efficient, bringing the number of efficient funds to 35. The results are indeed very similar to the analysis with eight criteria confirming the assumption that the five additional criteria capture little additional information in the data envelopment analysis setup. For practical purposes criteria with no or only marginal additional information should be dropped from the analysis.

TABLE IV-1: Characteristics of 477 hedge funds over a 120-month period

	Median				
	All funds	Efficient funds	Non-efficient funds	Minimum	Maximum
Output variables for DEA					
Returns p.a.	10.47%	14.89%	10.13%	-7.54%	28.38%
Skewness	-0.08	0.21	-0.11	-7.61	3.10
Proportion of pos. returns	61.67%	71.25%	61.67%	42.50%	96.67%
Alpha p.m.	0.40%	0.94%	0.38%	-2.19%	2.17%
Omega	1.51	2.96	1.44	0.67	22.30
Input variables for DEA					
Standard deviation	14.45%	9.15%	14.68%	1.37%	58.14%
Maximum drawdown	24.60%	8.45%	25.15%	0.27%	92.91%
Excess kurtosis	1.76	1.05	1.83	-0.41	74.73
Other perf. measures					
Sortino ratio	0.79	2.51	0.72	-0.67	26.99
Kappa (3rd order)	0.15	0.48	0.14	-0.15	5.12
Upside potential ratio	0.69	1.13	0.68	0.28	8.16
Calmar ratio	0.44	1.74	0.42	-0.11	38.95
Modified VaR	9.58%	4.75%	9.72%	0.70%	59.12%

The data envelopment analysis is based on the input-oriented variable return-to-scale approach. Three input and five output variables are used for the data envelopment analysis. Further performance measures are shown for illustrative purposes only. The characteristics are based on a sample of 477 hedge funds over a time period from May 1995 to April 2005. The data envelopment analysis reveals 35 efficient funds and 442 non-efficient funds. Median values are calculated for the various criteria for all funds, efficient funds and non-efficient funds. The alphas are derived from excess returns and an asset class factor model with four factors. The factors are the Goldman Sachs Commodity Index, the Wilshire Micro Cap Index, the CBOE Volatility Index and the Lehman Aggregate Bond Index. A 95% confidence interval is used for the value-at-risk approach.

The analysis is also repeated with a set of six evaluation criteria after dropping skewness and kurtosis from the original set of eight evaluation criteria. The number of efficient funds drops to 18, suggesting that skewness and kurtosis represent distinct performance dimensions containing information that can not be captured with the remaining six evaluation criteria, returns, proportion of positive months, standard deviation, alpha, maximum drawdown and omega.

To test the persistence of relative efficiencies over time, the sample period is divided into two sub-periods of 60 months each, one period referred to as in-sample time period from May 1995 to April 2000 and one period referred to as out-of-sample time period from May 2000 to April 2005. 473 hedge funds and the set of eight evaluation criteria are used in the analysis. In a first step the efficient frontier of the first sub-period, which is also referred to as the in-sample efficient frontier, is derived. The funds are then classified into efficient and non-efficient funds. In a second step both groups are investigated with regard to their efficiency in the out-of-sample period. In the in-sample time period 43 hedge funds are efficient and the remaining 430 hedge funds are non-efficient. The data envelopment analysis applied to the second period reveals 42 efficient funds and 431 funds with an efficiency score between zero and one. Of the 43 hedge funds that are efficient in the in-sample period, 14 hedge funds or 33% are also efficient in the out-of-sample period, while only 28 hedge funds or 7% of the group of 430 non-efficient hedge funds in the in-sample period are efficient in the out-of-sample period. A detailed description is given in Table 4.2. This table gives an initial indication of performance persistence of relative efficiencies.

TABLE IV-2: Number of efficient/non-efficient funds in- and out-of-sample

	Efficient funds		Non-efficient funds	
In-sample period May 1995 - April 2000	43 (9%)		430 (91%)	
	Efficient funds	Non-efficient funds	Efficient funds	Non-efficient funds
Out-of-sample period May 2000 - April 2005	14 (33%)	29 (67%)	28 (7%)	402 (93%)

The data envelopment analysis is conducted with 473 hedge funds in the periods from May 1995 to April 2000 and from May 2000 to April 2005 based on a set of eight evaluation criteria containing return, skewness, proportion of positive months, alpha, omega, standard deviation, maximum drawdown and excess kurtosis. In the first step the data sample is separated into efficient and non-efficient funds in the in-sample period. In a second step both, efficient as well as non-efficient funds are then investigated with regard to their efficiency in the out-of-sample period.

The median efficiency scores of efficient and non-efficient funds in- and out-of-sample are presented in Table 4.3. It is interesting to observe that funds that are classified as efficient with an efficiency score of one in the in-sample period also exhibit a higher median efficiency score of 0.770 in the out-of-sample period. On the other hand, the group of non-efficient funds in the in-sample period only exhibits a median efficiency score of 0.364 in the out-of-sample period.

The investigation of the characteristics of efficient funds versus non-efficient funds in the out-of-sample period reveals persistence in the efficiency scores. Efficient funds generally exhibit a substantially better performance also in the out-of-sample period according to most performance measures. In the out-of-sample period the group of efficient funds exhibits a median return of 8.36% p.a. versus 5.91% p.a. for non-efficient funds. The median monthly alpha of 0.32% of efficient funds is also substantially higher than the median monthly alpha of 0.08% for non-efficient funds. Efficient funds also exhibit superior out-of-sample characteristics with regard to the median values for skewness, proportion of positive returns, omega, Sortino ratio, kappa, upside potential ratio and Calmar ratio.

TABLE IV-3: Hedge fund characteristics in- and out-of-sample I

	Efficient funds (defined in the in-sample period)		Non-efficient funds (defined in the in-sample period)	
	In-sample	Out-of-sample	In-sample	Out-of-sample
Number of funds	43		430	
Median efficiency scores	1.000	0.770	0.395	0.364
Output variables for DEA				
Returns p.a.	14.41%	8.36%	10.08%	5.91%
Skewness	0.22	0.04	-0.13	-0.07
Proportion of pos. returns	68.33%	65.00%	61.67%	58.33%
Alpha p.m.	0.90%	0.32%	0.49%	0.08%
Omega	2.54	1.81	1.68	1.29
Input variables for DEA				
Standard deviation	9.52%	9.92%	14.78%	13.25%
Maximum drawdown	7.24%	11.25%	16.99%	23.13%
Excess kurtosis	1.02	0.74	1.84	0.64
Other perf. measures				
Sortino ratio	2.29	1.29	1.04	0.52
Kappa (3rd order)	0.45	0.26	0.20	0.11
Upside potential ratio	1.13	0.79	0.76	0.67
Calmar ratio	2.02	0.74	0.58	0.31
Modified VaR	6.44%	5.67%	10.26%	8.07%

The data envelopment analysis is based on the input-oriented variable return-to-scale approach. Eight evaluation criteria are used to derive the efficient frontier in the data envelopment analysis. Further performance measures are shown for illustrative purposes only. The in-sample time period is chosen from May 1995 to April 2000 and the out-of-sample time period from May 2000 to April 2005. The data is based on 43 (430) hedge funds that are classified as efficient (non-efficient) in the in-sample period. The alphas are derived from excess returns and an asset class factor model with four factors. The factors are the Goldman Sachs Commodity Index, the Wilshire Micro Cap Index, the CBOE Volatility Index and the Lehman Aggregate Bond Index. A 95% confidence interval is used for the value-at-risk approach.

For the input variables that are minimized in the data envelopment analysis efficient funds exhibit lower median values for standard deviation and maximum drawdown, but have a higher median value for excess kurtosis.

The number of funds with an efficiency score of one is substantially smaller than the number of funds with efficiency scores of less than one. For comparison purposes two equally sized groups are built according to their efficiency scores in the in-sample period. Funds with above median efficiency scores belong to the first group and funds with below median efficiency scores to the second. The characteristics of the two groups are presented in Table 4.4.

The results suggest that funds with above median efficiency scores in the in-sample period based on the data envelopment analysis with three input and five output variables also exhibit better performance characteristics across all performance dimensions in the out-of-sample period.

A similar observation can be made by comparing the efficiency scores and the performance criteria in the analysis with 13 evaluation criteria. Funds with above average efficiency scores in the in-sample period outperform on average across all evaluation criteria in the out-of-sample period.

In the analysis with six evaluation criteria, again, performance persistence can be observed in the efficiency scores. Funds with above average efficiency scores in the in-sample period outperform on average in the out-of-sample period across all six performance measures that have been optimized in the in-sample period.

The analysis with the 72-month in-sample and 48-month out-of-sample period confirms performance persistence in the efficiency scores. Funds with above average efficiency scores in the in-sample period outperform in six out of eight evaluation criteria in the out-of-sample period.

A similar result is obtained in the analysis with the 84-month in-sample and 36-month out-of-sample period. Efficiency scores are persistent over time. Funds with above average efficiency scores in the in-sample period outperform in seven out of eight evaluation criteria in the out-of-sample period.

TABLE IV-4: Hedge fund characteristics in- and out-of-sample II

	Funds with above median efficiency (defined in the in-sample period)		Funds with below median efficiency (defined in the in-sample period)	
	In-sample	Out-of-sample	In-sample	Out-of-sample
Number of funds	236		237	
Median efficiency scores	0.628	0.535	0.287	0.264
Output variables for DEA				
Returns p.a.	11.51%	6.31%	9.45%	5.70%
Skewness	0.03	0.02	-0.30	-0.18
Proportion of pos. returns	65.00%	61.67%	59.17%	56.67%
Alpha p.m.	0.69%	0.17%	0.36%	-0.02%
Omega	2.19	1.50	1.49	1.21
Input variables for DEA				
Standard deviation	10.50%	9.42%	18.11%	15.98%
Maximum drawdown	9.40%	13.44%	23.39%	29.77%
Excess kurtosis	1.13	0.46	2.21	0.93
Other perf. measures				
Sortino ratio	1.84	0.89	0.74	0.35
Kappa (3rd order)	0.36	0.18	0.15	0.07
Upside potential ratio	0.96	0.76	0.67	0.61
Calmar ratio	1.24	0.56	0.41	0.21
Modified VaR	7.32%	5.51%	12.96%	10.39%

The data envelopment analysis is based on the input-oriented variable return-to-scale approach. Eight evaluation criteria are used to derive the efficient frontier in the data envelopment analysis. Further performance measures are shown for illustrative purposes only. The in-sample time period is chosen from May 1995 to April 2000 and the out-of-sample time period from May 2000 to April 2005. The data is based on 236 (237) hedge funds with above (below) median efficiency scores in the in-sample period. A 95% confidence interval is used for the value-at-risk approach. The alphas are derived from excess returns and an asset class factor model with four factors. The factors are the Goldman Sachs Commodity Index, the Wilshire Micro Cap Index, the CBOE Volatility Index and the Lehman Aggregate Bond Index.

The persistence of efficiency scores over time is further investigated by testing the correlation between in- and out-of-sample efficiency scores. One challenge is the non-normal distribution of efficiency scores that is skewed to a relatively small number of outliers. Given the non-linearity of the relationship between in-sample and out-of-sample efficiency scores, standard statistical tests deliver biased results. One simple approach to overcome this issue is the determination of the rank of hedge funds according to their efficiency scores for the in-sample and the out-of-sample period. The Spearman rank correlation test is then applied to test the significance of rank correlations. The relationship between in-sample and out-of-sample efficiency scores has a rank correlation of 0.491 for the analysis with eight evaluation criteria and is statistically significant at the 1% significance level with a z-statistic of -10.168. For the analysis with 13 evaluation criteria the rank correlation is 0.506 and for the analysis with six evaluation criteria it even increases to 0.609. The findings of significant performance persistence are in contrast to results of previous studies from Agarwal and Naik (2000a) and Brown, Goetzmann and Ibbotson (1999) that measure performance persistence on individual criteria such as returns, Sharpe ratios or appraisal ratios. The combination of various performance measures in one efficiency score based on data envelopment analysis provides a more comprehensive performance measure. The large data set and the long time horizon used in this chapter also contribute to the accuracy of the results.

In an attempt to test the robustness of the results the persistence of the various evaluation criteria is tested separately. Rank correlation coefficients between the in-sample and out-of-sample values are calculated and z-statistics are used to test the significance of the correlation coefficients. The results are illustrated in Table 4.5. With the exception of alpha and upside potential ratio the persistence of all other criteria is statistically significant at the 1% significance level while it is statistically significant at the 5% significance level for the upside potential ratio. The results therefore confirm the performance persistence revealed in the approach based on the data envelopment analysis. The persistence is particularly strong for standard deviations, a result that is in line with the findings of Kat and Menexe (2003). In contrast to studies of Malkiel and Saha (2005) and Agarwal and Naik (2000a) that focus on short-term persistence based on quarterly, semi-annual or annual periods, this study is investigating long-term performance persistence by comparing two sub-periods of 60 months each. Since liquidity terms of hedge funds are often subject to long lock-up periods, quarterly redemptions with long notice periods or redemption gates the choice for long evaluation periods is in line with the long-term investment horizons of hedge fund investors.

TABLE IV-5: Persistence of individual evaluation criteria

	Rank correlation coefficient	Z-statistic	P-value
Returns p.a.	0.5723	-12.4323	0.0000
Skewness	0.6139	-13.3378	0.0000
Proportion of pos. returns	0.8586	-18.7138	0.0000
Alpha p.m.	0.0243	-0.5272	0.2990
Omega	0.2319	-5.0389	0.0000
Sortino ratio	0.1822	-3.9576	0.0000
Kappa (3rd order)	0.1556	-3.3786	0.0004
Upside potential ratio	0.1042	-2.2632	0.0118
Calmar ratio	0.5117	-11.1171	0.0000
Standard deviation	0.9415	-20.4542	0.0000
Maximum drawdown	0.6421	-13.9514	0.0000
Excess kurtosis	0.5031	-10.9289	0.0000
Modified VaR	0.7825	-17.0006	0.0000

Rank correlation coefficients are calculated between the in-sample and out-of-sample periods for each evaluation criteria. The in-sample time period is chosen from May 1995 to April 2000 and the out-of-sample time period from May 2000 to April 2005. The data sample is based on 473 hedge funds. A 95% confidence interval is used for the value-at-risk approach. The alphas are derived from excess returns and an asset class factor model with four factors. The factors are the Goldman Sachs Commodity Index, the Wilshire Micro Cap Index, the CBOE Volatility Index and the Lehman Aggregate Bond Index.

The stability of the results is further tested by using sub-periods with different breakpoints. In the analysis with two sub-samples of 72 months from May 1995 to April 2001 and 48 months from May 2001 to April 2005, the lack of persistence of alphas can be confirmed. In contrast to the analysis with two sub-periods of 60 months each, this analysis also rejects the persistence in annualized returns.

A third analysis with two sub-periods of 84 months from May 1995 to April 2002 and of 36 months from May 2002 to April 2005 suggests persistence in all 13 evaluation criteria.

Eleven out of 13 criteria exhibit persistence independent of the breakpoint. The analysis with different sub-periods indeed suggests that the time period chosen for the analysis has an impact on the results of persistence of returns and alphas. For evaluation criteria of higher order such as skewness and kurtosis sub-periods of 60 months or less can lead to instable results. The lack of a longer time horizon therefore limits the interpretation of the results for performance measures of higher order.

F SUMMARY OF FINDINGS

In the hedge fund industry hedge fund selection is primarily conducted based on qualitative judgment. The selection of hedge funds typically contains an assessment of the individual investment strategies, the background and integrity of the manager, organizational aspects, risk management procedures and many more criteria that are not quantifiable. Quantitative methods typically focus on the assessment of the track record of the manager and are used as an additional tool in the hedge fund selection process. A precondition for the usefulness of quantitative methods is the persistence of hedge fund performance characteristics in order to make future projections based on past return data.

This chapter investigates performance persistence in hedge funds with the methodology of data envelopment analysis. The benefit of this approach is based on the opportunity of taking several traditional and alternative evaluation criteria simultaneously into account without requiring return distribution assumptions. Efficient frontiers are derived based on sets of six, eight and 13 selected evaluation criteria including return, skewness, proportion of positive months, alpha, omega, Sortino ratio, kappa, upside potential ratio, Calmar ratio, standard deviation, maximum drawdown, excess kurtosis and modified value-at-risk. Relative efficiency scores are calculated with simultaneous linear optimizations for 477 hedge funds given the set of evaluation criteria. The approach ranks hedge funds based on their efficiency scores and differentiates between efficient and non-efficient hedge funds.

The results indicate a significant relationship between efficiency scores of the in-sample and out-of-sample period suggesting strong performance persistence. The relationship of the ranks of efficiency scores in- and out-of-sample is statistically significant at the 1% significance level for each set of evaluation criteria. The stability of the results can also be confirmed for different breakpoints dividing the two sub-periods. A separate analysis for each of the individual evaluation criteria confirms performance persistence in all evaluation criteria with the exception of alphas. This finding is particularly interesting with regard to previous studies that reveal little evidence on performance persistence based on individual performance measures such as returns, Sharpe ratios or appraisal ratios. In contrast to previous studies, the analysis in this chapter is focusing on long-term performance persistence and is therefore in line with long time horizons of hedge fund investors. Since data envelopment analysis takes several evaluation criteria simultaneously into account, this approach provides a more comprehensive assessment of performance persistence. A relatively large set of evaluation criteria is chosen to avoid the dependence on one or few individual criteria. The performance persistence of relative efficiencies over time validates the quantitative approach as an important additional tool in the selection of hedge funds.

Given the variety of strategy specific performance characteristics, performance persistence may also be investigated on a strategy level. The disadvantages of strategy specific research are the limited data set available for research purposes and the challenge in assigning individual hedge funds to specific strategies. Approaches for strategy classification of hedge funds are discussed in Chapter V.

V STRATEGY CLASSIFICATION AND PORTFOLIO CONSTRUCTION WITH HEDGE FUNDS

Portfolio construction in the hedge fund industry is primarily associated with the diversification across various hedge fund strategies. This chapter discusses the benefits of a quantitative k-means cluster analysis with respect to portfolio construction of hedge fund portfolios. Portfolio allocation methods are developed based on the results of the cluster analysis. The quantitative cluster-based classification is also compared with the qualitative self-reported classification of hedge fund managers. A major contribution of this section is also the investigation of the stability of clusters and the persistence of cluster characteristics over time.

A RESEARCH TOPIC III

The heterogeneity of the hedge fund universe raises the question of a proper classification scheme for hedge funds. Due to the relatively opaque nature of the hedge fund industry, no unique classification scheme exists. Various database providers use different classification schemes. Generally, hedge fund database providers allow each hedge fund manager to classify the strategy with respect to the classification scheme given by the database provider.

This chapter explores a quantitative k-means cluster analysis that is grouping hedge fund managers based on their past returns. The objective is to compare the results of the quantitative cluster analysis with the qualitative self-reported classification of the individual hedge fund managers. The quantitative method allows detecting managers that are classifying themselves differently than their past returns would indicate and therefore provides a tool to monitor style drifts of managers.

Extensive literature has been published about the methodology of cluster analysis with hedge fund data, but little information is available about the consistencies of clusters over time and further applications of the cluster analysis for portfolio construction purposes. This chapter is filling the gap. Cluster analysis is conducted over different time periods with a large unique data sample that combines six different commercial hedge fund databases as described in Chapter II. In addition to the traditional use of cluster analysis for classifying hedge funds this study goes one step further and evaluates potential benefits for portfolio construction of hedge fund portfolios. More specifically, it is tested whether portfolio diversification across clusters provides higher risk-adjusted returns than the general approach of diversification across qualitatively defined hedge fund strategies.

The structure of the chapter is the following: A literature overview can be found in section B. Section C discusses the data used for the empirical part of the study. Section D, E and F contain the methodology and empirical analysis. In the first step of the empirical study a principal component analysis is applied similar to Fung and Hsieh (1997a) to evaluate the heterogeneity of the data sample and the various hedge fund strategies. In a second step a cluster analysis is used to classify hedge funds. In a third step portfolio construction schemes are developed. Section G concludes and discusses the contribution of the study. The findings of this chapter are also discussed in Moerth (2006b).

B RELATED LITERATURE

A number of studies are dedicated to the systematic classifications of hedge funds. Brown and Goetzmann (2003) provide the most frequently quoted contribution in that space. The authors focus on stylistic differences across hedge funds by using a systematic, quantitative approach to understand and characterize the major categories of hedge fund styles. The article suggests a generalised style classification model that is effectively a k-means cluster analysis which clusters on monthly returns and has been modified as a generalised least squares (GLS) procedure in order to take into account the time varying and fund specific residual return variance. The GLS procedure accounts for heteroskedasticity by scaling the data observations by the inverse of the estimated standard deviation. The GLS methodology also reduces the impact that outliers may have on the classification algorithm thereby improving the results of the cluster analysis. Eight distinct style classifications are identified quantitatively that explain a greater percentage of the variability of subsequent returns than does the 17-category TASS classification. The authors conclude that the return-based quantitative classification shows a remarkable agreement with the classification of TASS for the three year period up to December 1999.

Maillet and Rousset (2003) classify hedge funds employing the Kohonen algorithm[27]. The algorithm allows characterizing families of funds, whose conditional densities are different one to another and to define a representative fund for each class. The article concludes that two separate groups of funds can be distinguished: two third of the data belongs to the first one, consisting of one class only, whilst one third belongs to the second one, consisting of nine other classes. The result suggests that one can distinguish between one homogenous group of funds, and some others that exhibit individual particularities. The analysis is based on a relatively small data set of only 294 funds that limits the significance of the results.

Baghai-Wadji et al. (2005) compare the proprietary classification of the CISDM database with a neural network return-based classification approach based on self-organizing maps.[28] The mapping procedure identifies nine proprietary hedge fund classes. In contrast to the research of Brown and Goetzmann (2003), the findings of Baghai-Wadji et al. (2005) indicate that a differentiated picture in the consistency of self-declared fund styles can be drawn: Short-selling and sector financial hedge funds, as well as managed futures are largely consistent in their self-declared strategies.

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[27] The originality of Kohonen algorithm is based on the concept of neighbourhood that organizes the different classes of observations. The Kohonen algorithm can be compared to Lloyd’s and k-means family algorithms. The classification method is robust, because it is less sensitive to outliers than most other techniques.

[28] The self-organizing map is an ideal tool for clustering and visualizing high-dimensional data. It is a single-layered unsupervised neural network which does not require any human intervention during the training process. The training process of the self-organizing map can be described as the procedure where the map identifies the key features of the input space via a given set of input vectors. After the completion of the training process, hedge funds exhibiting similar return characteristics will be represented as homogeneous clusters on a two-dimensional surface.

Martin (2000) uses a cluster analysis approach via a robust medoid method. In order to examine the effects of the events of August 1998 on the cluster algorithm, the analysis is conducted twice, once with and once without the data of August 1998. Experimentation leads to the conclusion that eight separate clusters generate the most useful results. The authors find that the first two moments of cluster characteristics are relatively stable for all clusters, with the exception of the "emerging markets: Latin America" cluster while higher order moments are less stable. The analysis also shows that there is significant heterogeneity in individual fund returns and their sensitivities, such that conclusions derived from aggregate data are likely to be only weakly applicable to individual funds.

Bianchia et al. (2005) disagree with the findings of five to eight quantitatively characterized styles from Fung and Hsieh (1997a) and Brown and Goetzmann (2003). The results of the authors are controversial to other studies as it suggests the statistical presence of only three hedge fund investment styles. The three hedge fund investment styles can be best described as quasi-long equity, non-directional and global directional. The paper contributes to the literature by improving the work of Brown and Goetzmann (2003) by estimating the number of hedge fund styles using the gap statistic[29] rather than the traditional likelihood ratio test.

Das and Das (2005) present a hedge fund classification technique using fuzzy neural networks.[30] The classification is based on asset classes the hedge funds invest in, incentive fees, leverage, liquidity of the investment strategy and fund sizes. 652 funds are used for the analysis. The study indicates that there are six possible hedge fund groups. The classification has not kept intact any category of the existing self-classification. The result suggests that the existing self-classification of hedge funds does not consider the attributes that are used for classification in their paper.

[29] The gap statistic effectively measures the most probable within sum-of-square distances from a set of Monte Carlo samples which are derived from the original data set. The search for a substitute for the likelihood ratio test has emerged with the development of the gap statistic. This new test statistic aims to better estimate the number of groups in a data set.

[30] Neural network based classifiers make weaker assumptions concerning the shapes of underlying distributions as compared to the traditional statistical classifiers. They may, therefore, prove to be more robust when distributions are generated by non-linear processes and are non-Gaussian. Neural networks can handle non-Gaussian noise, which is quite often found in the parameters that are used to characterize a hedge fund.

Das (2003) is applying a k-means cluster analysis in order to classify hedge funds according to qualitative attributes. Although this chapter is using the same cluster methodology, it follows a different objective. In this chapter no qualitative attributes are used and the focus is on past returns only. The objective is to investigate the strategies in the hedge fund industry with respect to their diversification potential of portfolios of hedge funds. Another contribution of this chapter is the investigation of the stability of clusters over time and the persistence of cluster characteristics.

C DATA SET

The return structure of hedge fund data set II, a large sample of hedge fund returns based on various databases, is analyzed in the empirical part of this section. Table 2.1 describes the data set used for the analysis. The data set is based on 1,349 hedge funds with a minimum track record of 60 months in the time period from May 2000 to April 2005. Some parts of the study use a data set of 480 hedge funds with a minimum track record of 120 months from May 1995 to April 2005 in order to test the stability of the results.

The analysis of the data on a strategy level is an additional challenge. Hedge fund data providers use different classification schemes concerning the strategy of hedge fund managers. A common classification scheme needs to be found and all hedge funds need to be classified manually according to this scheme. The strategy classification of TASS knows nine hedge fund strategies[31], one category for "other" strategies and one category for funds of hedge funds. The HFR database knows twelve hedge fund strategies that can be divided in up to 26 sub-strategies. Hedgefund.net knows up to 38 different categories including three categories for funds of hedge funds. A detailed description of the classification schemes of various database providers can be found in Das (2003). The classification scheme of TASS

[31] Event Driven is one of the nine strategies used by TASS and is broken down into four sub-strategies that are not taken into account in the nine main strategies.

is also incorporated in the CSFB-Tremont hedge fund indices[32], an index provider that is often used as a reference by hedge fund investors. The decision is made that the classification scheme of TASS is used for this study because its common use in the hedge fund industry makes it the most relevant classification scheme.

D PRINCIPAL COMPONENT ANALYSIS

The objective of the principal component analysis is to reduce the dimensionality of the data set. In other words the hedge fund returns of a large data sample can be explained with few influencing factors. The basic idea of a principal component analysis is to identify the factors that explain best the variance of return time series.

1 METHODOLOGY

Principal component analysis is an optimal linear dimension reduction technique in the mean-square sense. As much variance as possible is accounted for by each new factor. The commonalities, defined as the portion of the total variance of a variable that can be explained by all factors, are depending on the number of factors extracted and on the heterogeneity of the data sample. The more factors are extracted the more variance can be explained. Nevertheless the objective of the principal component analysis is to reduce the data sample to a limited number of explanatory factors. Once the number of factors is determined, the correlations between each factor and the individual hedge fund returns is calculated with the objective to find the factor loadings of each hedge fund in the sample.

The correlation matrix R using the standardized data matrix Z can be written as

$$R = \frac{1}{K-1} Z'Z \tag{5.1}$$

[32] The CSFB-Tremont indices are exclusively based on funds from the TASS database. Funds that are part of the Tremont Index must have a minimum track record of one year and at least ten million USD assets under management. The funds of the CSFB-Tremont indices can be regarded as a sub-sample of the TASS database.

where $z_{kj} = \frac{x_{kj} - \bar{x}_j}{s_j}$

with x_{kj} denoting the return of hedge fund *j* in month *k*,

$\bar{x}_j$ representing the average return of hedge fund *j*,

s_j representing the standard deviation of hedge fund *j*,

and z_{kj} representing the standardized value of hedge fund *j* in month *k*.

Principal component analysis is based on the assumption that each monthly return of all hedge funds can be reproduced by a linear combination of several hypothetical factors. This relationship can be presented with the equation

$$z_{kj} = \sum_{q=1}^{Q} a_{jq} p_{kq} \tag{5.2a}$$

with p_{kq} representing the value of factor *q* with respect to month *k*

and a_{jq} representing the factor *q* factor loading of hedge fund *j*.

Using a matrix notation this basic expression can be written as

$$Z = PA'. \tag{5.2b}$$

Using equation 5.2b the correlation coefficient in equation 5.1 can be expressed as follows

$$R = \frac{1}{K-1}(PA')'(PA'). \tag{5.3a}$$

This expression can be rewritten as

$$R = A\frac{1}{K-1}P'PA'. \tag{5.3b}$$

The expression $\frac{1}{K-1}P'P$ can be interpreted as the correlation matrix of the factors and can be denoted by *C* resulting in

$$R = ACA'. \tag{5.3c}$$

If the factors are uncorrelated, than C is the identity matrix and the expression can be further simplified to the fundamental theorem of factor analysis

$$R = AA' . \tag{5.3d}$$

The correlation matrix can therefore be represented by the factor loadings matrix A and the correlation between the factors defined as C.

In order to find the factor values P, matrix Z defined in equation 5.2b can be used. Both sides of the equation are multiplied with the inverse of the factor loadings matrix $(A')^{-1}$ in order to get

$$Z(A')^{-1} = PA'(A')^{-1} . \tag{5.4a}$$

Since $PE = P$, the factor values are

$$P = Z(A')^{-1} . \tag{5.4b}$$

The factor loadings matrix A is generally not quadratic since the objective is to find fewer factors than hedge funds. An inversion is therefore not possible. Alternatively the following approach can be used. Starting with equation 5.2b both sides are multiplied with A to get

$$ZA = PA'A . \tag{5.5a}$$

The matrix $A'(A')^{-1}$ is by definition quadratic and invertible and the equation can be extended to

$$ZA(A'A)^{-1} = P(A'A)(A'A)^{-1} . \tag{5.5b}$$

Since $P(A'A)(A'A)^{-1}$ provides the identity matrix, the final transformation leads to

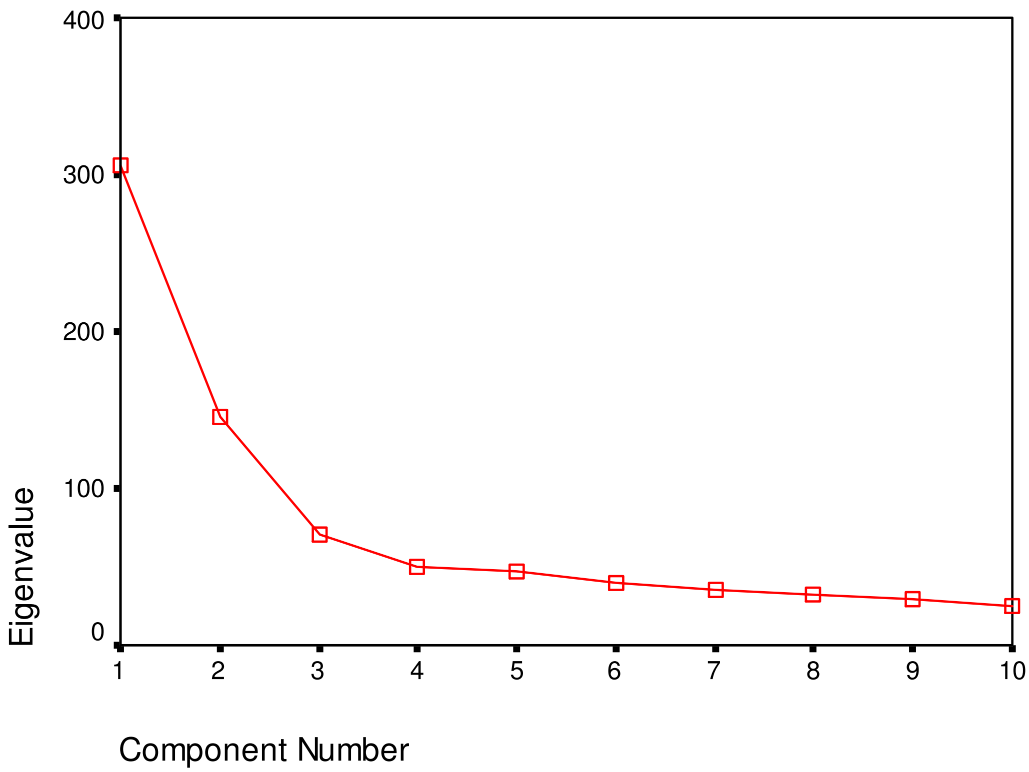
$$P = ZA(A'A)^{-1} . \tag{5.5c}$$

In some cases equation 5.5c can not be solved and therefore an estimation procedure is needed to derive a solution. Generally, a regression analysis is used to estimate the factor values.

2 EMPIRICAL RESULTS

In the empirical study a principal component analysis is applied to the data set of 1,349 hedge funds with 60 months track record from May 2000 to April 2005. The eigenvalues and the first ten components of the analysis are plotted on a chart illustrated in Figure 5.1. The eigenvalues $\sum_j a_{jq}^2$ are defined as the sum of the squared factor loadings of one factor over all hedge funds. The eigenvalues are a measure for the variance contribution of one single factor with respect to the total variance of all hedge funds. The first component has by far the largest eigenvalue and therefore the largest explanatory power compared to all other components.

FIGURE V-1: Scree plot of a principal component analysis with hedge funds



The figure illustrates the results of a principal component analysis conducted with a data sample of 1,349 hedge funds over a time period from May 2000 to April 2005. The eigenvalues and the first ten components are plotted in the chart.

The results of the analysis can be found in Table 5.1. The results basically confirm the general hypothesis of a high heterogeneity in the hedge fund industry. The first five principle components explain 45.97% of the cross-sectional variance of the 1,349 hedge funds in the data sample.[33]

TABLE V-1: Results of principal component analysis with 1,349 hedge funds

	Extraction sum of squared loadings			Rotation sum of squared loadings		
Component	Eigen-values	% of variance	Cumulative %	Eigen-values	% of variance	Cumulative %
1	305.66	22.66%	22.66%	276.10	20.47%	20.47%
2	146.05	10.83%	33.48%	134.68	9.98%	30.45%
3	71.01	5.26%	38.75%	54.96	4.07%	34.52%
4	50.55	3.75%	42.50%	49.12	3.64%	38.17%
5	46.86	3.47%	45.97%	46.13	3.42%	41.59%
6	40.06	2.97%	48.94%	43.41	3.22%	44.80%
7	34.97	2.59%	51.53%	40.11	2.97%	47.78%
8	31.64	2.35%	53.88%	32.72	2.43%	50.20%
9	29.17	2.16%	56.04%	22.50	1.67%	51.87%
10	25.54	1.89%	57.93%	21.37	1.58%	53.45%

The table illustrates the results of a principal component analysis conducted with a data sample of 1,349 hedge funds over a time period from May 2000 to April 2005. The eigenvalues, the percentage of variance explained by each component and the cumulative percentage of variance explained are illustrated for each of the first ten components. The results are presented before and after applying a factor rotation.

The first step serves to interpret the components. The factor values of the first ten components are then compared with common observable market factors in a simple correlation analysis. The first component has a significant correlation of 0.92 to the MSCI World and 0.96 to the Wilshire Small Cap 1750 Index. It is not surprising that equities are the most important influencing factor on hedge fund returns. Equity Long/Short is the most common hedge fund strategy and many Equity Long/Short Managers tend to have a long bias to the equity markets and in

[33] Fung and Hsieh (1997) applied a similar analysis on 297 Hedge Funds over a 36-month period and found five principal components explaining 43% of the cross-sectional variance. The difference can be explained by the different time periods used for the analysis and the different sample sizes.

particular to small cap stocks. The second component is far less important than the first component and more difficult to interpret. The highest factor correlation of the second component is 0.50 with the EUR/USD exchange rate. Most Global Macro hedge funds have a view on the EUR/USD exchange rate and implement their views in the portfolio. The explanatory power of the EUR/USD exchange rate could also come from unhedged currency exposures in various hedge fund portfolios. The third component can best be explained with high yield bonds reflected in a factor correlation of 0.53 with the Lehman High Yield Bond Index. The fourth component has its highest correlation with short-term interest rates expressed in a correlation of 0.58 with the 3-month LIBOR and 0.56 with 90-day T-Bill rates.

In the next step the sample is broken down into ten categories. Nine categories signify hedge fund strategies and one category is a pool for "other" strategies. The strategy classification follows the methodology applied by the TASS database.[34] The principal component analysis is then repeated for each strategy separately. In Table 5.2 the variance is explained by each of the first three principal components after a factor rotation for each strategy. Some strategies tend to be more homogeneous than others. For the strategies Dedicated Short Bias, Emerging Markets and Convertible Arbitrage the first three principal components explain more than 50% of the total variances after a factor rotation while the first three principal components of the strategies Equity Market Neutral, Fixed Income Arbitrage and Global Macro explain less than 30% of the respective total variances.

One advantage of the principal component analysis is the high statistical explanatory power. The shortcoming is based on the fact that the derived principal components have no immediate economic meaning and are not always easy to interpret. With regard to hedge fund returns the principal component analysis is a useful tool to get a basic understanding about the heterogeneity of hedge fund returns, but it is difficult to derive any direct implication for the construction of hedge fund portfolios. In order to learn more about the composition of the hedge fund sample, an alternative method needs to be applied. The next subsection

[34] The hedge fund industry does not know a standard method for strategy classifications. See section VI E for a more detailed discussion of strategy classification of hedge funds.

therefore discusses a classification methodology that takes the individual return series of the hedge funds in the sample into account.

TABLE V-2: Variance explained of rotated components for each strategy

Strategy	Funds	Component 1	Component 2	Component 3	Component 1 - 3
Convertible Arbitrage	54	30.17%	11.55%	10.92%	52.64%
Dedicated Short Bias	14	55.86%	12.36%	9.52%	77.73%
Emerging Markets	100	20.43%	19.62%	10.63%	50.68%
Equity Market Neutral	75	11.02%	9.58%	6.44%	27.04%
Event Driven	136	21.87%	14.53%	8.78%	45.18%
Fixed Income Arbitrage	61	12.46%	10.41%	5.85%	28.72%
Global Macro	65	9.05%	8.04%	7.48%	24.57%
Equity Long/Short	505	28.96%	6.94%	3.28%	39.18%
Managed Futures	264	34.53%	4.28%	3.97%	42.78%
Others	75	16.00%	14.76%	5.38%	36.13%

The table illustrates the variance explained by the first three components of a principal component analysis conducted for each strategy separately. The cumulative variance explained by the first three components can be seen as a measure of the homogeneity of the respective strategy.

E STRATEGY CLASSIFICATION AND CLUSTER ANALYSIS

Cluster analysis is a useful instrument to identify homogenous groups in a heterogeneous sample of hedge fund returns. In addition to the traditional use of the clustering method for classifying hedge funds, this section discusses potential benefits of clustering in a portfolio construction context.

1 CLUSTER METHODOLOGY

Different methods of cluster analysis exist that can be classified into two groups: hierarchical and partitioning cluster analysis methods. With respect to hierarchical cluster analysis, the literature differentiates between agglomerative and divisive methods. Agglomerative methods start with the smallest partitions and merges them by certain rules in fewer and fewer clusters until one conjoint set is left. Divisive methods work the other way around and start with one conjoint set that is split up in more and more subsets down to the smallest possible partitions.

Hierarchical clustering methods only allow for one assignment of any object with no possibility of regrouping. In contrast to hierarchical clustering methods, partitioning clustering methods start with initial groupings in a previously defined number of k clusters. Partitioning algorithms are used to shift objects between clusters until a given objective function reaches its optimum.

One of the most common partitioning methods is the k-means cluster analysis developed by MacQueen in 1967. The k-means cluster analysis starts with a random allocation to a specified number of clusters and then changes elements between clusters in various iterations in order to minimize the variation within clusters and to maximize the variation between clusters. The k-means cluster analysis accounts for larger variability than hierarchical methods and can be applied to larger data sets due to a fast and efficient algorithm. One disadvantage is that the partitioning algorithm may stop in some local optima instead of the global optimum. Due to the relatively large size of the data sample, a fast method is needed and therefore the k-means algorithm is used for the analysis.

In the first step a distance measure is selected to establish the distance matrix. Each element of the matrix represents the measure of distance of any pair of hedge funds. Two hedge funds are regarded as similar if their distance is small. The k-means cluster algorithm is generally based on the Euclidian distance and is relatively simple to calculate for larger data samples. The sum of Euclidian distances from the mean of each cluster is determined. The Euclidian distance is derived by using the second order of the Minkowski metrics.

$$d_{k,1} = \left[\sum_{j=1}^{J} \left| x_{kj} - x_{1j} \right|^{r} \right]^{\frac{1}{r}} \tag{6.6a}$$

where

$d_{k,1}$ is the distance of the hedge fund k and hedge fund 1,

x_{kj}, x_{1j} are the values of the time period j with the hedge funds k, 1 (j=1, 2 …J)

and $r \geq 1$ is the Minkowski-constant.

For the special case of $r = 2$ the Minkowski metric gives the Euclidean distance

$$d_{k,1} = \left[\sum_{j=1}^{J} \left| x_{kj} - x_{1j} \right|^2 \right]^{\frac{1}{2}} \quad . \tag{6.6b}$$

In various iterations the partitions are modified to reduce the sum of distances for each hedge fund from the mean of the cluster to which the hedge fund belongs. Means are calculated by using least squares. In an iteration procedure each hedge fund is allocated to the nearest of the *k* means of the previous partition. In the new partition the sum of the distances is strictly smaller than before and the cluster center changes at each iteration step. The iteration process is repeated until cluster means do not shift more than a given cut-off value. If the iteration step leads to less than *k* partitions, then the partition with the largest sum of distances is divided into two or more parts to reach the required number of *k* partitions.

Hedge fund managers are choosing the leverage and the volatility they want to allow for their fund. Funds with high volatility tend to have larger distances to the cluster centers. Therefore, it is possible that two hedge fund classes of the same hedge fund but with different leverage levels are falling in two different clusters even if they have perfect correlation. From a portfolio management perspective highly volatile funds typically get a lower allocation in order to avoid that a few risky investments are dominating the risk-return profile of a portfolio.

In order to account for the differences based on different implicit leverage levels of various hedge funds, the return series for all hedge funds are standardized. This adjustment eliminates any return or volatility differences and emphasizes on the dependency structure between the funds. The investigation of the dependency structure is the primary purpose of the cluster analysis. The standardization approach also reduces distorting effects of extreme outliers in the cluster analysis.

The disadvantage of this methodology is the fact that by eliminating the impact of differentiating returns and volatilities the potential alpha of certain managers relative to other managers is also eliminated. The standardization also implies that standard deviation is the ultimate risk measure for all hedge funds in the sample. Hedge funds with risks that are not captured in the standard deviation are therefore not taken into account. The focus on the dependencies between the various strategies intends to capture the differences between the various hedge fund styles and ignores differences in the volatility of individual managers.

In an alternative simplified approach the correlation matrix is sometimes used as an input for the cluster analysis. The disadvantage of this approach is loss of information captured in the time dimension. Therefore, this study uses standardized data of the available time series.

Silhouette values are calculated to visualize the clusters. The silhouette value for each hedge fund is a measure of how similar that hedge fund is to hedge funds in its own cluster compared to hedge funds in other clusters, and ranges from -1 to +1. It is defined as

$$S_j = \frac{(\min b(j,k) - a(j))}{\max(a(j), \min(b(j,k))} \qquad (6.7)$$

where $a(j)$ is the average distance from the hedge fund *j* to the other hedge funds in its cluster, and $b(j,k)$ is the average distance from the hedge fund *j* to hedge funds in another cluster *k*. By using a variety of cluster numbers in the analysis, the average silhouette value can be used to determine the optimal number of clusters.

2 EMPIRICAL CLUSTER ANALYSIS

The empirical analysis is based on a simplified categorization of the different classification schemes of the various database providers in four strategy groups: Relative Value, Equity Long/Short, Event Driven and Tactical Trading. These four strategy groups represent one of the most basic classifications in the hedge fund industry. Several large funds of hedge funds diversify across these four strategy groups and build their teams around this basic classification scheme. The strategy groups have distinct features.

The Relative Value group contains all non-directional strategies that are also known as arbitrage strategies. Relative Value strategies include among others Convertible Arbitrage, Fixed Income Arbitrage, Volatility Arbitrage and Statistical Arbitrage. Quantitative Equity Market Neutral managers also known as Statistical Arbitrage managers are classified in the Relative Value category and not in the

Equity Long/Short category since their mean reversion approach is relating them closer to arbitrage strategies than to fundamental Equity Long/Short strategies

The Equity Long/Short group is the largest group and includes all equity-based strategies with various degrees of exposures to the equity markets from long only to short selling. Equity Long/Short funds can also be focused on one particular sector or one particular region. Emerging Markets is a strategy that contains primarily equity-based funds and is therefore also classified in the Equity Long/Short group.

The Event Driven group contains the strategies Merger Arbitrage, Distressed Securities, High Yield, Special Situations and Activist strategies. Since many of the Event Driven strategies are primarily based on equities, many Event Driven funds have similar properties than Equity Long/Short funds.

The Tactical Trading group contains all directional trading funds, including systematic trading funds that are best known as Managed Futures as well as discretionary trading funds also known as Global Macro funds. In contrast to the other strategy groups, Tactical Trading funds are a group of funds investing across all different asset classes and implementing their strategies primarily with futures.

The grouping of funds facilitates the interpretation of the results. The choice for the initial number of clusters is derived from the qualitative classification of hedge fund strategy groups. The analysis therefore starts with four clusters.

The objective is to test whether the qualitative classification is consistent with the quantitative classification based on past returns. Each cluster can therefore be interpreted as one specific quantitatively defined strategy group.

Table 5.3 illustrates to what extent the cluster-based classification deviates from the qualitative classification. Cluster 2 is relatively homogenous and contains primarily funds of the category Tactical Trading. Cluster 1 contains most of the Relative Value funds, but in contrast to cluster 2, cluster 1 also contains a large number of funds from other strategy categories. Cluster 3 and cluster 4 are both dominated by Event Driven and Equity Long/Short funds. The result of the cluster analysis suggests that the differentiation between Event Driven and Equity Long/Short funds is more difficult from a quantitative perspective. Both Event Driven funds and Equity Long/Short funds have a positive correlation to equity markets on average and it can therefore be expected that they have similar return properties. Equity Long/Short is the strategy category with the largest number of funds and it is therefore not surprising that the strategy is dominating both cluster 3 and 4.

TABLE V-3: Cluster analysis with four clusters over a 60-month period

		Cluster 1 ("Relative Value")	Cluster 2 ("Tactical Trading")	Cluster 3 ("Equity L/S & Event Driven")	Cluster 4 ("Equity L/S & Event Driven")	Number of funds
Strategy	Relative Value	155	16	46	48	265
	Equity L/S	65	20	136	298	519
	Event Driven	28	0	80	128	236
	Tactical Trading	65	220	18	26	329
	Number of funds	313	256	280	500	1,349

A k-means cluster analysis is conducted with four clusters over the time period from May 2000 to April 2005. 1,349 funds from the TASS, HFR and Hedgefund.net databases are used for the analysis. All funds are qualitatively grouped into four strategy groups. The qualitative strategy classification is compared to the quantitative classification based on the cluster analysis.

In the k-means cluster analysis the number of clusters is determined in advance. The optimal number of clusters can be examined by repeating the analysis with a variety of cluster numbers. A criterion for the optimal number of clusters is the average silhouette value.

Table 5.5 presents the average silhouette values for cluster analyses with two to ten clusters. The table suggests that a smaller number of clusters goes hand in hand with a higher average silhouette value reflecting more distinct clusters. In other words, the choice of a larger number of clusters does not improve the average similarity of funds within the clusters relative to funds in other clusters. The analyses with two and three clusters have the highest average silhouette value. The analyses with four and six clusters have higher average silhouette values than the analyses with five, seven, eight, nine and ten clusters.

TABLE V-4: Cluster analysis with two to nine clusters over 60 months

	Average silhouette values May 1995 - April 2005 1,349 hedge funds	Number of funds per cluster 1	2	3	4	5	6	7	8	9	10
2 clusters	0.2263	552	797								
3 clusters	0.1852	681	415	253							
4 clusters	0.1377	313	256	280	500						
5 clusters	0.1232	354	256	305	226	208					
6 clusters	0.1378	158	69	221	430	218	253				
7 clusters	0.1313	68	225	139	190	288	233	206			
8 clusters	0.1224	156	190	144	65	178	118	155	343		
9 clusters	0.1229	184	127	64	173	132	148	167	121	233	
10 clusters	0.1219	171	63	281	53	189	119	99	169	65	140

K-means cluster analyses are conducted with two to ten clusters over the time period from May 2000 to April 2005. 1,349 funds from the TASS, HFR and Hedgefund.net databases are used for the analyses. The number of funds per cluster and the average silhouette values are illustrated.

The cluster analysis is repeated with two, three and six clusters instead of four clusters. The results are illustrated in Table 5.5, 5.6 and 5.7.

TABLE V-5: Cluster analysis with two clusters over a 60-month period

		Cluster 1 ("Relative Value & Tactical Trading")	Cluster 2 ("Relative Value, Equity L/S & Event Driven")	Number of funds
Strategy	Relative Value	147	118	265
	Equity L/S	98	421	519
	Event Driven	23	213	236
	Tactical Trading	284	45	329
	Number of funds	552	797	1,349

A k-means cluster analysis is conducted with two clusters over the time period from May 2000 to April 2005. 1,349 funds from the TASS, HFR and Hedgefund.net databases are used for the analysis. All funds are qualitatively grouped into four strategy groups. The qualitative strategy classification is compared to the quantitative classification based on the cluster analysis.

Table 5.5 shows that the smaller of the two clusters in the two cluster analysis is dominated by Tactical Trading funds and also contains the majority of Relative Value funds. Almost all equity-related funds of the strategies Equity Long/Short and Event Driven are forming the second cluster.

The analysis with three clusters is presented in Table 5.6. Interestingly here again, almost all Equity Long/Short and Event Driven funds fall in one cluster that is substantially larger than the other clusters. The second cluster contains most Relative Value funds and a mixture of funds of all other strategies while the third cluster is dominated by Tactical Trading funds, confirming the homogeneity of that strategy.

TABLE V-6: Cluster analysis with three clusters over a 60-month period

		Cluster 1 ("Equity L/S & Event Driven")	Cluster 2 ("Relative Value")	Cluster 3 ("Tactical Trading")	Number of funds
Strategy	Relative Value	77	172	16	265
	Equity L/S	380	125	14	519
	Event Driven	188	48	0	236
	Tactical Trading	36	70	223	329
	Number of funds	681	415	253	1,349

A k-means cluster analysis is conducted with three clusters over the time period from May 2000 to April 2005. 1,349 funds from the TASS, HFR and Hedgefund.net databases are used for the analysis. All funds are qualitatively grouped into four strategy groups. The qualitative strategy classification is compared to the quantitative classification based on the cluster analysis.

Interestingly, in the cluster analysis with six clusters presented in Table 5.7 a homogenous group of Relative Value funds is forming its own cluster. It can be observed that cluster 2 almost exclusively contains Relative Value funds while cluster 3 almost exclusively contains Tactical Trading funds. Cluster 1 represents an almost equal mix of Relative Value, Equity Long/Short and Tactical Trading funds while the clusters 4, 5 and 6 are dominated by Equity Long/Short and to a lesser extent Event Driven funds.

TABLE V-7: Cluster analysis with six clusters over a 60-month period

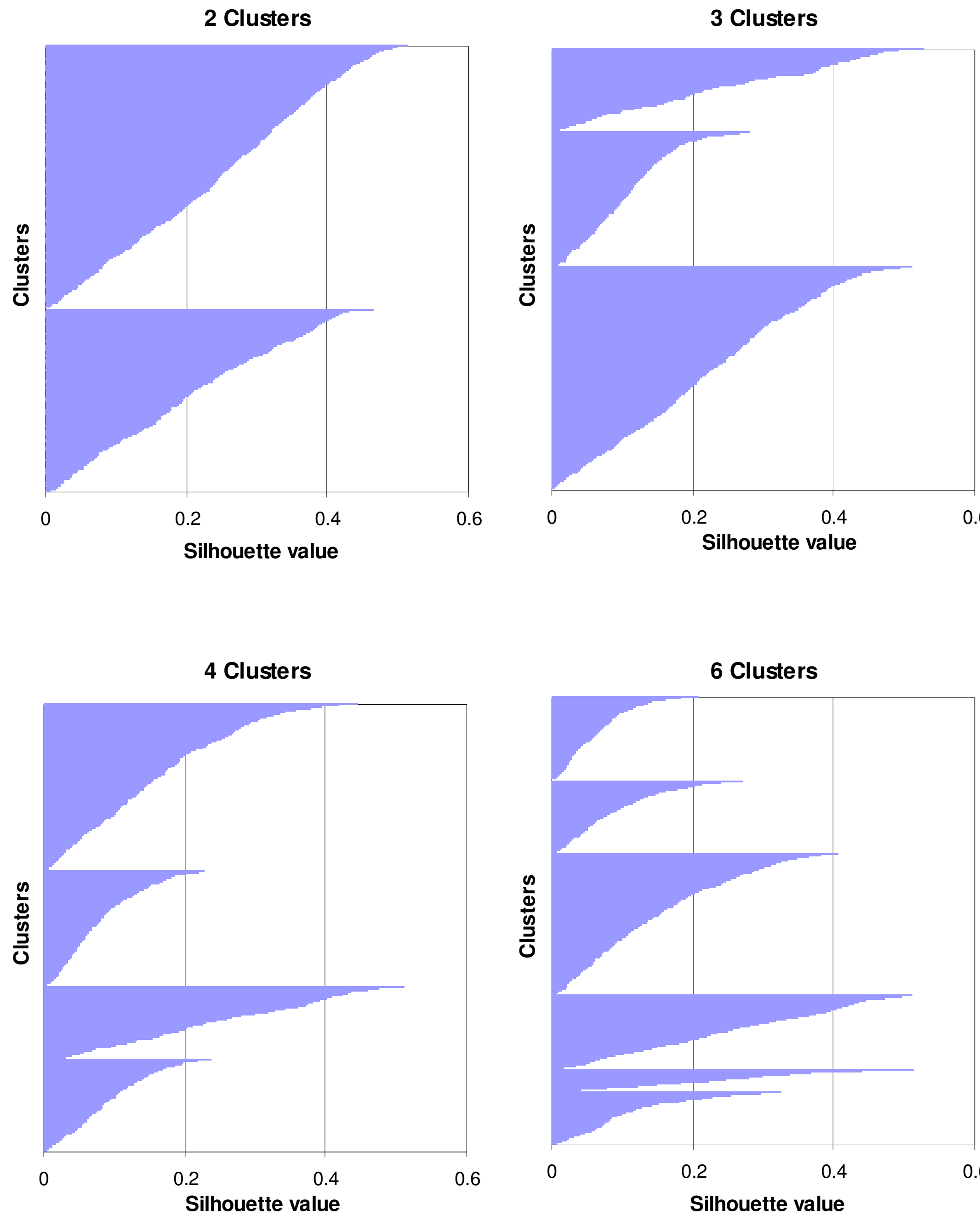
		Cluster 1 ("All strat.")	Cluster 2 ("Relative Value")	Cluster 3 ("Tactical Trading")	Cluster 4 ("Equ. L/S & ED")	Cluster 5 ("Equ. L/S & ED")	Cluster 6 ("Equ. L/S & ED")	Number of funds
Strategy	Relative Value	57	67	8	43	53	37	265
	Equity L/S	46	1	4	249	95	124	519
	Event Driven	3	0	0	121	52	60	236
	Tactical Trading	52	1	209	17	18	32	329
	All funds	158	69	221	430	218	253	1,349

A k-means cluster analysis is conducted with six clusters over the time period from May 2000 to April 2005. 1,349 funds from the TASS, HFR and Hedgefund.net databases are used for the analysis. All funds are qualitatively grouped into four strategy groups. The qualitative strategy classification is compared to the quantitative classification based on the cluster analysis.

In the analysis with four clusters as well as in the analysis with six clusters, Tactical Trading and Relative Value funds tend to dominate one cluster each while Equity Long/Short and Event Driven funds exhibit similar characteristics and are spread over several clusters.

The silhouette values of the cluster analyses with two, three, four and six clusters are presented in Figure 5.2. The different sizes of the clusters and the various degrees of homogeneity shape the form of the silhouettes. In the analysis with three and four clusters high silhouette values can be observed for the smallest cluster that is in both cases dominated by Tactical Trading funds. The largest clusters in all four analyses are dominated by Equity Long/Short and Event Driven funds. These clusters are also characterized by their gradually decreasing silhouette values exhibiting a similar shape in all four cluster analyses.

FIGURE V-2: Cluster silhouettes with two, three, four and six clusters



Silhouette values are illustrated for the k-means cluster analyses conducted with two, three, four and six clusters over the time period from May 2000 to April 2005. 1,349 funds from the TASS, HFR and Hedgefund.net databases are used for the analyses.

a. STABILITY OF CLUSTERS

The stability of clusters is investigated by conducting a cluster analysis in two different time periods with the same data sample. The 5-year time period is broken down into two sub-periods of 30 months each. The persistence of the cluster constitution is investigated over time and the consistence of the clusters is analyzed relative to the qualitative hedge fund classification. The results are illustrated in Table 5.8 for the analysis with four clusters.

In the first sub-period Cluster 1 contains an almost equal split between Relative Value, Equity Long/Short and Event Driven funds. Cluster 2 contains primarily Relative Value and Equity Long/Short funds while Cluster 3 is dominated by Equity Long/Short and Event Driven funds. Cluster 4 contains primarily Tactical Trading funds.

In the second sub-period the cluster constitution and the number of funds per cluster have changed. Relative Value funds are a stronger component in the first cluster. Cluster 2 and 3 primarily contain Equity Long/Short and Event Driven funds. Similar than in the first sub-period Cluster 4 is dominated by Tactical Trading funds.

The formation of the clusters in the second period reveals differences to the clusters derived from the first period. 52% of the funds remain in the same cluster, while 48% are falling in a different cluster. This compares to a 25% probability of staying within the same cluster in case of using random time series. The result that more than half of the funds are maintaining their cluster association suggests persistence in the cluster-based strategy classification. In other words the strategy characteristics of the majority of hedge funds are sufficiently stable to associate them with the same cluster in both time periods.

TABLE V-8: Cluster stability with four clusters over a 60-month period

Time period I		May 2000 - October 2002				
		Cluster 1 ("All strategies")	Cluster 2 ("Rel. Value & Equ. L/S")	Cluster 3 ("Equ. L/S & Event Driven")	Cluster 4 ("Tactical Trading")	Sum
Strategy	Relative Value	38%	32%	20%	10%	100%
	Equity L/S	23%	23%	46%	8%	100%
	Event Driven	34%	15%	51%	0%	100%
	Tactical Trading	8%	14%	5%	73%	100%
	Number of Funds	323	287	432	307	1,349

Time period II		November 2002 - April 2005				
		Cluster 1 ("Relative Value")	Cluster 2 ("Equ. L/S & Event Driven")	Cluster 3 ("Equ. L/S & Event Driven")	Cluster 4 ("Tactical Trading")	Sum
Strategy	Relative Value	65%	13%	17%	4%	100%
	Equity L/S	17%	32%	49%	1%	100%
	Event Driven	19%	41%	38%	1%	100%
	Tactical Trading	26%	9%	5%	60%	100%
	Number of Funds	393	330	409	217	1,349

K-means cluster analyses are conducted with four clusters over the time period from May 2000 to October 2002 and from November 2002 to April 2005. 1,349 funds from the TASS, HFR and Hedgefund.net databases are used for the analyses. All funds are qualitatively grouped into four strategy groups. The qualitative strategy classification is compared to the quantitative classification based on the cluster analysis and the development of the cluster-based classification is compared over both time periods.

The stability of clusters is further investigated over a longer time horizon. A data sample with 480 hedge funds that have returns over a 120-month period from May 1995 to April 2005 is used for the analysis. The ten year sample is divided in two sub-samples of five years each to analyze the stability of the clusters over time. Table 5.9 shows that the cluster analysis with 120 months of data based on 480 hedge funds indicates a higher stability of clusters and also a better matching of qualitative and quantitative hedge fund classification despite of the large differences in cluster sizes. It is obvious from the table that the first cluster is strongly dominated by Relative Value funds in both time periods. In the first sub-period the second cluster is by far the largest cluster and contains most of the Equity

Long/Short and Event Driven funds. In the second sub-period the Equity Long/Short and Event Driven funds are primarily distributed over two clusters. Tactical Trading funds are therefore dominating two smaller clusters in the first sub-period and only one cluster in the second sub-period. Similar than in the observation with the two sub-periods of 30 months each, Tactical Trading funds have very unique characteristics that are differentiating the strategy from other hedge fund strategies by forming separate clusters containing very few funds from other strategies.

TABLE V-9: Cluster stability with four clusters over a 120-month period

Time period I		May 1995 - April 2000				
		Cluster 1 ("Relative Value")	Cluster 2 ("Equ. L/S & Event Driven")	Cluster 3 ("Tactical Trading I")	Cluster 4 ("Tactical Trading II")	Number of funds
Strategy	Relative Value	77%	21%	0%	2%	100%
	Equity L/S	8%	80%	8%	4%	100%
	Event Driven	29%	69%	0%	2%	100%
	Tactical Trading	15%	9%	41%	35%	100%
	Number of funds	113	231	74	62	480

Time period II		May 2000 - April 2005				
		Cluster 1 ("Relative Value")	Cluster 2 ("Equ. L/S & Event Driven")	Cluster 3 ("Tactical Trading")	Cluster 4 ("All strategies")	Number of funds
Strategy	Relative Value	57%	11%	2%	30%	100%
	Equity L/S	20%	44%	0%	36%	100%
	Event Driven	12%	49%	0%	39%	100%
	Tactical Trading	27%	2%	57%	13%	100%
	Number of Funds	122	133	87	138	480

K-means cluster analyses are conducted with four clusters over the time period from May 1995 to April 2000 and from May 2000 to April 2005. 480 funds from the TASS, HFR and Hedgefund.net databases are used for the analyses. All funds are qualitatively grouped into four strategy groups. The qualitative strategy classification is compared to the quantitative classification based on the cluster analysis and the development of the cluster-based classification is compared over both time periods.

b. PERSISTENCE OF CLUSTER CHARACTERISTICS

In the next step the characteristics of clusters are investigated over time. In contrast to the stability analysis of clusters, in this part of the analysis the cluster formation is not changed over. The first sub-period, also referred to as in-sample period, is used to determine the cluster formation. The cluster characteristics are calculated for the in-sample period and are then compared with the cluster characteristics of the same clusters in the second sub-period that is also referred to as out-of-sample period. This approach allows testing whether the characteristics of the funds in the various clusters are stable over time. The clusters are characterized by calculating the first four moments of the return distribution for the in- and out-of-sample period. The return, standard deviation, skewness and kurtosis of the various clusters can be found in Table 5.10. The first view at the table indicates an inverse relationship between in-sample and out-of sample returns. The standard deviation appears to be highly consistent, while skewness and kurtosis indicate no obvious persistence over time.

TABLE V-10: Cluster characteristics over a 60-month period

	In sample May 2000 - October 2002				Out of sample November 2002 - April 2005			
Cluster	Return p.a.	Stand. Dev.	Skew-ness	Kur-tosis	Return p.a.	Stand. Dev.	Skew-ness	Kur-tosis
Cluster 1 ("Relative Value")	-0.59%	13.58%	-0.715	2.319	20.13%	8.73%	1.070	2.922
Cluster 2 ("Equ. L/S & ED")	4.05%	4.75%	-0.301	3.191	12.43%	4.38%	0.721	2.429
Cluster 3 ("Equ. L/S & ED")	11.57%	3.84%	-0.653	3.209	8.76%	2.77%	0.069	2.237
Cluster 4 ("Tactical Trading")	15.83%	11.19%	0.156	2.893	4.40%	9.48%	-0.116	2.317

K-means cluster analyses are conducted with four clusters over the time period from May 2000 to October 2002 and from November 2002 to April 2005. 1,349 hedge funds from the TASS, HFR and Hedgefund.net databases are used for the analyses. The first four moments of the hedge funds in the various clusters are illustrated for the in-sample and the out-of-sample period.

Table 5.11 gives an insight into the persistence of the cluster characteristics of the four clusters over the 120-month time period. The result indicates that hedge fund returns in the second sub-period are significantly lower than in the first sub-period and no relative return persistence can be observed for the clusters. The standard deviation is highly consistent similar than in the observation with the shorter sub-periods illustrated in Table 5.10. Concerning the skewness and kurtosis no relationship between the in-sample and out-of-sample period can be observed. The results of the analysis over the 10-year time period basically confirm the previous results of the analysis over the 5-year time period.

TABLE V-11: Cluster characteristics over a 120-month period

	In-sample May 1995 - April 2000				Out-of-sample May 2000 - April 2005			
Cluster	Return p.a.	Stand. Dev.	Skew-ness	Kur-tosis	Return p.a.	Stand. Dev.	Skew-ness	Kur-tosis
Cluster 1 ("Relative Value")	13.05%	2.59%	-1.744	7.312	8.27%	2.94%	0.066	2.512
Cluster 2 ("Equity L/S & ED")	22.20%	12.09%	-0.936	6.253	6.46%	9.46%	-0.196	2.235
Cluster 3 ("Tactial Trading I")	11.24%	14.01%	1.238	6.521	10.95%	12.97%	0.058	2.637
Cluster 4 ("Tactical Trading II")	13.95%	8.43%	0.460	2.951	7.74%	8.76%	0.645	3.562

K-means cluster analyses are conducted with four clusters over the time period from May 1995 to April 2000 and from May 2000 to April 2005. 480 hedge funds from the TASS, HFR and Hedgefund.net databases are used for the analyses. The first four moments of the hedge funds in the various clusters are illustrated for the in-sample and the out-of-sample period.

In order to better interpret the results, a persistence score is derived to compare in-sample with out-of-sample performance for each of the four moments. For each cluster and each moment the average performance values are calculated across all hedge funds. The differences of the average values between the clusters are standardized on a scale from zero to one.[35] The standardized average differences are then compared between the in-sample and the out-of-sample period. The differences between the in-sample and the out-of-sample period are deducted from one and averaged across all clusters to get the persistence score. A persistence score of one indicates perfect positive relationships between in- and out-of-sample data, while zero indicates a perfect negative relationship. The advantage of the persistence score is the valuation of the clusters relative to each other, an approach that is particularly useful from a portfolio construction point of view. Portfolio allocation models generally aim to be 100% invested in the best possible combination of a limited number of investment opportunities that exhibit stable characteristics over various time periods. The persistence scores are calculated for different lengths of in-sample and out-of sample periods. The results are summarized in Table 5.12. The persistence scores confirm that funds with a higher relative return in the in-sample period are on average underperforming in the out-of-sample period. The standard deviation is the only measure that is highly consistent over time for the various clusters. For skewness and kurtosis no specific relationship can be found between in-sample and out-of-sample data.

[35] For each moment all clusters are ranked according to their values in the in-sample and the out-of-sample period. For instance the cluster with the highest average return gets a score of one and the cluster with the lowest average return gets a score of zero. The scores of the other clusters are scaled between zero and one.

TABLE V-12: Cluster persistence scores over various time periods

In-sample period	Out-of-sample period	Number of funds	Persistence scores				
			Returns	St. Dev.	Skewness	Kurtosis	Total
30 months	30 months	1,349	0.33	0.87	0.42	0.19	0.45
36 months	24 months	1,349	0.27	0.91	0.43	0.44	0.51
48 months	12 months	1,349	0.37	0.91	0.55	0.68	0.63
60 months	60 months	480	0.43	0.94	0.61	0.23	0.55

K-means cluster analyses are conducted with four clusters over the time period from May 2000 to April 2005 in the first three analyses and over the time period from May 1995 to April 2005 in the fourth analysis. 1,349 funds from the TASS, HFR and Hedgefund.net databases are used for the analyses over the 60-month period and 480 funds are used for the analysis over the 120-month period. The first four moments of the hedge funds in the various clusters are compared between the in- and out-of-sample periods. Persistence scores ranging from zero to one are derived for each moment. A score of zero indicates perfect negative relationship between the ranks of the criteria in the in- and out-of-sample period, while a score of one indicates a perfect positive relationship.

In the next step the correlations between the various clusters and the persistence of the correlations are investigated. Table 5.13 indicates a low correlation between the cluster dominated by Relative Value funds and the cluster dominated by Equity Long/Short & Event Driven funds. The correlation between the two groups of Tactical Trading funds as well as the correlation between the cluster representing the Equity Long/Short & Event Driven funds and the cluster representing the Relative Value funds is high. The correlation between the Tactical Trading clusters and all the other clusters is very low or even negative. The persistence score of 0.90 of the correlations between the clusters in-sample compared with correlations out-of-sample is very high, indicating a stable dependency structure between clusters over time.[36] This result is very useful for portfolio construction purposes in particular in combination with the high persistence of the standard deviations of the various clusters over time.

[36] The in-sample and out-of-sample cluster correlations are standardized on a scale of zero to one and the differences between the standardized correlations in- and out-of-sample are deducted from one to derive the average persistence score of 0.9.

TABLE V-13: Cluster correlations over a 120-month period

	Time periods		Correlations	
	May 1995 - April 2000	May 2000 - April 2005	In sample	Out of sample
Cluster	"Tactical Trading I"	"Equ. L/S & Event Driven"	-0.26	-0.25
	"Tactical Trading I"	"Tactical Trading II"	0.64	0.90
	"Tactical Trading I"	"Relative Value"	-0.15	0.16
	"Equ. L/S & Event Driven"	"Tactical Trading II"	0.06	-0.02
	"Equ. L/S & Event Driven"	"Relative Value"	0.53	0.71
	"Tactical Trading 2"	"Relative Value"	0.00	0.28
	Persistence Score		0.90	

K-means cluster analyses are conducted with four clusters over the time period from May 1995 to April 2000 and from May 2000 to April 2005. 480 hedge funds from the TASS, HFR and Hedgefund.net databases are used for the analyses. The correlations between the clusters are exhibited for the in-sample and out-of-sample period. The in-sample and out-of-sample cluster correlations are standardized on a scale of zero to one and the differences between the standardized correlations in- and out-of-sample are deducted from one to derive the average persistence score. The persistence score therefore reflects the relationship between in- and out-of-sample cluster correlations.

F PORTFOLIO CONSTRUCTION BASED ON CLUSTERS

In this subsection the persistence of standard deviations and correlations observed in the cluster analysis is further investigated with respect to potential benefits for the construction of hedge fund portfolios.

Portfolios are constructed based on the classification of hedge funds according to the clusters defined in the previous section. The sample of 480 hedge funds is used over the 120-month time period from May 1995 to April 2005. Each portfolio consists of four funds, one from each cluster as defined in the first sub-period from May 1995 to April 2000. In order to construct the portfolios, the funds are selected randomly from each cluster with the help of a generic random number generator. With this approach 100 portfolios are constructed. For each portfolio the returns, the standard deviations and the average correlations of the funds within the portfolios are calculated for both the in-sample and the out-of-sample period.

With the same approach portfolios are constructed that diversify across the four qualitatively defined strategy groups. The average correlations of the funds within the 100 portfolios based on cluster diversification are 0.04 for the in-sample period and 0.06 for the out-of-sample period. The average correlations based on strategy diversification are 0.08 for the in-sample period and 0.09 for the out-of-sample period. The average correlations of both, the cluster-based approach as well as the strategy based approach, are significantly different from zero at the 1% significance level.

The standard deviation of the portfolios gives an indication of the diversification. The previous section indicates a high persistence of cluster standard deviations and correlations over time. In order to further test this relationship with simulated portfolios, the portfolio standard deviations of the out-of-sample returns is regressed on the portfolio standard deviations of the in-sample returns and the average correlations of in-sample returns. The results are illustrated in Table 5.14. The coefficients of the in-sample portfolio standard deviations as well as the in-sample correlations are significant at the 1% significance level. This result illustrates the dependence of out-of-sample portfolio standard deviations on in-sample portfolio standard deviations and in-sample correlations within the portfolios. The finding is in line with the persistence of standard deviations and correlations of clusters revealed in the previous section. The persistence of standard deviations and correlations in a portfolio context can be used to derive superior weighting schemes for hedge fund portfolios.

In the next step portfolios of four hedge funds from different clusters are created with three different weighting schemes. The weighting schemes are equally weighted, volatility weighted based on in-sample standard deviations and a mixture of volatility and correlation weighted. The standard deviations and correlations to derive the weighting scheme are taken from the in-sample period from May 1995 to April 2000.

TABLE V-14: Regression of cluster-based standard deviations/correlations

Dependent variable	Out-of-sample portfolio standard deviations			
Independent variables	Coefficient	Std. error	T-statistic	P-value
Intercept	0.016	0.006	2.732	0.75%
In-sample portfolio standard deviation	0.725	0.060	12.093	0.00%
In-sample portfolio correlation	0.070	0.017	4.065	0.01%
R Squared	0.644	Adjusted R Squared		0.637

K-means cluster analyses are conducted with four clusters over the in-sample period from May 1995 to April 2000 and the out-of-sample period from May 2000 to April 2005. 480 hedge funds from the TASS, HFR and Hedgefund.net databases are used for the analyses. 100 portfolios are constructed with four hedge funds each, one from each cluster given the cluster definition of the in-sample period. The portfolio constituents are randomly selected from each of the four clusters. The funds in the portfolios are equally weighted. Standard deviations are calculated for the portfolios in the in-sample and out-of-sample periods and average correlation of the funds within each portfolio are calculated for the in-sample period. The portfolio standard deviations of the out-of-sample returns are then regressed on the portfolio standard deviations of in-sample returns and in-sample portfolio correlations. The regression coefficients reflect the explanatory power of in-sample standard deviations and correlations for out-of-sample standard deviations for the 100 random portfolios.

Based on these weighting schemes portfolio returns, standard deviations and Sharpe ratios are calculated for the out-of-sample period from May 2000 to April 2005. The results are presented in Table 5.15. The table confirms the high predictability of past standard deviations for future standard deviations. The volatility weighted portfolios as well as the volatility and correlation weighted portfolios have lower standard deviations and higher Sharpe ratios than the equally weighted portfolios. The differences in standard deviations and Sharpe ratios are statistically significant at the 1% significance level. The result suggests that the persistence of standard deviations and correlations in clusters can be used to derive weighting schemes of portfolios leading to superior risk-return characteristics in the out-of-sample period.

TABLE V-15: Average characteristics of 100 cluster-based portfolios

	Equally weighted	Volatility weighted	P-value (equ. vs vol. weighted)	80% volatility & 20% correl. weighted	P-value (equ. vs mixed weighted)
Returns p.a.	7.89%	6.81%	4.93%	7.06%	12.52%
Standard dev. p.a.	8.90%	6.06%	0.00%	6.38%	0.00%
Sharpe ratios	0.64	0.94	0.08%	0.86	0.71%

K-means cluster analyses are conducted with four clusters over the in-sample period from May 1995 to April 2000 and the out-of-sample period from May 2000 to April 2005. 480 hedge funds from the TASS, HFR and Hedgefund.net databases are used for the analyses. 100 random portfolios are constructed with four hedge funds each, one from each cluster as defined in the in-sample period. Three different weighting schemes are used in the portfolio construction. In the volatility weighted scheme the weightings are proportional to the inverse of the standard deviations in the in-sample period. In the mixture of the volatility and correlation weighted scheme 80% of the weightings are based on the volatility weighted scheme while 20% are based on the correlation weighted scheme. Returns, standard deviations and Sharpe ratios of the portfolios are calculated for the in- and out-of-sample period for all three weighting schemes. The p-values refer to T-test statistics that are used to test the differences in returns, standard deviations and Sharpe ratios between the samples of equally weighted and volatility weighted as well as equally weighted and 80% volatility/20% correlation weighted portfolios.

G SUMMARY OF FINDINGS

In this chapter the topic of portfolio construction of hedge fund portfolios is approached with a k-means cluster analysis. A large data set based on the TASS, HFR and hedgefund.net databases is used for the empirical analysis.

In a first step a principal component analysis is used to determine the degree of heterogeneity in hedge fund returns. The analysis of individual hedge fund strategies shows that some strategies are more homogenous than others. Both the principal component analysis and the cluster analysis show that equity oriented strategies are dominating the data sample. The first factor in the principal component analysis has a correlation of 0.92 to the MSCI World and two out of four clusters in the cluster analysis are dominated by the strategy Equity Long/Short.

In a second step cluster analysis is used to classify hedge funds quantitatively. A comparison of the quantitative cluster-based classification and the qualitative self-classification of the managers reveals that certain strategies can be very well identified with the cluster analysis, while others have less distinct properties. Tactical Trading funds tend to form their own cluster in the various analyses with two, three, four and six clusters. Equity Long/Short and Event Driven funds exhibit similar properties that are distinct from most Tactical Trading and Relative Value funds. Relative Value funds tend to be spread over several clusters although they form an own cluster in the analysis with six clusters. The longer the time period for the cluster analysis the more similarities between the qualitative and the quantitative classification can be observed. The major limitation of cluster analysis with hedge funds is the need for long track records to fully satisfy the purpose of identifying homogenous groups in a heterogeneous sample of hedge fund returns. In this chapter 60-month and 120-month time periods are used for the analysis.

The investigation of the stability of clusters over time shows that in a cluster analysis with four clusters the majority of hedge funds maintain the same cluster association suggesting persistence in the cluster-based strategy classification.

The analysis of the characteristics of clusters over time reveals a low persistence in cluster returns, but a high persistence of standard deviations and a relatively high persistence in correlations. The persistence of standard deviations and correlations is further analyzed and later confirmed in a portfolio context. The finding builds the basis for the development of portfolio weighting schemes that diversify across various clusters. Portfolios based on a volatility weighting and a mixture of volatility and correlation weighting are then compared to equally weighted portfolios. The results suggest that volatility weighted portfolios and volatility/correlation weighted portfolios exhibit on average lower standard deviations and higher Sharpe ratios than equally weighted portfolios.

Generally, the quantitative classification of hedge funds based on cluster analysis provides an additional tool for the development of quantitative asset allocation models for portfolios of hedge funds. Given the high persistence of cluster standard deviations and correlations over time, the diversification across clusters is an interesting alternative to the diversification across qualitatively defined strategies.

VI FUND OF HEDGE FUNDS PERFORMANCE EVALUATION

This chapter investigates the performance of funds of hedge funds. A variety of methods is used to shed more light on different performance aspects. Multi-factor and single-factor models are used to explain excess fund of hedge funds returns. Cross-sectional regression analyses indicate that larger funds of hedge funds exhibit higher returns, lower standard deviations, higher Sharpe ratios and higher alphas based on a multi-factor model. Performance persistence in funds of hedge funds returns is tested with a comprehensive relative efficiency measure based on data envelopment analysis. The results suggest a certain degree of performance persistence in the long-term.

A RESEARCH TOPIC IV

Hedge fund investors have the choice of direct investments into individual hedge funds or alternatively select the more common approach of investing into funds of hedge funds. A thorough due diligence on individual hedge fund managers is time-consuming and requires expertise of the hedge fund industry. In addition to that, hedge funds generally require higher minimum investments and are therefore reducing the number of potential investors. Given the high barriers of direct hedge fund investments, investors are often selecting the alternative route over funds of hedge funds.

Funds of hedge funds generally have extensive resources dedicated to the evaluation of hedge funds and provide diversified portfolios of individual managers. Funds of hedge funds generally also accept lower initial investments and therefore open the opportunity to participate in hedge funds performance to a larger investor base.

The 2006 database study of Strategic Financial Solutions counts 6,100 funds of hedge funds compared to 4,150 funds of hedge funds in 2005 suggesting a 47% increase in the number of funds within a 12-month period. The assets in the fund of hedge funds industry in 2006 have grown to 700 billion USD representing almost 50% of the 1.41 trillion USD directly invested in hedge funds.[37] In 1990 the estimated size of the funds of hedge funds industry was 1.9 billion USD or 5% of the total hedge fund assets.[38] The strong growth can primarily be explained by the increasing interest of new investor types from pension funds to retail clients entering the field.

The objective of this chapter is to give more insight into the performance evaluation of funds of hedge funds. A comprehensive performance and survivorship analysis is conducted with a particular focus on the relationship between fund sizes and performance. A relative efficiency measure is discussed based on the relatively new technique of data envelopment analysis[39] with respect to its suitability for fund of hedge funds selection.

This chapter is structured as follows: A literature overview is provided in section B. The data set used in the empirical analysis is described in section C. Section D discusses the methodology applied. Section E contains the empirical analysis and section F summarizes. A detailed discussion of the results is also provided in Moerth (2006a).

B RELATED LITERATURE

Several studies have been conducted about performance measurement in funds of hedge funds. Fung and Hsieh (2000) provide a comprehensive study and find an annual survivorship bias of 1.4% p.a. for funds of hedge funds versus 3% p.a. for hedge funds, a median incubation period of 484 days for hedge funds versus 343 days for funds of hedge funds and an instant history bias of 0.7% p.a. for funds of hedge funds compared to 1.4% p.a. for hedge funds. The study is based on 322

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[37] The annual hedge fund database study of Strategic Financial Solutions examines the hedge fund listings from twelve of the major hedge fund databases. The numbers are adjusted for duplicate records.

[38] According to Standard & Poor's, "Overall growth continues in the fund of hedge funds industry". September 2006.

[39] A detailed description of the methodology of data envelopment analysis and the evaluation criteria used for the analysis is given in chapter IV D.

funds of hedge funds and 1,722 hedge funds over a four year time period from 1994 to 1998.

In a study of 597 funds of hedge funds over a time period from 1994 to 2001 Liang (2003b) finds a survivorship bias of 0.10% per month or 1.18% p.a. for funds of hedge funds. The overall fund of hedge funds sample containing both “living” and “dead” funds of hedge funds generates an average monthly return of 0.75% p.m. compared to 1.16% p.m. for hedge funds. The underperformance of funds of hedge funds relative to hedge funds is explained with the double fee structure of funds of hedge funds. The difference in the survivorship between hedge funds and funds of hedge funds is only 0.09% p. m. while the return difference between the two is 0.41% p.m. The higher fee structure of funds of hedge funds can therefore only partially be offset by a lower survivorship bias.

Brown, Goetzmann and Liang (2004) assess the additional fee load in funds of hedge funds. The study reveals a return of 0.61% p.m. for funds of hedge funds compared to 0.97% p.m. for hedge funds. The analysis is based on the TASS database with 3,439 hedge funds and 862 funds of hedge funds over a time period from February 1989 to December 2003.

In a recent study Agarwal and Kale (2007) show that multi-strategy hedge funds outperform funds of hedge funds on a risk-adjusted basis. The outperformance is between 2.6% and 4.8% p.a. on a net-of-fee basis suggesting that the double-layered fee structure of funds of hedge funds cannot be the full explanation for the performance differential. In contrast to that Ang, Rhodes-Kropf and Zhao (2005) argue that on average funds of hedge funds deserve their additional fee load.

Kat and Palaro (2006) show that the majority of funds of hedge funds fail to outperform a passive trading strategy using the S&P 500, T-bond and Eurodollar futures.

Gregoriou (2003a) investigates the mortality of funds of hedge funds using parametric, semi-parametric and non-parametric methods over a 12-year period. The findings suggest that the median survival time of funds of hedge funds is 7.5 years while variables such as assets under management, minimum investment, performance fee, leverage, monthly returns and redemption period impact mortality expectations.

Kat (2002) discusses opportunities for a portfolio containing a diversified fund of hedge funds to offer skewness protection. Two alternative strategies, buying stock index puts plus leveraging and buying puts on the fund itself, are investigated. Davies, Kat and Lu (2005) discuss fund of hedge funds selection by taking investor preferences for return distributions' higher moments in a polynomial optimization model into account. The results suggests that the introduction of preferences for skewness and kurtosis in the portfolio decision-making process yields portfolios far different from the mean-variance optimal portfolio with much less attractive mean-variance characteristics.

Ineichen (2002a) argues that the value added by fund of hedge funds managers is primarily related to hedge fund selection and monitoring as opposed to portfolio construction. The barriers to enter in hedge fund selection are assumed to be higher than in portfolio construction. Ineichen (2002b) elaborates on the view that funds of hedge funds operate in an inefficient market and therefore have a strong value proposition.

Acito and Fisher (2002) discuss challenges of the fund of hedge funds industry based on their findings in numerous interviews with industry players. Gregoriou (2003b) introduces the technique of data envelopment analysis for the selection of funds of hedge funds.

This chapter contributes to the existing literature of funds of hedge funds with a discussion of the impact of fund sizes on performance. The relationship between fund sizes and returns, standard deviations, Sharpe ratios as well as alphas derived from a four asset class factor model is investigated. Two different methods are used to analyze the relationship between alphas and fund sizes. The first approach is based on percentiles of funds as described in Ammann and Moerth (2005). In a second new approach excess fund returns are directly regressed on the factors without grouping the funds in percentiles. A further contribution is the analysis of the persistence of a relative efficiency measure over different time periods. The relative efficiency measure is derived with the method of data envelopment analysis and is based on a variety of traditional and alternative performance measures.

C DATA SET

The fund of hedge funds data set used in this chapter is based on the TASS databases as described in Chapter II. The data quality is documented in Table 2.5. 662 funds of hedge funds and the time period from January 1994 to April 2005 are used for the analysis.

For the factor analysis based on percentiles a reduced time period from July 1994 to April 2005 is used due to a lack of sufficient data for the time period from January to May 1994. For the data envelopment analysis a 60-month time period and a 120-month time period are used. For the 60-month period from May 2000 to April 2005 the sample contains 167 funds of hedge funds while for the 120-month period from May 1995 to April 2005 the sample contains 55 funds of hedge funds.

D METHODOLOGY

An asset class factor model with eleven factors is used to derive alphas and explain excess returns.[40] The same factors described in the analysis with hedge funds in Chapter III are used for the analysis with funds of hedge funds.[41] The factors are the MSCI World Index, the NASDAQ Composite Index, the Russell 2000 Index, the Wilshire Micro Cap Index, the Lehman Aggregate Bond Index, the Lehman High Yield Credit Bond Index, the JP Morgan Government Bond Index, the Goldman Sachs Commodity Index, crude oil, the London Gold Bullion USD Index and the Chicago Board Options Exchange SPX Volatility Index. The eleven factors are divided into four asset classes and tested for the optimal factor of each asset class. A four-factor model is derived from the optimal combination of factors

[40] The 90-day T-Bill rate is deducted from the funds of hedge funds returns to derive the excess returns.

[41] A detailed description of the factor model and the asset class factors used for the analysis is given in chapter III E.

from all asset classes. [42] The Newey-West method is used in the calculation of the standard errors in the regression analysis to account for serial correlation and heteroskedasticity.

The impact of fund sizes on fund of hedge funds performance is investigated by breaking the sample into 100 percentiles according to the fund sizes. Annualized returns, annualized standard deviations and annualized Sharpe ratios for the 100 percentiles are then regressed on the natural logarithms of the average fund sizes. A detailed description of the methodology can be found in Ammann and Moerth (2005). The time period from July 1994 to April 2005 is used for this part of the analysis.[43]

Alphas are calculated for each individual percentile based on the previously derived four-factor model. The relationship between alphas derived from the 100 factor models and average fund sizes for the 100 percentiles is then also investigated with a cross-sectional regression.

In a second new approach dedicated to the investigation of the relationship between fund sizes and alphas, excess returns are directly regressed on the four factors of the factor model. Individual alphas for the funds of hedge funds are therefore derived without grouping the funds in percentiles. For this analysis the sample of 662 funds of hedge funds is reduced to all funds with at least 12 months track record in any given time period. 624 funds of hedge funds qualify for the analysis. In a first step, 624 alphas are derived and, in a second step, the resulting alphas are regressed on the logarithms of the average fund sizes.

The key advantage of this approach is the possibility to use more data points in the analysis. The data series are also directly representing the individual funds and no regrouping of data series according to asset percentiles is required. The disadvantages are the elimination of funds with insufficient track records and a potential distorting impact of outliers in the regression analysis. A further disadvantage is the loss of the time component with respect to the development of

[42] The methodology used to derive the factor models is extensively discussed in chapter III and Ammann and Moerth (2005).

[43] The time period from January 1994 to June 1994 is dropped due to insufficient data for this approach.

fund sizes over time since individual fund sizes are averaged over time before they are used in the cross-sectional regressions.

A relatively new and promising technique in the selection of funds of hedge funds is data envelopment analysis.[44] Data envelopment analysis provides a measure of relative efficiency for funds of hedge funds. The analysis is based on the technique introduced in Chapter IV. The key strength of data envelopment analysis is the ability to take multiple input and multiple output criteria simultaneously into account. In this chapter eight evaluation criteria, three input criteria and five output criteria are used simultaneously. The input criteria to be minimized contain standard deviation, drawdown and kurtosis. The output criteria to be maximized contain return, skewness, proportion of positive months, omega and alpha derived from a four-factor model.[45] The stability of the results is tested by repeating the data envelopment analysis with an extended set of 13 evaluation criteria. The Sortino ratio, kappa, upside potential ratio and Calmar ratio are used as additional input variables. Modified value at risk is used as an additional output variable.

E EMPIRICAL RESULTS

The empirical part of the chapter contains subsections dedicated to performance analysis, survivorship analysis, asset class factor models, an investigation of the size-performance relationship and a performance evaluation approach based on data envelopment analysis.

1 PERFORMANCE ANALYSIS

The average equally weighted return of funds of hedge funds over the time period from January 1994 to April 2005 is 6.53% p.a. compared to 8.42% p.a. for hedge funds.[46] The performance difference can primarily be explained by the additional fees charged by funds of hedge funds. A common fee structure for funds

[44] A detailed description of the methodology is given in Nguyen-Thi-Than (2006) and Eling (2006).

[45] The various alternative risk measures are described in chapter IV.

[46] According to Ammann and Moerth (2005)

of hedge funds is 1% management fee and 10% performance fee. The application of this fee structure to the average hedge fund returns would result in an additional fee load of 1.84% p.a. for funds of hedge funds.[47] This number is indeed very close to the actual performance difference of 1.89% p.a. The result compares to an average monthly performance of funds of hedge funds of 0.75% p.m. or 9.4% p.a. over a time period from 1994 to 2001 described in Liang (2003b) and 0.61% p.m. or 7.6% p.a. over a time period from 1989 to 2003 described in Brown, Goetzmann and Liang (2004). The differences in the performance numbers can partially be explained by the use of a different data source[48] as well as below average performance of funds of hedge funds from 2001 to 2005, a time period that is not covered by the study of Liang (2003b) and only partially covered by the study of Brown, Goetzmann and Liang (2004). The return difference between hedge funds and funds of hedge funds is 0.41% p.m. according to Liang (2003b) and 0.36% according to Brown, Goetzmann and Liang (2004) indicating annualized differences of 4.4% p.a. and more than 5% p.a. respectively.

Table 6.1 illustrates the differences between equally and asset weighted returns, standard deviations and Sharpe ratios. Asset weighted returns of funds of hedge funds are higher than equally weighted returns by an annualized rate of 1.09% in the time period from January 1994 to April 2005. The outperformance over the 136-month period is statistically significant at the 5% significance level. The finding suggests that larger funds of hedge funds generate higher returns than smaller funds of hedge funds and is particularly interesting with regard to the opposite relationship for hedge funds described in Ammann and Moerth (2005).

In general, capacity issues discussed in the analysis with single manager hedge funds are not applicable to funds of hedge funds. One possible argument for the outperformance of large funds of hedge funds may be a better access to hedge funds

[47] The calculation for the additional fee load of 1.84% p.a. is based on the assumption of a 10% performance fee applied to the average hedge fund performance of 8.42% resulting in a fee component of 0.842% in addition to the average 1% management fee. This calculation is an approximation with inherent biases caused by the negative performance of individual fund of hedge funds that reduce the average performance leading to a lower performance fee estimate than the actual performance fee impact.

[48] The study of Liang (2003b) is based on the database of Zurich Capital Markets. 597 funds of hedge funds are used in the analysis. The study of Brown, Goetzmann and Liang is based on the database of TASS. 862 funds of hedge funds are used for the analysis

that are closed or only selectively open for investments. Successful hedge fund managers are carefully choosing their investors. Potentially longer industry relationships of large established funds of hedge funds may act in their favour in case of limited capacity. Existing investors are generally benefiting from a preferred treatment over potential new hedge fund investors.

A further argument is a potentially lower fee structure for large funds of hedge funds that primarily target large institutional investors. Larger funds of hedge funds also tend to have more resources available for the selection of hedge funds and portfolio construction.

TABLE VI-1: Return comparison of funds of hedge funds

	Jan 94 - Apr 05	Jan 94 - Aug 99	Sep 99 - Apr 05
Equally weighted return p.a.	6.53%	6.75%	6.31%
Standard deviation p.a.	5.14%	5.64%	4.64%
Sharpe ratio	0.53	0.33	0.76
Asset weighted return p.a.	7.62%	8.19%	7.06%
Standard deviation p.a.	5.76%	6.65%	4.75%
Sharpe ratio	0.66	0.50	0.90
Annualized differences in returns	1.09%	1.44%	0.75%
Standard deviation p.a.	1.73%	2.27%	0.90%
T-statistic	2.13	1.50	1.97

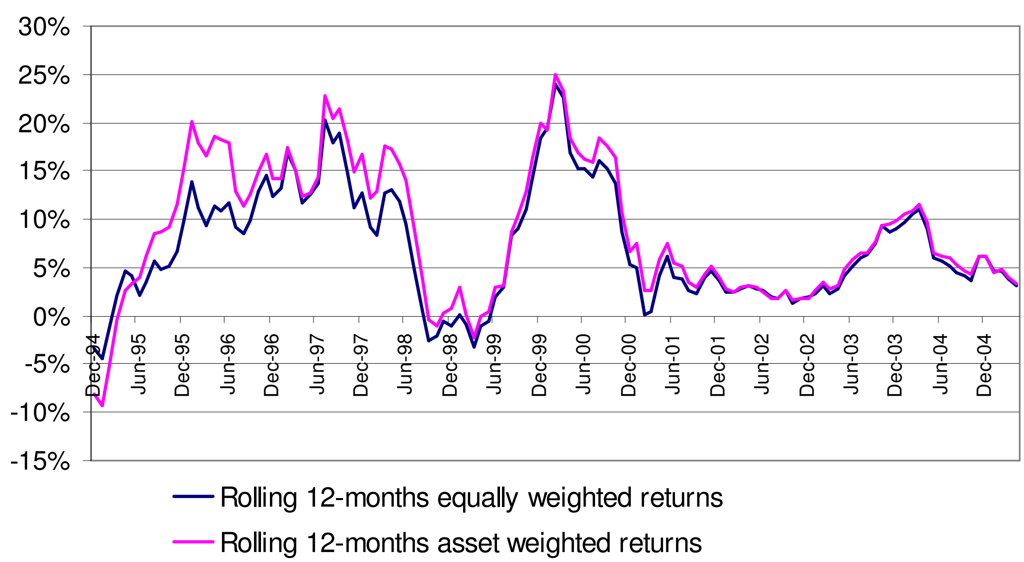
The analysis is conducted over a 136-month time period from January 1994 to April 2005 as well as two sub-periods from January 1994 to August 1999 and from September 1999 to April 2005. The significance of the return differences are tested with T-Statistics. The equally weighted and asset weighted returns and standard deviations refer to a sample with 662 funds of hedge funds.

Large funds of hedge funds groups often have a large variety of products and may choose to selectively present only the best-performing products to the public. The self-selection bias of funds of hedge funds affects the fund of hedge funds returns and is difficult to estimate. Funds of hedge funds provided by large institutions are often promoted over internal distribution channels. If they fail to achieve competitive returns, then they often do not report performance data to the database providers to avoid any negative impact on their reputation. On the other hand, smaller funds of hedge funds may be unwilling to report their fund size and therefore drop out of the data sample in the data cleaning process.

The higher asset weighted returns also go hand in hand with higher Sharpe ratios, suggesting that the higher standard deviations can only partially explain the increased returns.[49]

In Figure 6.1 rolling 12-month equally weighted returns are compared with rolling 12-month asset weighted returns of funds of hedge funds. The performance difference is larger in the period from January 1994 to August 1999. The difference may also be affected by the smaller data sample in the earlier years of the time period starting with only 81 funds of hedge funds in January 1994. The graphical representation indicates the below-average performance in more recent years that explains some of the performance differences if compared to previous studies.

FIGURE VI-1: Equally versus asset weighted funds of hedge funds returns



Rolling 12-month equally weighted and rolling 12-month asset weighted returns are calculated over a 136-month time horizon from January 1994 to April 2005. 662 funds of hedge funds from the TASS databases are used for the analysis.

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[49] The standard deviations and Sharpe ratios presented are calculated based on the equally weighted and assets weighted returns of the total sample over the entire time period and therefore differ from the average of all standard deviations and Sharpe ratios of the funds of hedge funds in the sample.

2 SURVIVORSHIP ANALYSIS

The survivorship analysis with funds of hedge funds is illustrated in Table 6.2 and Figure 6.2. The survivorship bias derived from equally weighted returns is 1.71% p.a. and compares to a survivorship bias of 3.54% p.a. for hedge funds over the same time period. This result is in line with previous findings. Fung and Hsieh (2000) report a survivorship bias of 1.4% p.a. for funds of hedge funds versus 3% p.a. for hedge funds and Liang (2003b) reports a survivorship bias of 1.18% p.a. for funds of hedge funds versus 2.32% p.a. for hedge funds.

The analysis with funds of hedge funds also indicates a significantly higher survivorship bias for equally weighted returns than for asset weighted returns for the entire 136-month period as well as for both sub-periods from January 1994 to August 1999 and from September 1999 to April 2005.

TABLE VI-2: Survivorship analysis of funds of hedge funds

	Jan 94 - Feb 05	Sep 99 - Feb 05	Jan 94 - Aug 99
Equally weighted survivorship bias	1.71%	1.57%	1.84%
Asset weighted survivorship bias	0.32%	0.29%	0.36%
Differences in survivorship bias p.a.	1.39%	1.29%	1.48%
Standard deviation p.a.	0.92%	0.94%	0.91%
T-statistic	4.99	3.18	3.86

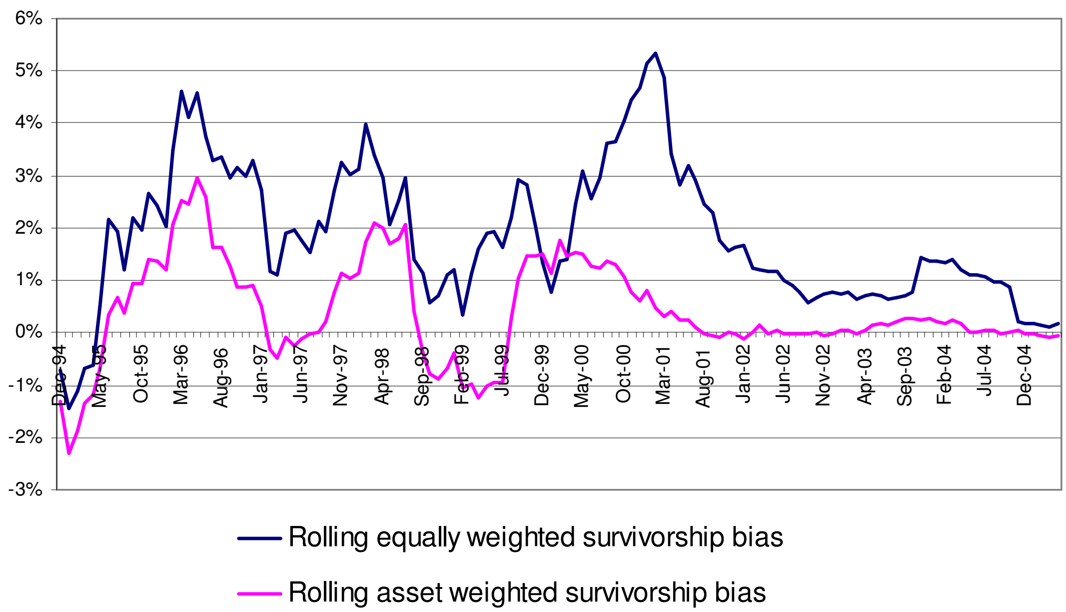
The analysis is conducted over a 136-month time period from January 1994 to April 2005, as well as two sub-periods from January 1994 to August 1999 and from September 1999 to April 2005. The significance of the differences in the survivorship biases are tested with T-Statistics.

This results show that smaller funds that stopped reporting to the database underperformed substantially. Funds with a decreasing asset base may be more reluctant in reporting data to database providers given the strong growth in the fund of hedge funds industry.

Funds of hedge funds that are facing redemptions are not only suffering from a decreasing asset base, but also have higher costs if they have to pay redemption fees to liquidate positions in underlying hedge funds. Redemption fees, lock-up periods and redemption gates are covenants used by successful hedge fund managers to assure a stable asset base. Hedge funds with restrictive liquidity provisions are not suitable for funds of hedge funds with volatile asset bases or funds of hedge funds that promise high liquidity to investors.

The graphical representation of 12-month rolling survivorship biases emphasizes the dependency of the survivorship bias on the time period. Generally, it can be observed that the survivorship bias decreases in the last few years of the time period.

FIGURE VI-2: 12-month rolling survivorship biases of funds of hedge funds



Rolling 12-month equally weighted and rolling 12-month asset weighted survivorship biases are calculated over a 136-month time horizon from January 1994 to April 2005. 662 funds of hedge funds from the TASS database are used for the analysis.

3 ASSET CLASS FACTOR MODELS

Single factor models for eleven asset class factors are illustrated in Table 6.3. All four single-factor models based on equity indices have a statistically significant coefficient at the 1% significance level with R-Squares between 25% and 45%. The dominance of equity factors is nevertheless weaker than in the analysis with hedge funds where individual factor models based on equities explain more than 55% of excess returns.

TABLE VI-3: Single factor models to explain fund of hedge funds returns

Asset class	Factor	Factor beta	R-Squared	Monthly alpha
EQUITIES				
	WILSHIRE MICRO CAP IND.	0.147 (0.017)***	0.4410	0.02%
	RUSSELL 2000	0.159 (0.024)***	0.3549	0.11%
	NASDAQ	0.100 (0.022)***	0.2867	0.13%
	MSCI WORLD	0.187 (0.038)***	0.2622	0.10%
BONDS				
	LEHMAN BOND INDEX	0.166 (0.097)*	0.0225	0.23%
	JPM GL. GOV. BOND IND.	0.072 (0.104)	0.0046	0.22%
	LEHMAN HIGH YIELD IND.	0.011 (0.008)	0.0094	0.21%
COMMODITIES				
	GSCI	0.046 (0.017)***	0.0312	0.19%
	CRUDE OIL	0.024 (0.012)**	0.0228	0.19%
	GOLD INDEX	0.062 (0.036)*	0.0228	0.22%
VOLATILITY				
	VIX	-0.023 (0.009)**	0.0778	0.26%

Eleven single asset class factor models are used to explain excess returns of 662 funds of hedge funds of the TASS database. Monthly alphas and adjusted R-Squares are calculated for each model. Newey-West covariance matrix estimators are used to account for heteroskedasticity and serial correlation. The time period from January 1994 to April 2005 is used for the regression analysis. *, **, *** indicate significance at the 10%, 5% and 1% significance levels respectively.

The single-factor model based on equity volatility also shows a statistically significant factor exposure at the 5% significance level. The factor exposure of the factor model based on the Lehman Aggregate Bond Index is statistically significant at the 10% significance level, a relationship that has not been significant in the analysis with hedge funds. In the commodity area the single-factor model based on the Goldman Sachs Commodity Index reveals a significant relationship at the 1% significance level. The factor models based on crude oil indicate a significant relationship at the 5% significance level and the factor model based on gold is still significant at the 10% significance level.

In summary, nine out of eleven single factor models have statistically significant coefficients at least at the 10% significance level. The two factor models that fail to exhibit statistically significant relationships are based on the JP Morgan Government Bond Index and the Lehman High Yield Credit Bond Index.

Table 6.4 illustrates the results of a multiple regression of the returns of the sample of 662 funds of hedge funds on eleven asset class factors.[50] The eleven factor model explains 56.3% of the excess returns in funds of hedge funds. The factors are ranked by their explanatory power. Equities have the highest explanatory power similar to the study based on hedge fund data. Small cap equities represented by the Wilshire Micro Cap Index are topping the list before the MSCI World Index. In contrast to the analysis with hedge funds, the analysis with funds of hedge funds reveals the CBOE Volatility Index as a third explanatory factor that is statistically significant at the 10% significance level. The alpha of funds of hedge funds is not statistically significant. This finding is in contrast to the results of the analysis with hedge funds.

Due to high correlations of variables used in the multi-factor approach, multicollinearity impacts the p-values. Therefore the number of factors in the multi-factor models is reduced to account for multicollinearity and to facilitate the interpretation of the results.

[50] The eleven factors are discussed in chapter III in the analysis with hedge funds data. The methodology is explained in the corresponding methodology section.

TABLE VI-4: Eleven factor model for funds of hedge funds

Independent variable	Coefficient
ALPHA	-0.001 (0.001)
WILSHIRE MICRO CAP INDEX	0.207 (0.047)***
MSCI WORLD	0.206 (0.058)***
NASDAQ	-0.057 (0.026)**
VIX	0.015 (0.009)*
RUSSELL 2000	-0.081 (0.054)
GSCI	0.038 (0.029)
GOLD INDEX	0.033 (0.025)
JPM GL. GOV. BOND INDEX	0.188 (0.261)
LEHMAN HIGH YIELD INDEX	-0.001 (0.007)
CRUDE OIL	-0.001 (0.021)
LEHMAN BOND INDEX	-0.007 (0.262)
R-squared	0.563
Adjusted R-squared	0.524

Eleven single asset class factor models are used to explain excess returns of 662 funds of hedge funds of the TASS database. Monthly alphas and adjusted R-Squares are calculated for each model. Newey-West covariance matrix estimators are used to account for heteroskedasticity and serial correlation. The time period from January 1994 to April 2005 is used for the regression analysis. *, **, *** indicate significance at the 10%, 5% and 1% significance levels respectively.

Similar to the analysis with hedge funds the objective is to find the best factor combination with one factor from each of the four asset classes, equities, bonds, commodities and volatility. The R-Squares of various four-factor models are illustrated in Table 6.5.

TABLE VI-5: R-Squares of factor models based on four asset classes

Equities	Bonds	Commodities	Volatility	Adjusted R-Squared
WILSHIRE MICRO	LEHMAN BOND	GSCI	VIX	0.4791
MSCI WORLD	LEHMAN BOND	GSCI	VIX	0.3625
NASDAQ	LEHMAN BOND	GSCI	VIX	0.3545
RUSSELL 2000	LEHMAN BOND	GSCI	VIX	0.4295
WILSHIRE MICRO	LEHMAN HY	GSCI	VIX	0.4297
WILSHIRE MICRO	JPM GOV BOND	GSCI	VIX	0.4702
WILSHIRE MICRO	LEHMAN BOND	GOLD	VIX	0.4717
WILSHIRE MICRO	LEHMAN BOND	CRUDE OIL	VIX	0.4734

An asset class factor model with four factors representing each asset class is used to explain equally weighted excess returns of funds of hedge funds. The initial asset class factors are derived from the highest adjusted R-Squares within each asset class from the single-factor models. For each asset class all asset class factors are tested given the asset class factors of the other asset classes. Adjusted R-Squares are calculated for each model. Newey-West covariance matrix estimators are used to account for heteroskedasticity and serial correlation. The time period from January 1994 to April 2005 is used for the regression analysis. 662 funds of hedge funds of the TASS database are used for the analysis

The highest explanatory power with an adjusted R-Squared of 47.91% can be found in the four-factor model containing the Wilshire Micro Cap Index, the Lehman Aggregate Bond Index, the Goldman Sachs Commodity Index and the CBOE Volatility Index. The four-factor model is specified in Table 6.6. The annualized alpha of the model is not statistically significant.

TABLE VI-6: Four-factor model for funds of hedge funds

Independent variable	Coefficient
ALPHA	0.000 (0.001)
WILSHIRE MICRO CAP	0.152 (0.018)***
GSCI	0.031 (0.012)
LEHMAN BOND INDEX	0.188 (0.077)*
VIX	0.005 (0.008)
R-squared	0.486
Adjusted R-squared	0.471

A multi asset class factor model with four factors is used to explain equally weighted excess returns of funds of hedge funds. Standard errors and p-values are calculated for each factor. The time period from January 1994 to April 2005 is used for the regression analysis. Newey-West covariance matrix estimators are used to account for heteroskedasticity and serial correlation. 662 funds of hedge funds of the TASS database are used for the analysis. *, **, *** indicate significance at the 10%, 5% and 1% significance levels respectively.

4 IMPACT OF FUND SIZES ON PERFORMANCE

The increasing asset base of the hedge fund industry and the strong inflows into funds of hedge funds raise the question of the capacity of the industry. This question is addressed with a detailed analysis of the relationship between funds of hedge funds sizes and returns, standard deviations, Sharpe ratios and alphas.

In Table 6.7 deciles of fund sizes are illustrated with the average returns for each decile. The average fund of hedge funds in the sample has a fund size of 80.7 million USD while the average fund size of the funds in the lowest decile is 1.7 million USD and the average fund size of the funds in the highest decile is 490.9 million USD. This range is lower than the range for individual hedge funds with an average of 1.4 million USD in the lowest decile and an average of 710.6 million USD in the highest decile. The analysis with deciles confirms a positive relationship between fund sizes and returns. The result is supported with an F-Test that indicates a significant relationship at the 10% significance level.

TABLE VI-7: Fund of hedge funds sizes and returns

Percentile	Average fund sizes		Average returns
91st-100th	490,912,281		8.15%
81st-90th	126,356,062		8.00%
71st-80th	68,836,230		8.03%
61st-70th	43,072,780		7.17%
51st-60th	29,350,184		6.50%
41st-50th	19,980,756		6.62%
31st-40th	13,745,540		8.47%
21st-30th	8,627,685		7.07%
11th-20th	4,718,940		5.48%
1st-10th	1,739,117		4.30%
Average	80,733,957		6.98%
F-statistic	1.9446	P-value	5.54%

The sample of 662 funds of hedge funds is classified in percentiles and deciles according to their fund sizes. The second column illustrates the average fund sizes of each decile. The third column shows the average returns for each decile. An F-Test is conducted to find out whether the average returns of the deciles are different from each other. A one tailed F-distribution is used. The time period from July 1994 to April 2005 is used for the analysis.

The sample is further broken into 100 percentiles according to their fund sizes and cross-sectional regressions are applied.[51] The regression of the average excess returns of the 100 sub-samples on the logarithms of the average fund sizes presented in Figure 6.3 and Panel A of Table 6.8 shows a positive relationship. In contrast to hedge funds, funds of hedge funds with a larger asset base are outperforming their smaller competitors. The relationship is statistically significant at the 1% significance level.

[51] The methodology is discussed in the methodology section of Chapter III.

FIGURE VI-3: Fund sizes versus returns of funds of hedge funds

The funds are ranked according to their fund sizes and 100 asset percentiles are built in each month. In the regression analysis the average annualized returns are regressed on the logarithms of the average assets of each of the 100 percentiles. The time period from July 1994 to April 2005 and a sample of 662 funds of hedge funds are used for the analysis.

The relationship between standard deviations and fund sizes is illustrated in Figure 6.4 and Panel B of Table 6.8. Similar to the analysis with hedge funds a negative relationship between standard deviations and fund sizes can be found suggesting that large funds of hedge funds are taking less risk. The relationship is statistically significant at the 1% significance level.[52]

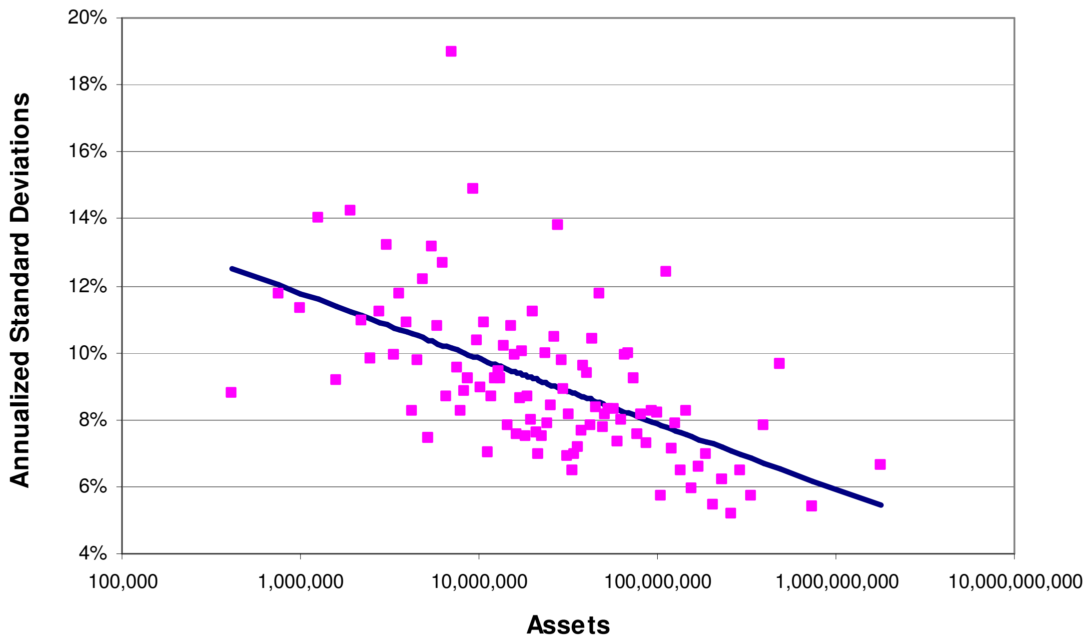
[52] The standard deviations refer to percentiles and therefore portfolios of hedge funds, rather than individual hedge funds. The volatility of portfolios of hedge funds is generally lower than the volatility of individual hedge funds due to diversification benefits.

TABLE VI-8: Regression results of fund sizes versus performance criteria

Dependent variable	Constant	Log(fund sizes)	R-squared	Adjusted R-squared
	Panel A: Annualized returns			
Annualized returns	-0.0340	0.0061	0.1269	0.1180
	(0.024)	(0.001)***		
	Panel B: Annualized standard deviations			
Annualized stand. dev.	0.2349	-0.0085	0.3348	0.3280
	(0.020)***	(0.001)***		
	Panel C: Annualized Sharpe ratios			
Annualized Sharpe ratios	-1.3613	0.1032	0.2479	0.2402
	(0.2395)***	(0.014)***		
	Panel D: Annualized alphas - percentile approach			
Annualized alphas	-0.0882	0.0051	0.0907	0.0814
	(0.0182)***	(0.001)***		
	Panel E: Annualized alphas - panel approach			
Annualized alphas	-0.2760	0.0174	0.1194	0.1180
	(0.0542)***	(0.003)***		

The funds of hedge funds are ranked according to their fund sizes and 100 asset percentiles are built in each month. In the regression analyses the average annualized returns, the annualized standard deviations, the annualized Sharpe Ratios and the annualized Alphas of each of the 100 percentiles are regressed on the logarithms of the average fund sizes of the percentiles. The alphas are derived from excess returns and an asset class factor model with four factors. The factors are the Goldman Sachs Commodity Index, the Wilshire Micro Cap Index, the Lehman Aggregate Bond Index and the CBOE Volatility Index. Newey-West covariance matrix estimators are used to account for heteroskedasticity and serial correlation. The time period from July 1994 to April 2005 and a sample with 662 funds of hedge funds are used for the analysis. *, **, *** indicate significance at the 10%, 5% and 1% significance levels respectively.

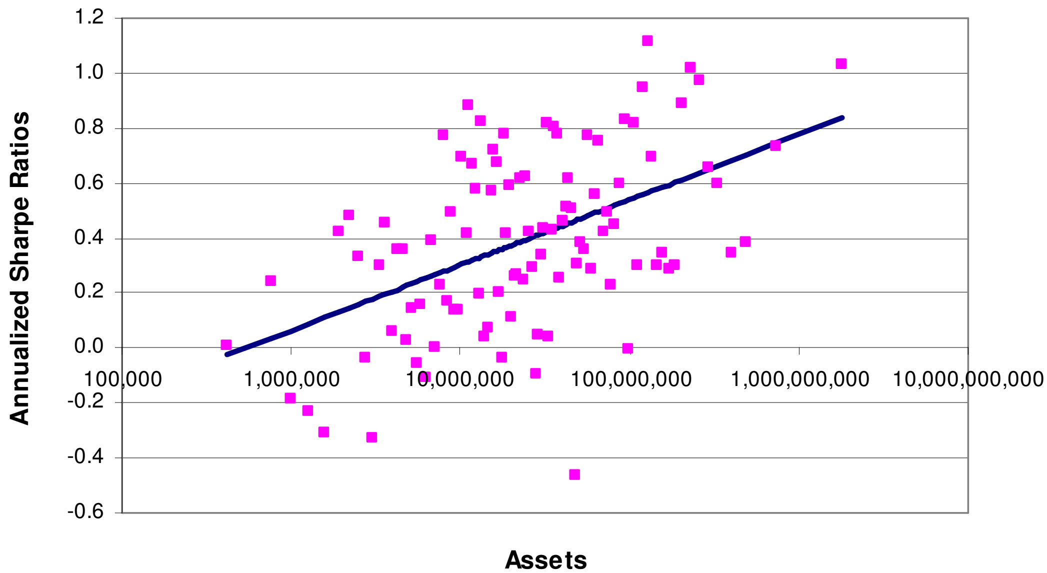
FIGURE VI-4: Fund sizes vs. standard deviations of funds of hedge funds



The funds are ranked according to their fund sizes and 100 asset percentiles are built in each month. In the regression analysis the average annualized standard deviations are regressed on the logarithms of the average assets of each of the 100 percentiles. The time period from July 1994 to April 2005 and a sample of 662 funds of hedge funds are used for the analysis.

The relationship between Sharpe ratios and fund sizes is illustrated in Figure 6.5 and Panel C of Table 6.8. Large funds of hedge funds tend to have higher Sharpe ratios. The relationship is statistically significant at the 1% significance level.

FIGURE VI-5: Fund sizes versus Sharpe ratios of funds of hedge funds



The funds are ranked according to their fund sizes and 100 asset percentiles are built in each month. In the regression analysis the average Sharpe ratios are regressed on the logarithms of the average assets of each of the 100 percentiles. The time period from July 1994 to April 2005 and a sample of 662 funds of hedge funds are used for the analysis.

The relationship between alphas derived from the four-factor model illustrated in Table 6.6 and the fund sizes is tested with two approaches. The first approach is based on percentiles and the findings are presented in Figure 6.6 and Panel D of Table 6.8. The relationship is positive and statistically significant at the 1% significance level. The relationship with Sharpe ratios and the relationship with alphas are both in contrast to the findings of the analysis with hedge funds.[53]

[53] A discussion of the results with hedge funds is given in Ammann and Moerth (2005).

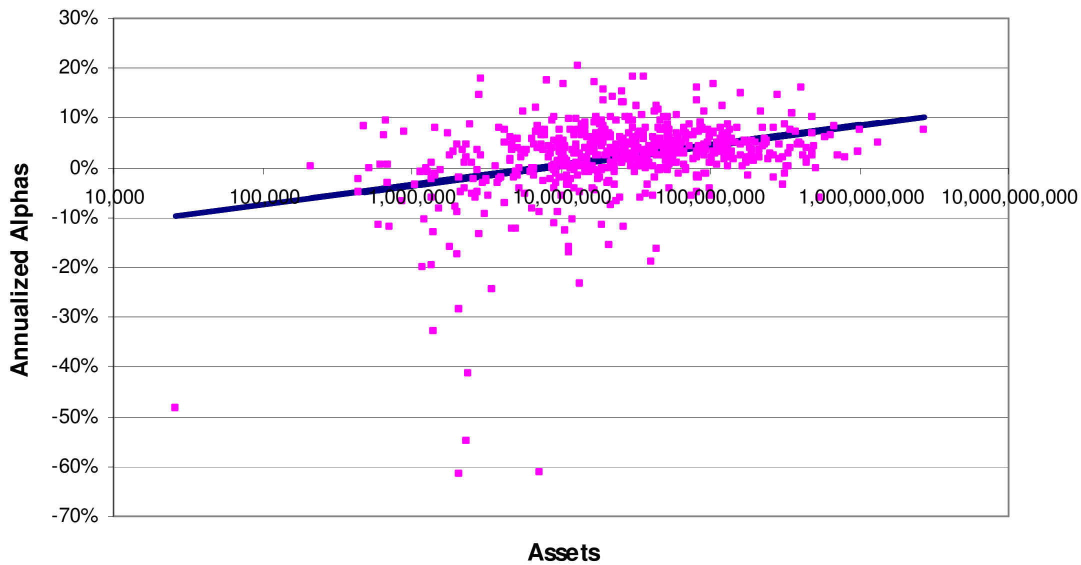
FIGURE VI-6: Fund sizes versus alphas of funds of hedge funds – part I

The alphas are derived from funds of hedge funds excess returns and a multi asset class factor model with four factors. The factors are the Goldman Sachs Commodity Index, the Wilshire Micro Cap Index, the CBOE Volatility Index and the Lehman Aggregate Bond Index. For the regression analysis the funds are ranked according to their fund sizes and 100 asset percentiles are built in each month. In the regression analysis the alphas derived from the four-factor models for each of the 100 percentiles are regressed on the logarithms of the average assets of each of the 100 percentiles. The time period from July 1994 to April 2005 and a sample with 662 funds of hedge funds are used for the analysis. Each data point represents the average returns and average fund sizes of the funds grouped in a percentile.

In a second approach the relationship between fund sizes and alphas is investigated based on a direct regression of the four factors of the factor model on the excess returns of funds of hedge funds.[54] The results are illustrated in Figure 6.7 and Panel E of Table 6.8. The analysis confirms a statistically significant relationship between fund sizes and alphas at the 1% significance level. The results are therefore in line with the results of the first approach.

[54] The advantages and disadvantages of this approach are discussed in the methodology section of this chapter.

FIGURE VI-7: Fund sizes versus alphas of funds of hedge funds – part II



Alphas are derived from excess returns and an asset class factor model with four factors. The factors are the Goldman Sachs Commodity Index, the Wilshire Micro Cap Index, the CBOE Volatility Index and the Lehman Aggregate Bond Index. The time period from July 1994 to April 2005 and a sample of 662 funds of hedge funds are used for the analysis. The excess returns of the funds are directly regressed on the factors without the construction of asset percentiles.

The robustness of the results of the cross-sectional regression analysis is confirmed by repeating the analysis over two sub-periods of 65 months from July 1994 to November 1999 and from December 1999 to April 2005. The relationship between fund sizes and returns, standard deviations and Sharpe ratios is statistically significant at the 1% significance level in both sub-periods. The relationship between fund sizes and alphas is significant at the 5% significance level for the first sub-period and at the 1% significance level for the second sub-period.

To test the stability of the alphas, four three-factor models are derived by dropping one of the original four factors each time. Using the alphas based of the four three factor models for the cross-sectional regression analysis a statistically significant relationship between fund sizes and alphas can be confirmed at the 1% significance level in each of the four cases.

Quadratic regressions with fund sizes and returns, standard deviations, Sharpe ratios and alphas reveal that the coefficients of the quadratic terms are not statistically significant. The results are therefore not displayed.

5 DATA ENVELOPMENT ANALYSIS

Data envelopment analysis is conducted with the objective to derive a relative efficiency measure for the evaluation of funds of hedge funds. In a comprehensive analysis eight evaluation criteria, three input variables and five output variables, are used simultaneously to benchmark the funds.[55] The analysis is based on a data set of 167 funds of hedge funds over the 60-month time period from May 2000 to April 2005. The data envelopment analysis differentiates between efficient and non-efficient funds. In the analysis with 167 funds, eleven funds are classified as efficient and span the efficient frontier. The remaining 156 funds are non-efficient. The analysis shows that efficient funds exhibit better median characteristics across all eight evaluation criteria. The results are presented in Table 6.9. Further performance and risk measures are shown for illustrative purposes only. Median values are illustrated instead of average values to avoid any distorting impact of potential outliers. Minimum and maximum values are shown to indicate the presence of outliers.

[55] Gregoriou (2003b) uses the first three partial moments of the upper (lower) side of return distributions as input (output) criteria in a data envelopment approach applied to funds of hedge funds.

TABLE VI-9: Data envelopment analysis with funds of funds/60 months

	Median				
	All funds	Efficient funds	Non-efficient funds	Minimum	Maximum
Output variables for DEA					
Returns p.a.	5.58%	7.93%	5.49%	-4.87%	18.78%
Skewness	-0.09	0.04	-0.09	-5.34	2.23
Proportion of pos. returns	68.33%	81.67%	66.67%	43.33%	96.67%
Alpha p.m.	0.30%	0.62%	0.30%	-0.88%	1.51%
Omega	2.55	9.07	2.42	0.18	30.40
Input variables for DEA					
Standard deviation	4.19%	3.02%	4.21%	1.54%	37.54%
Maximum drawdown	4.48%	1.35%	4.64%	0.16%	50.34%
Excess kurtosis	0.60	0.34	0.61	-0.87	36.42
Other perf. measures					
Sortino ratio	1.78	7.60	1.77	-1.02	24.87
Kappa (3rd order)	0.33	1.43	0.32	-0.18	4.18
Upside potential ratio	0.60	1.42	0.59	0.20	3.83
Calmar ratio	1.15	7.85	1.12	-0.12	46.60
Modified VaR	2.80%	2.47%	2.85%	1.28%	22.40%

The analysis is conducted with 167 funds of hedge funds over the time period from May 2000 to April 2005. Three input and five output variables are used in the data envelopment analysis. Further performance and risk measures are shown for illustrative purposes only. 11 funds are classified as efficient and 156 funds are classified as non-efficient. Alphas are derived from excess returns and an asset class factor model with four factors. The factors are the Goldman Sachs Commodity Index, the Wilshire Micro Cap Index, the Lehman Aggregate Bond Index and the CBOE Volatility Index. A modified value-at-risk measure based on a Cornish-Fisher expansion is used. A 95% confidence interval is used for the modified value-at-risk measure.

To investigate the persistence of the results, a further analysis is conducted over a 120-month time period with a smaller data set of 55 funds of hedge funds. The data envelopment approach classifies nine funds as efficient and 46 funds as non-efficient. The results are illustrated in Table 6.10. The median values of the efficient funds are again better than the median values of the non-efficient funds across all evaluation criteria.

TABLE VI-10: Data envelopment analysis with funds of funds/120 months

	Median				
	All Funds	Efficient Funds	Non-efficient Funds	Minimum	Maximum
Output variables for DEA					
Returns p.a.	8.99%	11.07%	8.96%	-1.08%	19.20%
Skewness	-0.21	0.59	-0.33	-7.25	1.57
Proportion of pos. returns	66.67%	79.17%	65.00%	47.50%	93.33%
Alpha p.m.	0.49%	0.66%	0.48%	-0.36%	1.56%
Omega	1.72	4.01	1.66	0.76	7.72
Input variables for DEA					
Standard deviation	8.30%	4.20%	8.64%	2.32%	40.17%
Maximum drawdown	13.02%	4.69%	15.46%	1.73%	81.92%
Excess kurtosis	3.35	1.81	3.35	-0.59	68.42
Other perf. measures					
Sortino ratio	1.09	3.29	0.95	-0.22	6.35
Kappa (3rd order)	0.20	0.44	0.16	-0.03	1.12
Upside potential ratio	0.75	1.09	0.67	0.20	2.17
Calmar ratio	0.67	2.76	0.60	-0.02	5.51
Modified VaR	5.73%	3.90%	6.33%	1.77%	36.51%

The analysis is conducted with 55 funds of hedge funds over the time period from May 1995 to April 2005. Three input and five output variables are used in the data envelopment analysis. Further performance and risk measures are shown for illustrative purposes only. Nine funds are classified as efficient and 46 funds are classified as non-efficient. Alphas are derived from excess returns and an asset class factor model with four factors. The factors are the Goldman Sachs Commodity Index, the Wilshire Micro Cap Index, the Lehman Aggregate Bond Index and the CBOE Volatility Index. A modified value-at-risk measure based on a Cornish-Fisher expansion is used. A 95% confidence interval is used for the modified value-at-risk measure.

The persistence of the results in the data envelopment analysis is further investigated by separating the 120-month time period into two sub-periods of 60 months each, also referred to as in-sample and out-of-sample periods. In a first step the funds are classified as efficient and non-efficient in the in-sample period. Nine funds are classified as efficient and 46 funds are classified as non-efficient. In a second step the fund characteristics of the efficient and non-efficient funds in the out-of-sample period are compared. The results are presented in Table 6.11.

TABLE VI-11: Fund of hedge funds characteristics in- and out-of-sample I

	Efficient funds (defined in the in-sample period)		Non-efficient funds (defined in the in-sample period)	
	In-sample	Out-of-sample	In-sample	Out-of-sample
Number of funds	9		46	
Median efficiency scores	1.000	0.802	0.387	0.625
Output variables for DEA				
Returns p.a.	15.81%	5.12%	12.17%	4.97%
Skewness	0.56	0.00	-0.59	-0.24
Proportion of pos. returns	73.33%	65.00%	70.00%	64.17%
Alpha p.m.	0.95%	0.36%	0.76%	0.21%
Omega	3.38	1.67	2.09	1.28
Input variables for DEA				
Standard deviation	8.13%	5.82%	10.63%	5.05%
Maximum drawdown	4.17%	7.09%	12.20%	6.05%
Excess kurtosis	1.27	0.16	2.22	0.68
Other perf. measures				
Sortino ratio	3.57	1.01	1.52	0.46
Kappa (3rd order)	0.53	0.15	0.26	0.09
Upside potential ratio	1.34	0.58	0.74	0.73
Calmar ratio	2.47	1.01	1.02	0.78
Modified VaR	5.46%	3.91%	8.07%	3.42%

The analysis is conducted with 55 funds of hedge funds over the time period from May 1995 to April 2005. Three input and five output variables are used in the data envelopment analysis. Further performance and risk measures are shown for illustrative purposes only. Alphas are derived from excess returns and an asset class factor model with four factors. The factors are the Goldman Sachs Commodity Index, the Wilshire Micro Cap Index, the Lehman Aggregate Bond Index and the CBOE Volatility Index. A modified value-at-risk measure based on a Cornish-Fisher expansion is used. A 95% confidence interval is used for the modified value-at-risk measure.

The median efficiency score of efficient funds is 0.802 in the out-of-sample period and is therefore higher than the median efficiency score of 0.625 for non-efficient funds. In the out-of-sample period efficient funds have better median values compared to non-efficient funds in six out of eight evaluation criteria used in the data envelopment analysis. Efficient funds are outperforming with regard to return, skewness, proportion of positive months, alpha, omega and exhibit a lower excess kurtosis. The outperformance comes at the expense of a higher standard deviation and a higher maximum drawdown.

Given the relatively small number of efficient funds with an efficiency score of one, the comparison is repeated by dividing the sample into two equally sized groups, one with above median efficiency scores and one with below median efficiency scores in the in-sample period. The characteristics of the two equally sized groups are presented in Table 6.12. The comparison shows that funds with above median efficiency scores are outperforming in all evaluation criteria used in the data envelopment analysis.

The data envelopment analysis is repeated with an extended set of 13 evaluation criteria. The results confirm the findings of the analysis with eight evaluation criteria. Efficient funds in the in-sample period outperform across all 13 evaluation criteria in the out-of-sample period.

Finally, the persistence of relative efficiencies over time is tested with a Spearman rank correlation test applied to relative efficiency scores in the in-sample and out-of-sample time period. The rank correlation is 0.26 for the sample with 55 funds of hedge funds, but is not statistically significant. The lack of statistical significance may be due to the small sample size of only 55 funds of hedge funds.[56]

[56] Ammann and Moerth (2006a) find statistical significance at the 1% significance level in a similar persistence analysis based on a set of 473 hedge funds.

TABLE VI-12: Fund of hedge funds characteristics in- and out-of-sample II

	Funds with above median efficiency (defined in the in-sample period)		Funds with below median efficiency (defined in the in-sample period)	
	In-sample	Out-of-sample	In-sample	Out-of-sample
Number of funds	28		27	
Median efficiency scores	0.784	0.747	0.269	0.467
Output variables for DEA				
Returns p.a.	14.63%	5.07%	11.32%	4.23%
Skewness	-0.09	-0.19	-0.67	-0.24
Proportion of pos. returns	79.17%	70.00%	66.67%	60.00%
Alpha p.m.	0.94%	0.29%	0.56%	0.13%
Omega	2.84	1.42	1.72	1.01
Input variables for DEA				
Standard deviation	6.11%	3.99%	12.15%	5.81%
Maximum drawdown	7.94%	4.32%	16.06%	12.56%
Excess kurtosis	1.83	0.34	2.41	0.66
Other perf. measures				
Sortino ratio	2.51	0.74	1.10	0.02
Kappa (3rd order)	0.42	0.14	0.18	0.01
Upside potential ratio	1.05	0.86	0.71	0.63
Calmar ratio	1.86	1.13	0.73	0.52
Modified VaR	5.18%	3.12%	9.37%	3.67%

The analysis is conducted with 55 funds of hedge funds over the time period from May 1995 to April 2005. Three input and five output variables are used in the data envelopment analysis. Further performance and risk measures are shown for illustrative purposes only. Alphas are derived from excess returns and an asset class factor model with four factors. The factors are the Goldman Sachs Commodity Index, the Wilshire Micro Cap Index, the Lehman Aggregate Bond Index and the CBOE Volatility Index. A modified value-at-risk measure based on a Cornish-Fisher expansion is used. A 95% confidence interval is used for the modified value-at-risk measure.

F SUMMARY OF FINDINGS

This chapter investigates the performance of funds of hedge funds. The subject is approached from a variety of perspectives. The study reveals new findings on the relationship between fund sizes and performance. A further analysis investigates the persistence of a relative efficiency measure based on data envelopment analysis with mixed results.

The analysis reports a performance difference between funds of hedge funds and hedge funds that is in line with the additional fee load charged by funds of hedge funds. The survivorship bias for funds of hedge funds is found to be lower than for hedge funds. A survivorship analysis indicates a substantially lower survivorship bias for larger funds of hedge funds as opposed to smaller funds of hedge funds.

Asset-class factor models applied to excess returns indicate that funds of hedge funds fail to generate significant alphas. This result is in contrast to findings in the analysis for hedge funds and confirms the negative impact of the additional fee load of funds of hedge funds. 56.3% of the return variance of excess returns can be explained by an eleven-factor model, where equities are revealed as the predominant explanatory factor for funds of hedge funds.

The relationship between performance and fund sizes is analyzed by regressing returns, standard deviations, Sharpe ratios and alphas derived from a four-factor model on the logarithms of fund sizes. In contrast to hedge funds, funds of hedge funds with a larger asset base are out-performing their smaller competitors. The standard deviations for larger funds of hedge funds are smaller, while the Sharpe ratios and the alphas are higher. All relationships are statistically significant at the 1% significance level. Investors in larger funds of hedge funds may benefit from a better performance and a higher survival probability.

A comprehensive relative efficiency measure based on eight traditional and alternative performance and risk measures is applied. The evaluation criteria are return, skewness, proportion of positive months, omega, alpha, standard deviation, maximum drawdown and kurtosis. The data envelopment analysis differentiates between efficient funds that span an efficient frontier according to the eight evaluation criteria and non-efficient funds. Funds that are classified as efficient in the in-sample period also exhibit superior performance and risk characteristics in the out-of-sample period suggesting the presence of performance persistence based on a comprehensive relative efficiency measure. The result is confirmed in a second data envelopment analysis based on an extended set of thirteen evaluation criteria. The findings are particularly interesting with regard to the selection of funds of hedge funds. The long-term persistence in performance and risk characteristics suggests that a quantitative approach can contribute to the selection process of funds of hedge funds.

VII CONCLUSION

The thesis critically assesses potential added values in hedge fund selection and portfolio construction of hedge fund portfolios. A particularly large set of hedge fund data based on a combination of several of the largest commercial databases from various data providers is used for the analysis.

Chapter III is investigating a potential capacity issue of hedge funds and CTAs, one of the most discussed topics in the hedge fund industry. Hedge funds generally apply specific investment strategies that may face additional challenges if asset levels are growing too large. It can be shown that large hedge funds are underperforming smaller funds. The analysis presented is based on cross-sectional regression analysis testing the relationship between fund sizes and hedge fund returns, standard deviations, Sharpe ratios and alphas derived from a multi asset class factor model. Although large hedge funds tend to have lower standard deviations, the reduced standard deviations are not sufficient to compensate for the reduced returns leading to lower Sharpe ratios. Hedge funds exhibit a statistically significant alpha derived from various factor models. Similar to returns and Sharpe ratios, alphas are also decreasing with increasing fund sizes. It is also discussed that hedge fund managers seeking a maximum income are willing to increase their fund sizes beyond the optimal size from a pure performance perspective. Similar results are obtained in a separate analysis based on a sample of CTAs. Larger CTAs have lower returns, lower standard deviations, lower Sharpe ratios and lower alphas than smaller CTAs.

One major contribution is the development of a relative efficiency measure for the performance analysis of hedge funds that indicates performance persistence over long time periods. The efficiency measure is derived from different sets of six, eight and 13 traditional and alternative evaluation criteria. A data envelopment analysis approach is used to derive the relative efficiency measure. The study reveals a statistically significant dependence of the efficiency scores in the out-of-sample period on the efficiency scores in the in-sample period. The relationship holds for different sets of evaluation criteria and different breakpoints between the in-sample and out-of-sample periods. The relationship suggests the possibility of selecting funds with superior characteristics based on their past performance characteristics. Although the selection of hedge funds is typically based on qualitative criteria, the application of a relative efficiency measure as discussed in Chapter IV of the thesis may provide a useful additional tool for hedge fund investors.

A further major contribution of the thesis is the analysis of strategy classification schemes and its implications for portfolio construction presented in Chapter V. The variety of classification schemes of various commercial database providers suggests the alternative of a quantitative classification based on cluster analysis. The application of a principal component analysis indicates that certain strategies are more homogenous than others. A comparison of a broad qualitative classification scheme with quantitatively defined clusters based on a k-means cluster analysis suggests a relatively good fit between clusters and strategies for Tactical Trading funds. Equity Long/Short and Event Driven funds exhibit similar return characteristics, while Relative Value funds are more difficult to capture with a cluster analysis approach. The analysis indicates evidence of cluster stability over time. An investigation of the persistence of cluster characteristics reveals no persistence for returns, but statistically significant persistence for standard deviations and correlations. These findings are useful results with regard to the development of weighting schemes for hedge fund portfolios. An empirical analysis reveals superior out-of-sample characteristics of portfolios diversified across clusters with weightings derived from in-sample standard deviations and a mixture of standard deviations and correlations. The findings validate cluster-based portfolio construction as a useful tool for hedge fund allocations.

The most popular and easiest way for investors to enter the hedge fund area is via investments in funds of hedge funds. Chapter VI is dedicated to the performance analysis of funds of hedge funds. The analysis shows that the additional fee load of funds of hedge funds matches approximately the lower average returns compared to hedge funds. A factor analysis approach based on standard asset class factors shows that funds of hedge funds generally fail to generate statistically significant alphas. One factor that has a significant influence on fund of hedge funds performance is the fund size. In contrast to the findings in the analysis with hedge funds, larger funds of hedge funds tend to generate higher returns, higher Sharpe ratios and higher alphas. The relationship between standard deviations and fund sizes is negative and in line with the analysis based on hedge fund data. The analysis of performance persistence based on data envelopment analysis suggests persistence in most of the eight traditional and alternative evaluation criteria. The interpretation of the result is limited by the relatively small sample size of funds of hedge funds with long track records.

Further research opportunities in the hedge fund area may focus on the investigation of individual strategies and a possible quantification of general principals of the underlying investment approaches. The possible replication of generic hedge fund strategies also provides further research opportunities concerning the role of hedge funds in the asset allocation process. The entry of a broader investor base into the hedge fund industry with increasing demands for transparency in combination with improving research efforts in the hedge fund arena substantially contribute to the understanding of the asset class of hedge funds and its role in the asset allocation process.

This thesis provides evidence for the added value of quantitative methods for hedge fund selection and portfolio construction from a performance perspective. Although not every hedge fund manager will choose to accept improved transparency standards and despite the wide spread perception of the hedge fund arena as a primarily skill-based alpha-oriented investment field for specialists, the avenue of quantitative research in that field is playing an important part in supporting the transformation process of hedge funds from an alternative asset class to a traditional component of any investment portfolio.

REFERENCES

Acito, C. and P. Fisher, 2002, "Fund of Hedge Funds: Rethinking Resource Requirements", *Journal of Alternative Investments*, 4(4), 25-35.

Ackermann, C., R., McEnally R., and D. Ravenscraft, 1999, "The Performance of Hedge Funds: Risk, Return and Incentives", *Journal of Finance*, 59(3), 833-74.

Agarwal, V., N. D. Daniel and N. Y. Naik, 2005, "Role of Managerial Incentives, Flexibility, and Ability: Evidence from Performance and Money Flows in Hedge Funds, Working Paper, Georgia State University and London Business School.

Agarwal, V., and J. Kale, 2007, "On the Relative Performance of Multi-Strategy and Funds of Hedge Funds", *Journal of Investment Management*, Forthcoming.

Agarwal, V. and N. Y. Naik, 2000a, "Multi-Period Performance Persistence Analysis of Hedge Funds", *Journal of Financial and Quantitative Analysis*, 35(3), 327-42.

Agarwal, V. and N. Y. Naik, 2000b, "Performance Evaluation of Hedge Funds with Option-Based and Buy-and-Hold Strategies", Working Paper, London Business School.

Agarwal, N., and N. Y. Naik, 2004, "Risks and Portfolio Decisions Involving Hedge Funds", *Review of Financial Studies*, 17(1), 63-98.

Amenc, N., Curtis, S., and L. Martellini, 2004, "The Alpha and Omega of Hedge Fund Performance", Working Paper, EDHEC Graduate School of Business.

Amenc, N., El Bied, S., and L. Martellini, 2003, "Predictability in Hedge Fund Returns", *Financial Analysts Journal*, 59(5), 32-46.

Amenc N. and L. Martellini, 2003, "The Brave New World of Hedge Fund Indices", Working Paper, EDHEC Graduate School of Business.

Ammann, M., and P. Moerth, 2005, "Impact of Fund Size on Hedge Fund Performance", *Journal of Asset Management*, 6(3), 219-38.

Ammann, M., and P. Moerth, 2006a, "Fund of Hedge Funds Performance Evaluation", Working Paper, University of St. Gallen.

Ammann, M., and P. Moerth, 2006b, "Impact of Fund Size and Fund Flows on Hedge Fund Performance", Working Paper, University of St. Gallen.

Ang, A., Rhodes-Kropf, M., and R. Zhao, 2005, "Do Funds-of-Funds Deserve their Fees-on-Fees?“, Working Paper, Columbia University.

Baghai-Wadji, R., El-Berry, R., Klocker, S., and M. Schwaiger, 2005, "The Consistency of Self-Declared Hedge Fund Styles – A Return-Based Analysis with Self-Organizing Maps", *Financial Stability Report*, 9, Österreichische Nationalbank, 64-76.

Baquero, G., J. ter Horst, and M. Verbeek, 2005, "Survival, Look-Ahead Bias and the Persistence in Hedge Fund Performance", *Journal of Financial and Quantitative Analysis*, 40(3), 493-517.

Bares, P.-A., R. Gibson, and S. Gyger, 2003, "Performance in the Hedge Funds Industry: An Analysis of Short and Long-Term Persistence", *Journal of Alternative Investments*, 6(3), 25–41.

Bianchia, R., Drewa, M., Veeraraghavanb, M., and P. Whelana, 2005, **"**An Analysis of Hedge Fund Styles using the Gap Statistic**"**, Working Paper, School of Economics and Finance, Queensland University of Technology.

Boyson, N. M., and M. J. Cooper, 2004, "Do Hedge Funds Exhibit Performance Persistence? A New Approach", Working Paper.

Brealey, R.A. and E. Kaplanis, 2001, "Changes in Factor Exposures of Hedge Funds", Working Paper, London Business School.

Brown, S. J., and W. N. Goetzmann, 2003, "Hedge Funds with Style", *Journal of Portfolio Management*, 29, 101.

Brown, S. J., Goetzmann, W. N., and B. Liang, 2004, "Fees of Fees in Funds of Funds", Working Paper, Yale International Center for Finance.

Brown, S. J., Goetzmann W. N., and R. G. Ibbotson, 1999, "Offshore Hedge Funds: Survival & Performance 1989 – 1995", *Journal of Business*, 72, 91-117.

Capocci, D., Corhay, A., and G. Hubner, 2005, "Hedge Fund Performance and Persistence in Bull and Bear Markets, *European Journal of Finance*, 11(5), 361-92.

Capocci, D., and G. Hubner, 2004, "Analysis of Hedge Fund Performance", *Journal of Empirical Finance*, 11(1), 55-89.

Clark, A., 2003, "Does Fund Size Affect Performance?", *Lipper Research Study*.

Cooper, W. W., Seiford, L. M., and J. Zhu, Handbook on Data Envelopment Analysis, Kluwer Academic Publishers, Boston, 2004.

Das, N., 2003, "Hedge Fund Classification using K-means Clustering Method", Working Paper of 9th International Conference on Computing in Economics and Finance, University of Washington.

Das, N., and R. Das, 2005, "Hedge Fund Classification Technique using Self-Organizing Feature Map Neural Network", Conference paper, Annual Meetings of the Financial Management Association International, Chicago.

Davies, R. J., Kat, H. M., and S. Lu, 2005, "Fund of Hedge Funds Portfolio Selection: A Multiple-Objective Approach", Working Paper.

De Souza, C., and S. Gokcan, 2004, "Hedge Fund Investing: A Quantitative Approach to Hedge Fund Manager Selection and De-Selection", *Journal of Wealth Management*, 6(4), 52-73.

Diez de los Rios, A., and R. Garcia, 2007, "Assessing and Valuing the Non-Linear Structure of Hedge Fund Returns", Working Paper, Université de Montréal.

Edwards, F., and J. Liew, 1999, "Hedge Funds versus Managed Futures as Asset Classes", *Journal of Derivatives*, 6(4), 45-65.

Edwards, F. R., and M. Caglayan, 2001, "Hedge Fund Performance and Manager Skill", *Journal of Futures Markets*, 21(11), 1003-28.

Eling, M., 2006, "Performance Measurement of Hedge Funds Using Data Envelopment Analysis", *Financial Markets and Portfolio Management*, 20(4), 442-71.

Eling, M., 2007, "Does Hedge Fund Performance Persist? Overview and New Empirical Evidence", Working Paper, University of St. Gallen.

Fama, E. F., and K. R. French, 1993, "Common Risk Factors in the Returns on Stocks and Bonds", *Journal of Financial Economics*, 33(1), 3-56.

Fama, E. F., and K. R. French, 1996, "Multi-Factor Explanations of Asset Pricing Anomalies", *Journal of Finance*, 51(1), 131-155.

Favre, L., and J.-A. Galeano, 2002, "Mean-Modified Value-at-Risk Optimization with Hedge Funds", *Journal of Alternative Investments*, 5(2), 21-5.

Fishburn, P. C., 1977, "Mean-Risk Analysis with Risk Associated with Below-Target Returns", *American Economic Review*, 67, 116-26.

Fung W., and D. Hsieh, 1997a, "Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds", *Review of Financial Studies*, 10(2), 275-302.

Fung, W., and D. Hsieh, 1999, "Is Mean-Variance Analysis Applicable to Hedge Funds", *Economics letters*, 53-8.

Fung W., and D. Hsieh, 2000, "Performance Characteristics of Hedge Funds and Commodity Funds: Natural versus Spurious Biases", *Journal of Financial and Quantitative Analysis*, 35, 291-307.

Fung, W., and D. Hsieh, 2002, "Asset-Based Style Factors for Hedge Funds", *Financial Analysts Journal*, 58, 16-27.

Fung, W., and D. Hsieh, 2004, "Hedge Fund Benchmarks: A Risk-Based Approach", *Financial Analysts Journal*, 60(5), 65-80.

Fung, W., D. Hsieh, N. Naik, and T. Ramadorai, 2007, "Hedge Funds: Performance, Risk and Capital Formation", *Journal of Finance*, Forthcoming.

Getmansky, M., 2004, "The Life Cycle of Hedge Funds: Fund Flows, Size and Performance", Working Paper, MIT.

Goetzmann, W., Ingersoll, J., and S. Ross, 2003, "High Water Marks and Hedge Fund Management Contracts", *Journal of Finance*, 58(4), 1685-717.

Gregoriou, G. N., 2003a, "The Mortality of Funds of Hedge Funds", *Journal of Wealth Management*, 6(1), 42-53.

Gregoriou, G. N., 2003b, "Performance Appraisal of Funds of Hedge Funds Using Data Envelopment Analysis", *Journal of Wealth Management*, 5(4), 88-95.

Gregoriou, G. N., and F. Rouah, 2001, "Last Year's Winning Hedge Fund as this Year's Selection: A Simple Trading Strategy", *Derivatives Use, Trading & Regulation*, 7(3), 269-74.

Gregoriou, G. N., and F. Rouah, 2003, "Large versus Small Hedge Funds: Does Size Affect Performance?", *Journal of Alternative Investments*, 5(3), 75-7.

Gregoriou, G. N., Sedzro, K., and J. Zhu, 2005, "Hedge Fund Performance Appraisal Using Data Envelopment Analysis, *European Journal of Operational Research*, 164(2), 555-71.

Harri, A., and B. W. Brorsen, 2004, "Performance Persistence and the Source of Returns for Hedge Funds", *Applied Financial Economics*, 14(2), 131-41.

Hedges, R. J., 2003, "Size vs. Performance in the Hedge Fund Industry", *Journal of financial transformation*, 10, 14-7.

Herzberg M. M., and H. A. Mozes, 2003, "The Persistence of Hedge Fund Risk: Evidence and Implications for Investors", *Journal of Alternative Investments*, 6(2), 22-42.

Ineichen, A. M., 2002a, "Funds of Hedge Funds: Industry Overview", *Journal of Wealth Management*, 4(4), 47-62.

Ineichen, A. M., 2002b, "The Alpha in Funds of Hedge Funds", *Journal of Wealth Management*, 5(1), 8-25.

Jagannathan, R., A. Malakhov, and D. Novikov, 2006, "Do Hot Hands Persist Among Hedge Fund Managers? An Empirical Evaluation", Working Paper.

Jaeger, L., and C. Wagner, 2005, "Factor Modelling and Benchmarking of Hedge Funds: Can passive investment strategies in hedge funds deliver?", Partners Group, Baar-Zug.

Kanji, G. K., 100 statistical tests, SAGE Publications, London, 1999.

Kaplan, P. D., and J. A. Knowles, 2004, "Kappa: A Generalized Downside Risk-Adjusted Performance Measure", Working Paper, Morningstar Associates and York Hedge Fund Strategies.

Kat, H., 2002, "In Search of the Optimal Fund of Hedge Funds", Working Paper, City University, London.

Kat, H., and F. Menexe, 2003, "Persistence in Hedge Fund Performance: The True Value of a Track Record", *Journal of Alternative Investments*, 5(4), 66-72.

Kat, H. M., and H. P. Palaro, 2006, "Replication and Evaluation of Fund of Hedge Fund Returns", Working Paper, Cass Business School.

Kat, H. M., and H. P. Palaro, 2007, "FundCreator-Based Evaluation of Hedge Fund Performance", Working Paper, Cass Business School.

Kazemi, H., and Schneeweis, 2003, "Conditional Performance of Hedge Funds", Working Paper, Isenberg School of Management, University of Massachusetts, Amherst.

Keating, C., and W. Shadwick, 2002, "A Universal Performance Measure", Working Paper, The Finance Development Center, London.

Koh, F., W. T. H. Koh, and M. Teo, 2003, "Asian Hedge Funds: Return Persistence, Style, and Fund Characteristics", Working Paper, Singapore Management University.

Kosowski, R., N. Y. Naik, and M. Teo, 2007, "Do Hedge Funds Deliver Alpha? A Bayesian and Bootstrap Analysis", *Journal of Financial Economics*, 84(1), 229-64.

Kouwenberg, R., 2003, "Do Hedge Funds Add Value to a Passive Portfolio?", Journal *of Asset Management*, 3(4), 361-82.

Liang, B., 1999, "On the Performance of Hedge Funds", *Financial Analysts Journal*, 55(4), 72-85.

Liang, B., 2000, "Hedge Funds: The Living and the Dead", *Journal of Financial and Quantitative Analysis*, 35(3), 309-25.

Liang, B., 2001, "Hedge Fund Performance: 1990-1999", *Financial Analysts Journal*, 57(1), 11-8.

Liang, B., 2003a, "The Accuracy of Hedge Fund Returns", *Journal of Portfolio Management*, 29(3), 111-22.

Liang, B., 2003b, "On the Performance of Alternative Investments: CTA's, Hedge Funds, and Funds-of-Funds", Working Paper, Isenberg School of Management, University of Massachusetts, Amherst.

Markowitz, H., 1959, Portfolio Selection: Efficient Diversification of Investments, John Wiley and Sons, New York.

Maillet B., and P. Rousset, 2003, "Classifying Hedge Funds with Kohonen Maps", *Connectionist Approaches in Economics and Management Sciences,* Series in Advances in Computational Science 6, Kluwer Academic Publisher, 233-59.

Malkiel, B., 1995, "Returns from Investing in Equity Mutual Funds 1971 to 1991", *Journal of Finance*, 50(2), 549-72.

Malkiel, B. G., and A. Saha, 2005, "Hedge Funds: Risk and Return", *Financial Analysts Journal*, 61(6), 80-8.

Martin, George, 2000, **"**Making Sense of Hedge Fund Returns: What Matters and What Doesn't"**,** *Derivatives Strategy*.

Moerth, P., 2006a, "A Relative Efficiency Measure to Evaluate Hedge Funds", Working Paper, University of St. Gallen.

Moerth, P., 2006b, "Portfolio Construction with Hedge Funds", Working Paper, University of St. Gallen.

Nawrocki, D. N., 1991, "Optimal Algorithms and Lower Partial Moment: Ex-Post Results", *Applied Economics*, 23(3), 465-70.

Nawrocki, D., 1999, "The Case for the Relevancy of Downside Risk Measures", Working Paper , Villanova University,.

Newey, W., and K. West, 1987, "A simple positive-definite heteroskedasticity and autocorrelation consistent covariance matrix", *Econometrica*, 55, 703-8.

Nguyen-Thi-Thanh, H., 2006, "On the Use of Data Envelopment Analysis in Hedge Fund Selection", Working Paper, Laboratoire d'Economie d'Orléans.

Plantinga, A., and S. de Groot, 2001," Risk-Adjusted Performance Measures and Implied Risk-Attitudes", Working Paper, University of Groningen.

Park, J. M., and J. C. Staum, 1998, "Performance Persistence in the Alternative Investment Industry", Working Paper, PARADIGM Capital Management, Inc.

Schneeweis, T., Kazemi H. and G. Martin, 2003, "Understanding Hedge Fund Performance: Research Issues Revisited – Part II", *Journal of Alternative Investments*, 5(4), 8-30.

Sharpe, W. F., 1992, "Asset Allocation: Management Style and Performance Measurement", *Journal of Portfolio Management*, 18(2), 7-19.

Sortino, F. A., and R. van der Meer, 1991, "Downside Risk", *Journal of Portfolio Management*, 17, 27-31.

Sortino, F. A., van der Meer, R., and A. Plantinga, 1999, "The Dutch Triangle", *Journal of Portfolio Management*, 26(1), 50-8.

Sortino, F., Kordonsky, M., and H. Forsey, 2006, “Evidence – Based Portfolio Management”, Working Paper, San Francisco State University.

Young, T. W., 1991, “Calmar Ratio: A Smoother Tool”, *Futures*, 20(1), 40.

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