Hedge Fund Selection -
An Investment Approach Based on Risk-adjusted Performance Measures

D I S S E R T A T I O N
of the University of St. Gallen,
School of Management,
Economics, Law, Social Sciences,
and International Affairs
to obtain the title of
Doctor of Philosophy in Management

Submitted by

Martin Raasch
from
Germany

Approved on the application of:

Prof. Dr. Andreas Grüner
and
Prof. Dr. Dr.h.c. Klaus Spremann

Dissertation no. 4104

Difo-Druck GmbH,
Bamberg 2013

The University of St. Gallen, School of Management, Economics, Law, Social Sciences, and International Affairs hereby consents to the printing of the present dissertation without hereby expressing any opinion on the views herein expressed.

St. Gallen, October 29, 2012

The President:

Prof. Dr. Thomas Bieger

To my Family

With Love and Gratitude

Acknowledgements

It would not have been possible to write this thesis without the help and support of the people around me, to only some of whom it is possible to give particular mention here.

First and foremost, I owe my deepest gratitude to my supervisor, Professor Dr. Andreas Grüner, who granted me the opportunity to undertake this endeavour. It was his encouragement, guidance, and support from the initial to the final stages that made this thesis possible. His advice and friendship have been invaluable on both an academic and a personal level, for which I am extremely grateful.

Furthermore, I am heartily thankful to Professor Dr. Dr. h.c. Klaus Spremann for co-supervising my dissertation. By providing numerous valuable hints and suggestions, he led me to many new insights into my topic and contributed immensely to the success of my dissertation.

Moreover, I am indebted to Professor Francis Koh of Singapore Management University (SMU), to Professor Song Fengming of Tsinghua University, and to Professor G. Sabarinathan of the Indian Institute of Management Bangalore (IIMB) for hosting and supporting me during my extended sojourns at their institutes. Conducting my research abroad was a truly stimulating and rewarding experience.

Finally, I would like to show my gratitude to my close friends and my family, who supported me during this endeavour. While it is not possible to enumerate all of them, I would like to express my thanks to my wife Ingeborg, my sister Christina, and my friends and colleagues Roman, Ivan, Roger, Christian, and Yin who constantly supported and encouraged me.

Last but not least, words of deep gratitude go to my parents; I dedicate this dissertation to them for their unwavering support, care, and love.

St.Gallen, October 2012
Martin Raasch

List of Abbreviations

Abbreviation	**Long Form**
AD	Average drawdown
AuM	Assets under management
CCRL	Current cumulative return level
CDD	Conditional drawdown
CMGR	Compound monthly growth rate
CML	Capital market line
CVaR	Conditional value at risk
DD	Drawdown
ERoPS	Excess return on probability of shortfall
ERoVaR	Excess return on value at risk
FoF	Fund of hedge funds
HF	Hedge fund
HNWI	High net worth individual
HWM	High-water-mark
LPM	Lower partial moment
M&A	Mergers & acquisitions
MD	Maximum drawdown
MV	Mean variance
MVaR	Modified value at risk
MVP	Minimum variance portfolio
MVSK	Mean variance skewness kurtosis
MPPM	Manipulation-proof performance measure
RAPM	Risk-adjusted performance measure
RoW	Rest-of-World
SEC	Securities and Exchange Commission
UPM	Upper partial moment
VaR	Value at risk

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Abstract

In recent years, portfolio management within a large universe of hedge funds has become a key area of research. In this thesis, the author proposes a strictly quantitative hedge fund investment approach that is of straightforward practical relevance for family office practitioners. It can be shown that portfolios constructed under the new approach are able to considerably outperform an equally-weighted index of hedge funds and an equally-weighted index of funds of hedge funds in an out-of-sample analysis. Thus, there seems to be evidence that the proposed approach represents a valuable tool for investors.

Abstract (German)

In den letzten Jahren ist das Management von Hedgefonds-Portfolios zu einem beliebten Forschungsgebiet herangewachsen. Der Autor dieser Dissertation entwickelt einen quantitativen Ansatz für Investitionen in Hedgefonds, welcher von unmittelbarer praktischer Relevanz für Family Offices ist. Es wird gezeigt, dass Portfolios, welche auf diesem Ansatz basieren, gleich gewichtete Indizes von Hedgefonds und Dachfonds von Hedgefonds in Bezug auf Risiko und Rendite übertreffen können. Es scheint daher, dass der vorgeschlagene Ansatz ein wertvolles Werkzeug für Hedgefonds-Investoren darstellt.

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1 Introduction

1.1 Background

Since the early 1990s, there has been tremendous growth in the hedge fund (HF) industry (Dichev & Yu, 2011). Along with the impressive growth of the HF industry, the number of funds of hedge funds (FoFs) has also increased dramatically. These FoFs are managed investment vehicles for investments in HF portfolios. They offer their investors risk diversification across several HFs, as well as professional management and ongoing portfolio overseeing. On the negative side, such FoFs cost their investors an additional layer of fees. Furthermore, their lack of transparency implies that the investor must have extreme faith in the fund manager. Despite these drawbacks, however, FoFs are a popular route into HFs for many private and institutional investors (Maslakovic, 2009).

Academic research into HFs and FoFs did not begin until the late 1990s, when sufficient data eventually became available (Kat & Palaro, 2006). In the following years, portfolio management within a large universe of HFs has become a key area of research. Since then, a variety of portfolio management approaches have been discussed in the academic literature.

Unfortunately, however, existing academic designs are not easily applicable to the reality of family offices seeking HF exposure, because they fail to consider the significant practical restrictions that family office practitioners face. Against such a background, and considering the rapid growth of the HF and FoF industries, it has become necessary to develop a portfolio management approach that is straightforward and one that is of practical relevance to family office practitioners. In this dissertation, the author seeks to develop such a portfolio management approach in an attempt to narrow this gap.

1.2 Research Gap

This dissertation aspires to make a worthwhile contribution to the existing academic literature in the field of portfolio management within an ever-increasing HF universe. To the author's best knowledge, there is not a single academic study that is 1:1 applicable to the reality of family office practitioners seeking HF investment. This is due, in part, to the researchers' negligence of practical limitations and is compounded by the lack of an adequate preparation of the debatable data. Both arguments are discussed below.

There is, to date, not a single academic study that conscientiously considers all of the major relevant practical restrictions that HF investors are faced with, even though such limitations have a significant impact. The major limitations include *buy and sell lags, lock-up periods, minimum investment sizes, and transaction costs*.

- In this dissertation '*buy and sell lags*' are defined as the lapse between the actual month-end, when HF results are realized, and the date on which investors are able to react to them. While the vast majority of studies neglect these lags, they can undoubtedly be of great importance to investors.

- '*Lock-up period*' is defined as the length of time during which investors in a HF cannot sell their investment. These lock-up periods vary widely within the HF universe, with many HFs demanding 12-month lock-ups or even longer. This renders many academic approaches to portfolio management, which are based on monthly portfolio reshuffling, quite useless to practitioners.

- Many HFs have high *minimum investment requirements* of up to US$1 million or higher (Eurekahedge, 2009c). These minimum investment requirements impose considerable restrictions on fund allocation. This fact, however, is entirely ignored by most of the existing academic approaches and makes them hard to implement for practitioners.

- For the sake of simplicity, many academic studies also ignore the effect of *transaction costs*. The result is a number of academic designs that centre on frequent portfolio reorganisation. This, of course, is infeasible from a practitioner's point of view.

Apart from the negligence of practical limitations, however, many previous studies are based on data sets of questionable relevance for practitioners. Some academic studies calculate risk and performance measures on the basis of HF indices, rather than on individual funds, while others, which do calculate these measures on the basis of individual funds, either include non-investable funds or exclude dead funds from the sample. As a result, such studies suggest designs that are not based on the actual investable investment universe that practitioners face.

For the reasons described above, existing research seems to be of arguable value to family office investment professionals. This dissertation is targeted on overcoming such limitations and offering a robust, fully transparent and readily implementable investment heuristic to help close this research gap.

1.3 Research Objectives

This dissertation addresses portfolio management within a large HF universe, with the overall objective of developing a practically-relevant HF investment approach that is strictly quantitative, fully transparent and based on existing academic literature. Thereby, the author explicitly takes the view of a small family office seeking investment in a broadly diversified portfolio of HFs. This overall research objective can be further broken down into three underlying research objectives.

The first objective is to operationalize the major restrictions and limitations, which family office practitioners face, into a strictly quantitative investment approach. The author develops an approach that considers buy and sell lags, lock-up periods, and minimum investment requirements and takes the existence of transactions costs into account. Through the operationalization of these restrictions and limitations, the author strives to create a close-to-practice setting that by and large mirrors the reality of industry practitioners.

The second objective is to test several different risk-adjusted performance measures (RAPMs) in the HF space. RAPMs are popular tools among academics and practitioners to identify the HFs with the best risk / return relationships. Current academic discussion of HF performance debates several RAPMs. In this dissertation, the author will analyze the power of these RAPMs under close-to-reality conditions.

The third objective is to closely investigate the statistical characteristics of real-life HFs, FoFs, and portfolios constructed under the suggested investment approach. This will be achieved through a series of out-of-sample tests.

1.4 Contribution to Academic Literature and Value for Practitioners

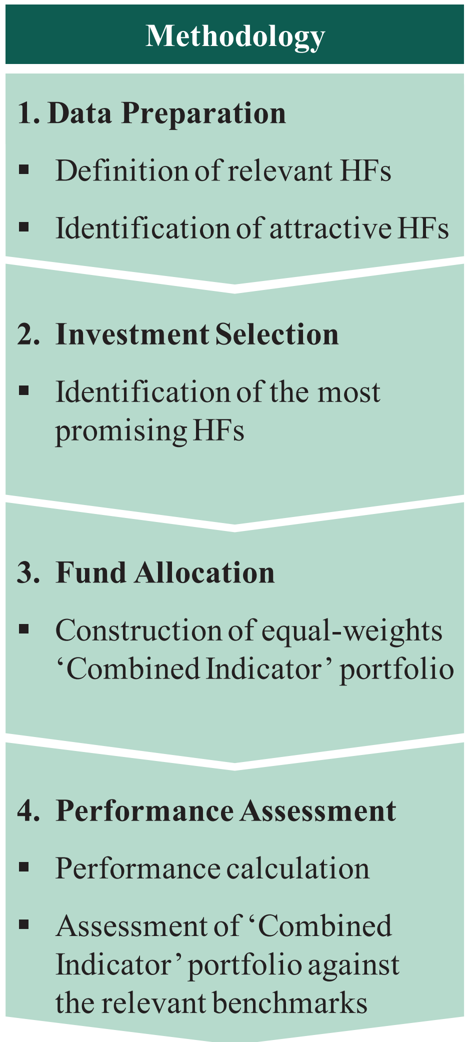
In this dissertation the author strives to make a distinctive contribution to the existing literature in the field of portfolio management within a large HF universe. While there are several studies on HF portfolio management, they usually fail to consider the major practical limitations and restrictions mentioned before. Few studies, such as Jöhri and Leippold's (2006), have tried to bridge this gap. This dissertation follows their research line further by incorporating a larger number of practically relevant restrictions; in contrast to Jöhri and Leippold's work, this dissertation considers individual lock-up periods, minimum investment requirements, and transaction costs. Therefore, it must be regarded as one of the most inclusive works on HF investment in a close-to-reality setting.

In addition to its contribution to academic literature, this dissertation also aims to enhance the investment management processes of family offices by providing an easy-to-implement and inexpensive-to-operate approach to HF investment.

1.5 Research Methodology

This dissertation aims to develop a fully-transparent and strictly quantitative portfolio management approach that is specifically targeted at family offices. This approach is fundamentally based on previous academic research and developed in several steps.

Figure 1: Simplified Overview of Research Design



Source: Author's own illustration

Firstly, commencing from a comprehensive HF database, the author defines the relevant HF universe from a practitioner's point of view. After that, the most attractive HFs for investment are identified based on their size and age. Secondly, several different RAPMs are calculated for each attractive HF; thereby, the most promising HFs are identified under each RAPM. Then, these different HF rankings are merged into one single equally-weighted ranking, the so-called 'Combined Indicator' ranking.[1] Thirdly, an equally-weighted portfolio that comprises the 10 most promising HFs under the 'Combined Indicator' is created. This portfolio is reallocated periodically. Fourthly, the performance of the constructed 'Combined Indicator' portfolio is benchmarked and assessed against an equal-weights index of HFs and an equal-weights index of FoFs.

After this brief outline of the research methodology, the next paragraph will give an overview of the structure of this thesis.

1 This procedure is based on a study by Jöhri and Leippold (2006).

1.6 Structure of the Dissertation

Figure 2: Structure

Source: Author's own illustration

As illustrated by Figure 2, on the right, this thesis is divided into five individual parts. After a short introduction to the topic (part 1), there is a brief description of family offices. Moreover, the current state of the HF and FoF industries is outlined and the research problem is identified (part 2). This is followed by a discussion of the relevant academic literature on the topic. Against the background of previous research, the author addresses the existing gap in the academic research in this area and outlines the objectives of this study. Furthermore, the distinctive features of this dissertation, in contrast to previous studies, are demonstrated (part 3). Then, based on relevant research, a research design is specified. Findings from the resulting analysis are presented in this same section (part 4). Drawing on these findings, the suggested investment approach is revisited and exemplified; in addition, the author provides a comprehensive summary, draws his conclusions and highlights what he considers to be the academic contribution and the practical value of this dissertation (part 5).

2 Background Information

The HF and FoF industries are rather opaque and diverse, so that the reader is provided with a clearer insight into the subject in this second part of the thesis, beginning with an introduction to family offices.

2.1 Introduction to Family Offices

Family offices are privately-owned companies that manage the capital of wealthy individuals or families.[2] They provide a variety of services to their clients. Typical examples are the oversight of family-owned companies as well as investment, insurance, and tax services, wealth transfer planning, financial record keeping, and family foundation management (FOX, 2011; Isdale, 2006). In addition, some family offices provide a variety of softer services, such as arranging vacations, personal security, and educating family members about their wealth (Silverman, 2008).

According to FOX[3], wealthy families start family offices in order to take advantage of a number of benefits: First of all, family offices serve as a one-stop-solution for information on, advice about, and oversight of all financial matters. Secondly, they offer services at a more competitive price than the individual family members could possibly obtain. This is because the family group can take advantage of its pooled purchasing power. Thirdly, family offices do not have conflicts of interest and are solely focussed on their clients' goals. Finally, family offices warrant cross-generation continuity on questions such as values, heritage, trusts, and philanthropy (FOX, 2011).

Two classical types of family offices can be distinguished: single-family offices and multi-family offices. Single-family offices are founded by a rich family with investable assets in excess of US$100 million to manage their wealth (Silverman, 2008). Multi-family offices, on the other hand, serve several different client families

[2] These organizations are often established following the realization of significant liquidity, i.e. after the sale of family business (FOX, 2011).

[3] Family Office Exchange (FOX), headquartered in Chicago, is a leading consulting company in the family office space.

and require significantly lower minimum investments.[4] Often times, family offices start off as single-family offices and are opened to other families and thus converted to multi-family offices later in order to spread the costs over a larger investor base (Breuer et al., 2009). A further type of family office is represented by so-called 'virtual family offices'. These are networks of financial services, accounting, law, and technology firms that offer service bundles, such as the coordination of financial advisers and provision of back-office services, which are specifically targeted towards prosperous families (Silverman, 2008). Furthermore, several banks have established family office units in recent years.[5] Given these different shapes, it does not come as a surprise that there is no commonly-accepted definition of the term 'family office'. In dependence on Breuer et al. (2010), this dissertation defines family offices as companies that offer wealth management services exclusively to high net worth individuals (HNWIs) and "act purely from the perspective of the owners of the assets they manage and focus exclusively on their individual investment wishes and requirements" (Breuer et al., 2010, p. 11).

Family offices typically need a critical mass of US$100 million in AuM in order to operate efficiently; most family offices are indeed much larger (Preqin, 2009; Silverman, 2008).[6] Taking a long-term approach to investing, these family offices normally allocate their funds across a broad range of asset classes like equities, fixed income, and alternative assets. In this context, HFs are assumed to play in prominent role. In fact, a survey of American and European single-family offices has shown that 12-14% of managed family wealth was actually invested in HFs (Amit et al., 2008); Figure 3 illustrates their observations. These findings were echoed by a further study that found North American family offices to have an average exposure to HFs of 14% and an even higher target allocation of 16.1% (Preqin, 2009).[7]

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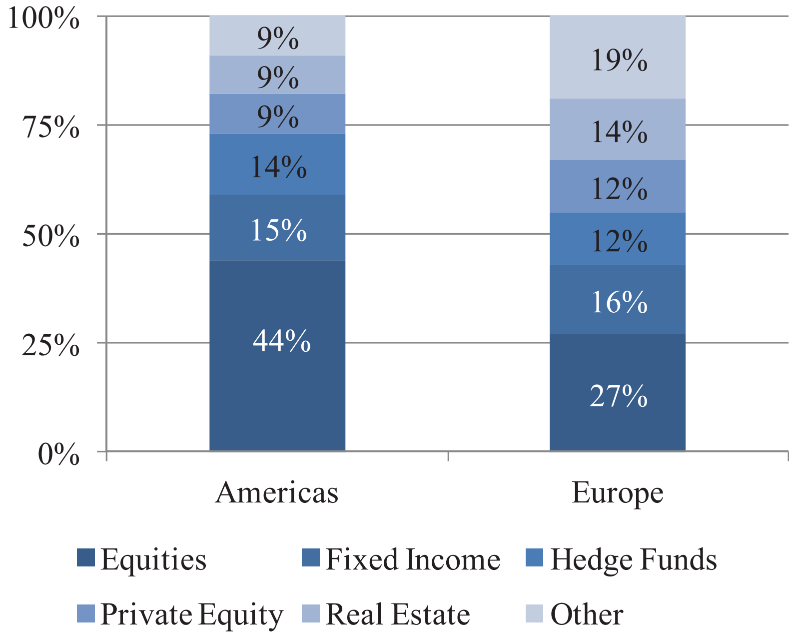
4 Usually in the range of US$10 million (Silverman, 2008).

5 Examples include Citigroup, Wachovia, the Bank of Montreal and others.

6 A recent survey of 64 German and Swiss family offices found that only ca. 10% of them had AuM below €300 million, ca. 50% had AuM of €300-1,000 million, and ca. 40% managed more than €1,000 million in AuM (Breuer, et al., 2010).

7 Preqin is a research company that focused on alternative investment classes; it is headquartered in London, UK.

Figure 3: Asset Allocation of Single-Family Offices[8]



Source: Amit et al. (2008)

When seeking HF exposure, family office practitioners take different routes: They either pursue a direct investment in one or more HFs or invest in a FoFs. These approaches may also be combined. Preqin (2009) found that the average North American family office had ten different HF investments, comprising of both HF and FoF investments. While there are no quantitative studies on the question of whether family offices prefer direct HF investments or FoFs, both routes appear to be popular and to play a significant role. Against this background, it seems worthwhile to study HFs and FoFs in closer detail. In order to provide the reader with a comprehensive introduction to both, the author examines the HF industry (2.2) and the FoF industry (2.3) in the next chapters.

[8] Information based on over 40 interviews and on 138 completed surveys.

2.2 The Hedge Fund Industry

This chapter provides a brief but comprehensive introduction to HFs. First, the author presents the reader with a definition of HFs (2.2.1). After which, there is a brief outline of today's HF industry (2.2.2). This is followed by a critical reflection on HF investment (2.2.3) and a brief summary (2.2.4).

2.2.1 What is a Hedge Fund?

Up to the present date, there is still no legal definition of the term 'HF', despite the sustained regulatory attention given to it; the term was originally used to describe funds that reduced risk with regard to the direction of the market by combining long and short positions (Lhabitant, 2006). However, as many of today`s HFs are not actually hedged, the term has become a misnomer (Titman & Tiu, 2011; Ineichen & Silberstein, 2008). In fact, there is a plethora of vastly diverse funds that are commonly labelled as HFs.

While both the academic literature and the practitioners offer an abundance of HF definitions, none of them has been unanimously accepted. Still, most of today's HFs are identifiable by a number of common characteristics that set them apart from the traditional asset classes. Several analogous enumerations of HF characteristics can be found in academic and practical literature. The one below is sourced from Lhabitant's 'Handbook of Hedge Funds' (2006) except where quoted/annotated, a standard work in the industry:

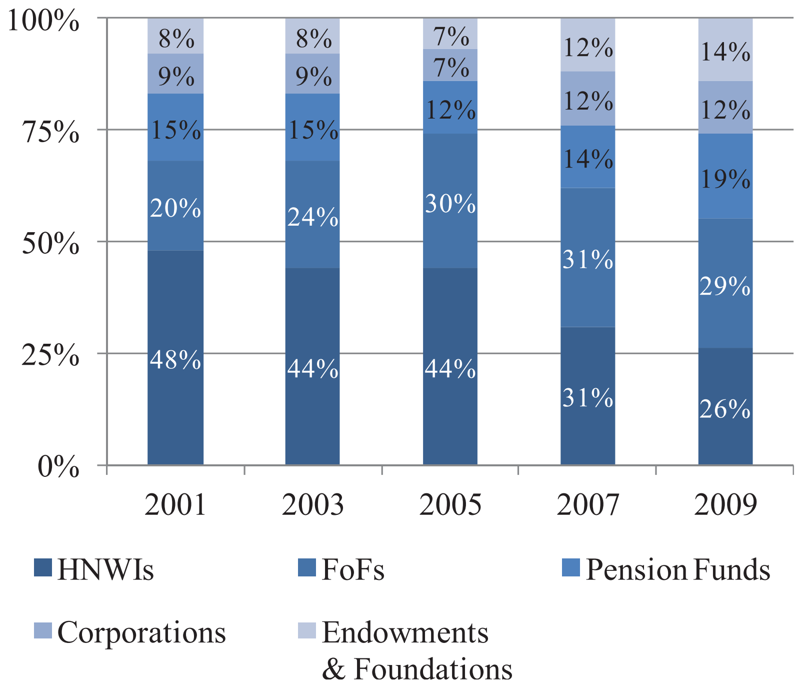
- HFs are actively managed investment vehicles: HF managers strive to create value through active management.

- HFs employ unusual legal structures: HFs are usually organized as limited partnerships, limited liability companies, or off-shore investment companies in order to minimize their taxation.

- HFs have limited transparency: In fact, most HFs are characterized by a lack of transparency (Maxam et al., 2006; Aggarwal & Jorion, 2012). This is due mainly to two reasons: First, because their unusual legal structures do not require them to disclose much information (Gregoriou & Duffy, 2006), and secondly, because the disclosure of detailed investment strategies or individual fund holdings could adversely affect both the HFs themselves and their respective investors.[9]

- HFs target specific groups of investors: Most legislations require that only institutional or qualified investors may have access to HF investments (Dubi, 2011). Typical HF investors are HNWIs, FoFs, corporations, and endowments and foundations. As illustrated in Figure 4, HNWIs traditionally constituted the main group of HF investors, but have recently been surpassed by FoFs.[10]

Figure 4: Sources of Global HF Capital



Source: Maslakovic (2010)

9 Moreover, the disclosure of earnings could be considered public marketing, which is prohibited (Lhabitant, 2006).

10 When seeking HF exposure, family office practitioners take different routes: They pursue a direct investment in HFs and/or invest in a FoFs. Although family offices are not treated as a distinct category in Figure 4, they are included in the 'HNWIs' and 'FoFs' categories.

- HFs seek absolute returns: HFs typically strive to provide their investors with absolute returns irrespective of current market developments (Jordan & Simlai, 2011; Eling, 2005; H. Fung et al., 2004). Thus, adding HFs to a portfolio of traditional assets can improve the risk and return profile (Jaggi et al., 2011). This is particularly true during bear markets (Könberg & Lindberg, 2001).

- HFs employ flexible investment strategies: Unlike mutual fund managers, HF managers are usually provided with a large extent of freedom to invest in different types of assets and to follow different investment styles (Li et al., 2011).

- HF liquidity is normally limited: Most HFs restrict their investors' redemption possibilities and uphold a minimum investment policy (Dubi, 2011).

- HF managers are partners: HF managers usually have a significant stake in their funds (Teo, 2011; Li et al., 2011). This is supposed to avoid principal-agent conflicts by aligning their interests with those of their investors (Gregoriou & Duffy, 2006).

- HFs charge performance-related fees: In contrast to mutual funds, HFs charge a management fee[11] as well as a performance fee[12] (Brown, 2012). In order to circumvent agency problems such as disproportionate risk-taking, HFs usually employ a hurdle rate and/or a high-water- mark. The hurdle rate indicates the minimum performance that must be achieved in order to charge performance-related fees (Gregoriou & Duffy, 2006; Lhabitant, 2006). The high-water-mark requires that previous losses have to be off-set by new profits in order to apply the incentive fee; this mechanism shields investors from paying incentive fees although they are still recovering from previous losses (Lhabitant, 2006).[13]

[11] Usually between 1-3% (Eurekahedge, 2009c)
[12] Usually between 15-25% (Eurekahedge, 2009c)
[13] This mechanism can be illustrated by pointing to the economic crisis of 2007 - 2009: While stock markets soared during most of 2009 and investment banking boni were a vividly debated, many HFs did not distribute bonus payments to their employees. This is why they were just recovering from previously incurred losses.

In summarizing the characteristics of HFs as they are presented above, it can be stated that HFs are loosely regulated, and professionally managed investment vehicles that are only accessible to sophisticated investors. These vehicles are actively managed by partners who charge performance-based fees and seek absolute returns by employing flexible investment strategies.

While this definition provides a fairly accurate view on the majority of HFs, however, it does not really encompass all of the funds that are relevant to this study. The author will therefore introduce a much broader definition as provided by Eurekahedge[14] (2010a) according to which, a HF is "any absolute-return fund investing within the financial markets and/or applying non-traditional portfolio management techniques." This HF definition will hold throughout in the remainder of this study.

Up to this point, our discussions have centred mainly on HFs as an asset class. However, it must be pointed out that this sort of asset class is by no means homogeneous. In fact, the HF universe is highly heterogeneous. This is outlined in the next paragraph.

2.2.2 Overview of Today's Hedge Fund Industry

This paragraph provides an overview of the HF industry in terms of size, growth, fragmentation, investment geography, and performance. It must be pointed out that estimates of these figures vary because there are no official sources of data. Thus, academics and practitioners have to rely on information gathered by private database vendors (Gregoriou & Duffy, 2006). In order to ensure full data consistency, academics usually decide to base their research contributions on one single data set. This thesis takes the same approach and therefore, the descriptive analyses presented in the following paragraphs are largely based on Eurekahedge data.

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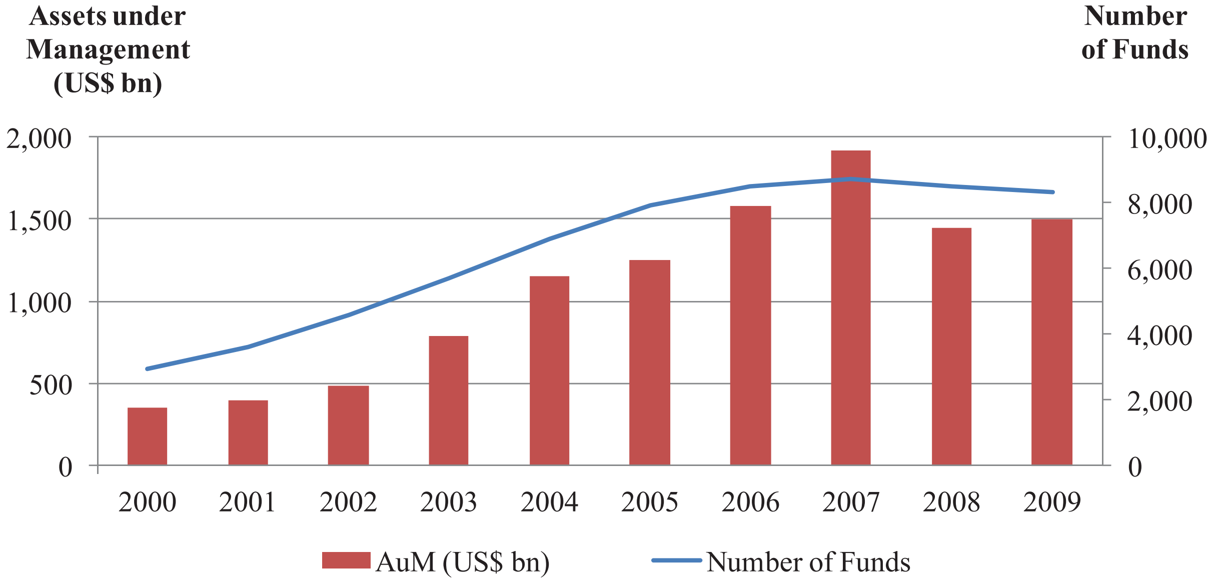
[14] Eurekahedge, based in Singapore, is a data vendor in the alternative investments space. It is now considered as one of the world's largest providers of HF data.

Hedge Fund Industry Size and Growth

The HF industry has shown remarkable growth in recent years with HF investments reaching US$1.9 trillion in 2007 (Eurekahedge, 2010b). This represents an increase of almost four hundred percent in assets under management (AuM) over a five-year period. As Figure 5 illustrates, the number of HFs has also increased considerably.

Figure 5: Development of the Global HF Industry



Source: Eurekahedge (2010b)

During the following ‘bear market’, however, HFs have failed to generate positive returns and experienced a considerable setback (Jawadi & Khanniche, 2012; Avramov et al., 2011). With the many HFs reporting losses, total HF AuM dropped below US$1.5 billion.[15] With the global economic recovery from 2009 on, however, the industry’s growth has rebounded.

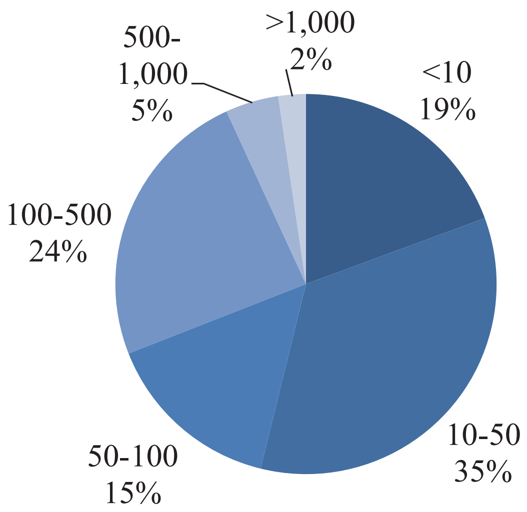
[15] The negative performance is believed to be mainly attributable to

- tumbling market prices: Most HFs are not (fully) hedged but have an overall long bias),
- a liquidity crisis increasing financing costs, and
- investors’ capital withdrawal: As many HFs operate in illiquid markets, a sudden and sizable withdrawal of funds can have a negative impact on asset prices in these markets, thus further deteriorating AuM.

Hedge Fund Size

In terms of size, there are huge disparities within the HF universe (Bali et al., 2011). As Figure 6 shows, 19% of HFs have less than US$10 million in AuM and another 35% have less than US$50 million AuM. At the other end of the spectrum, there are a few established funds that manage more than US$1 billion each.

Figure 6: Breakdown of HF Universe by Fund Size in US$ m (June 2009)[16]

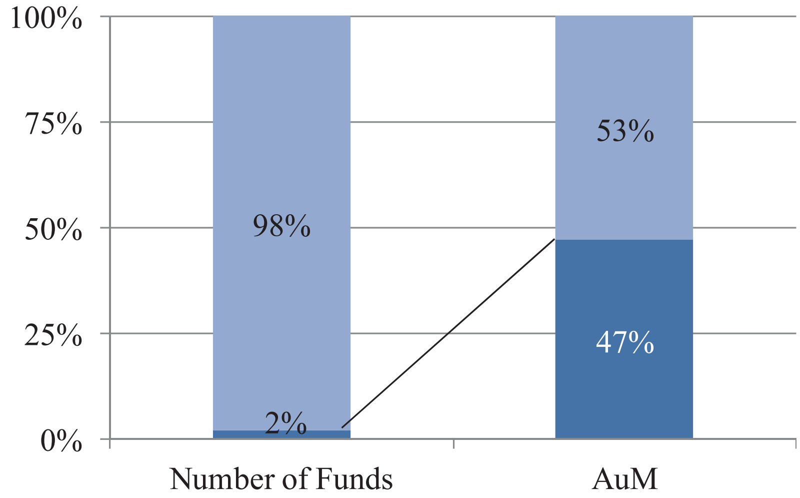


Source: Author's own illustration based on Eurekahedge (2009c)

These large players, that manage more than US$1 billion each, only make up for 2% of all HFs but control 47% of the total HF AuM (Figure 7). They tend to be better organized, have longer track records, use multiple managers, and rely on improved risk management systems; unsurprisingly, these funds are often quoted in the media, but they are not necessarily representative of the HF industry (Lhabitant, 2006).

[16] Breakdown of 3,609 HFs reporting AuM. This includes closed and non-flagship funds.

Figure 7: Concentration of HF AuM (June 2009)[17]



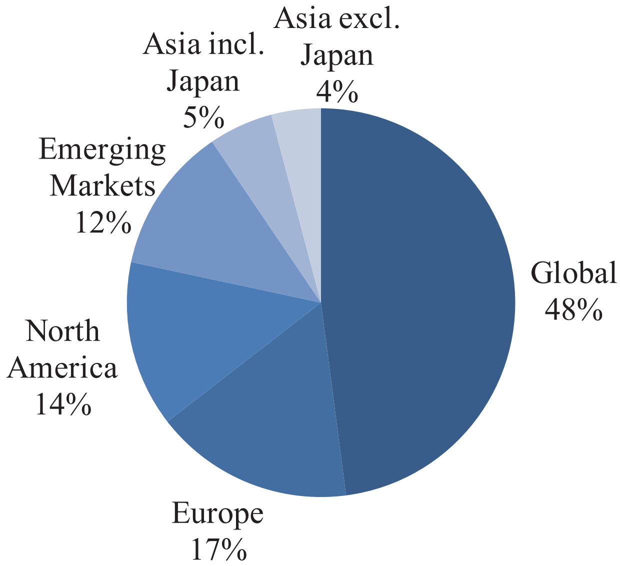
Source: Author's own illustration based on Eurekahedge (2009c)

Hedge Fund Offices and Investment Geographies

A geographical analysis of HFs is also instructive. Most HFs are headquartered in the USA (64%), followed by Europe (16%). Nevertheless, most HFs allocate their capital globally as illustrated by Figure 8: 48% of HF capital is invested under a worldwide mandate, 17% of HF investments are conducted with a purely European focus, followed by North American investments at 14%. While Europe has only recently surpassed North America, the focus is now turning towards Asia, where the growth of the emerging economies is increasingly attracting more HF attention (Song, 2010).

[17] Breakdown of 3,609 HFs reporting AuM. This includes closed and non-flagship funds.

Figure 8: Breakdown of HF AuM by Investment Geography (June 2009)[18]



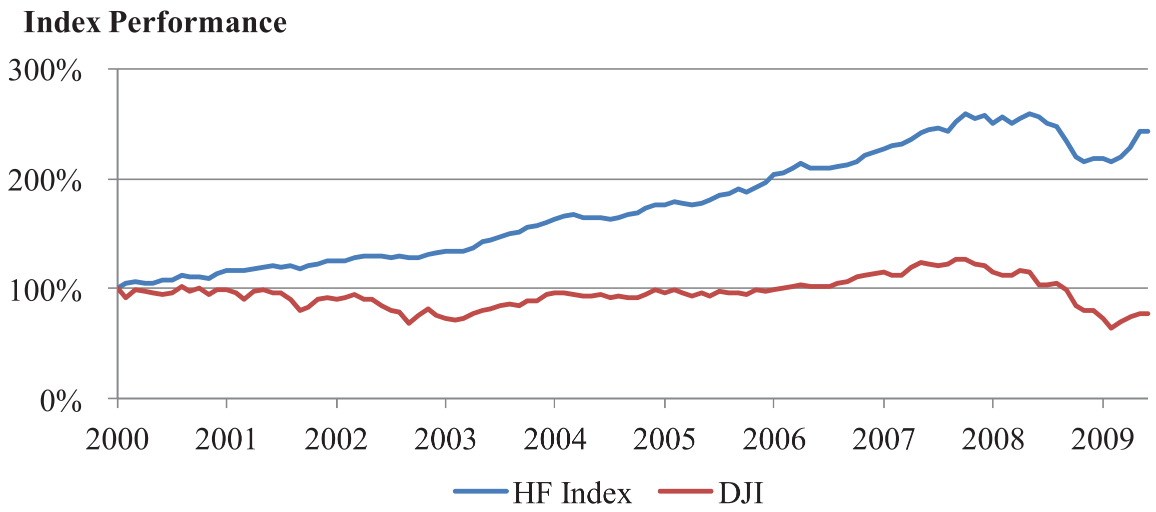
Source: Author's own illustration based on Eurekahedge (2009c)

Hedge Fund Performance

In the past years, HFs have shown a strong performance as compared to traditional asset classes. Figure 9 compares the performance of a comprehensive HF index to that of the Dow Jones Industrial Average Index (DJI) between January 2000 and June 2009. As the figure clearly illustrates, the HF index shows a noticeably higher performance during the observation period. At the same time, the standard deviation of its monthly returns (1.8%) is considerably lower than that of the DJI (4.5%). As it seems sensible to critically review this pronounced outperformance, the author uses the next paragraph to comment on this observation.

[18] Breakdown of 3,609 HFs reporting AuM. This includes closed and non-flagship funds. 'Emerging Markets' include Latin America, Eastern Europe and Russia, the Middle East and Africa.

Figure 9: HF Index vs. Dow Jones Industrial Average Index (June 2009)[19]



Source: Author's own illustration based on Eurekahedge (2009c) and Capital IQ (2009)

2.2.3 A Critical Review of Hedge Fund Investment

In order to provide the reader with an impartial analysis of HF investments, the findings outlined above have to be examined with care. While the HF returns described previously seem to be quite impressive, it must be pointed out that the underlying observation period is relatively short.

Moreover, it must be pointed out that the data presented here has been sourced from the Eurekahedge Global Hedge Fund Database. While HF databases provide researchers with quantitative information on a non-transparent and opaque industry, they nevertheless suffer from a number of data biases. In essence, these biases result in an over-estimation of returns and an under-estimation of risk (Lhabitant, 2004). Such biases are further examined in Part 3 of this dissertation.

Finally, it should also be mentioned that HF strategies are not scalable, which is why the number of promising investments in global markets is rather limited. Event-driven HFs, for instance, depend on the global M&A volume and the number

[19] Equally-weighted HF index based on Eurekahedge data. Includes closed and non-flagship funds. The shown returns are net of management and performance fees and calculated in the base currency of every HF. Both indices are subject to share splits and dividend payments.

of companies in or close to distress. With more capital flowing into the strategy, returns are inevitably eroded. Similarly, all absolute return strategies have limited capacities, as they are restricted by the availability of market opportunities, and the unchecked influx of funds will ultimately erode performance, due to diminishing returns to scale (W. Fung & Hsieh, 2008). Thus, it is improbable that the industry will maintain the high return levels previously shown.

2.2.4 Summary

As illustrated in the previous paragraphs, there is no generally-accepted definition of the term 'HF'. However, most of the funds that are widely labelled 'HFs' have a number of characteristics in common, such as active management, an unusual legal structure, limited transparency, a focus on sophisticated investors, the quest for absolute returns, flexible investment strategies, limited liquidity, managing partners, and performance-related fees. In the context of this study and in accordance with Eurekahedge (2010a), the author considers "any absolute-return fund investing within the financial markets and/or applying non-traditional portfolio management techniques" to be a HF.

The HF industry has grown significantly in recent years, but it has also experienced a considerable setback during the financial crisis of 2007-2009. In the course of the recent recuperation of the global economy, however, the industry's growth is on the rebound. The HF universe, in general terms, is quite heterogeneous. While the majority of HFs are relatively small and are focused on regional niche markets, there are others that manage assets that exceed US$1 billion and do operate globally.

While HFs seem to have exhibited high-return / low-risk profiles in recent years, such results have very likely been influenced positively by data biases. In the long term, however, high HF returns accompanied by low risk levels appear to be rather unsustainable due to limited market opportunities combined with the increasing capital influx into the industry.

Having now concluded the discussion on the HF industry, the following chapter provides a closer look at FoFs as one of the preferred routes for HF investment.

2.3 The Fund of Hedge Funds Industry

This chapter provides a brief but comprehensive introduction to FoFs. First, a definition of FoFs is presented (2.3.1), along with an explanation of the current state of the FoF industry (2.3.2). This is followed by a brief overview of FoF investment processes (2.3.3), after which, there is a short summary (2.3.4).

2.3.1 What is a Fund of Hedge Funds?

Unlike HFs, FoFs are fairly easy to characterize. They are basically investment vehicles that do not invest directly in bonds, shares or other forms of securities, but rather in HFs (Berenyi, 2006).[20] In recent years, FoFs have become increasingly popular among both private and institutional investors and are one of the preferred routes into HFs (Elkaim & Papageorgiou, 2006; Maslakovic, 2010). This is mainly because FoFs offer valuable benefits over direct investment in HFs, such as accessibility, risk diversification, and professional management. Lhabitant (2006) describes these features in detail:[21]

- A major advantage that FoFs have over direct HF investment is their accessibility. While HFs are usually accessible only for qualified investors, FoFs are available to all investors (Gregoriou & Duffy, 2006). Moreover, many HFs have high minimum investment requirements and impose lock-up periods (Eurekahedge, 2009c). FoFs, in contrast, usually have low minimum investment demands and offer greater liquidity (Eurekahedge, 2009b). Several FoFs are even exchange-traded, making FoF investments very uncomplicated (Eurekahedge, 2009b). As a consequence, FoFs are popular capital-collection points for investors with limited capital who seek HF exposure.

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[20] Consequently, FoFs and HFs both offer the same positive diversification benefits to a portfolio of traditional assets (Hagelin et al., 2006; Kooli, 2006; Lee et al., 2006).

[21] Several analogous descriptions of these features exist in academic and practical literature. The one below is sourced from Lhabitant (2006) except where quoted/annotated.

- Furthermore, while direct HF investments can result in non-liquid and defectively diversified portfolios (Brunel, 2006), FoFs provide effective diversification over a broad range of investment strategies. Therefore, they significantly reduce individual fund and manager risk (Fjelstad & Ross, 2006). Thus, they deliver more consistent returns than individual HF investments do (Amin & Kat, 2003; Duong, 2008; Kat, 2004).

- Finally, the task of selecting and monitoring the most promising HFs requires professional expertise. Moreover, it is very costly and time-consuming (Ang et al., 2008). FoFs, therefore, relieve their investors from this burden (Lhabitant, 2006).

When all of these factors are taken into consideration, it becomes quite evident why investors with limited capital, tight time constraints, and/or little expertise in the field, often chose FoFs as their preferred vehicle for HF investment (Lhabitant, 2006). Despite these many benefits, however, FoFs have several disadvantages, compared to a direct HF investment. Their main drawbacks are their second layer of fees, their lack of control, and their liquidity buffers. Lhabitant (2006) provides a detailed description of these features:[22]

- The main disadvantage of FoFs, from the investor's point of view, is certainly their second layer of fees (Black, 2006). Most FoFs charge management fees in the range of 1% annually on AuM plus performance-related fees in the range of 5-10% (Eurekahedge, 2009b). Considering that many HFs charge fees of 2% on AuM and 20% on performance (Eurekahedge, 2009c), this can amount to a total of 3% in annual fees, plus more than 25% in performance-fees.

- Another issue, from the investor's perspective, is the lack of control. Investors have no influence over the FoF's selection of HFs and their strategies (Jones, 2006). Furthermore, FoF managers themselves have little power over the actions of HF managers in their portfolios (Schmidt, 2002). Finally, investors have no

[22] Several analogous descriptions of these features exist in academic and practical literature. The one below is sourced from Lhabitant (2006) except where quoted/annotated.

control regarding whether FoF managers act with the appropriate diligence when choosing and monitoring their investments (Lhabitant, 2006).

- Finally, FoFs usually have much more flexible redemption policies than HFs do (Eurekahedge, 2009b). In other words, they offer greater liquidity than their underlying investments (Jones, 2006). In order to provide such liquidity, FoFs have liquidity buffers, which are characterized, naturally, by very low returns. As a direct consequence of this liquidity, FoF investors are paying management and performance fees on their entire investment without being fully invested in HFs at the same time (Lhabitant, 2006).

In summarizing these findings, therefore, FoFs may well be defined as investment vehicles that invest exclusively in HFs and which offer valuable benefits over a direct investment in HFs, such as their accessibility, their liquidity, their risk diversification, and their professional management. Such benefits, however, come at certain costs, which are a second layer of fees, a lack of control, and the need to have liquidity buffers.

After this brief introduction to FoFs, the current state of the FoF industry is outlined in the following paragraph.

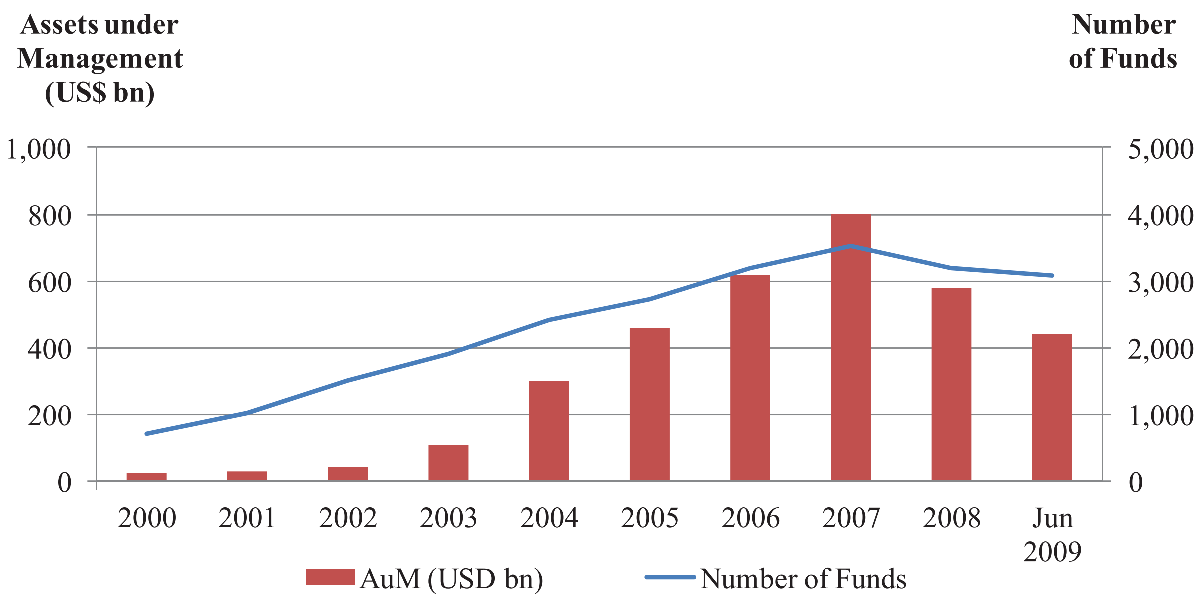
2.3.2 Overview of Today's Fund of Hedge Funds Industry

This paragraph provides an overview of the FoF industry in terms of size, growth, fragmentation, and investment geography. As in the case of HFs, these figures vary because there are no official sources of data and researchers have to rely on information gathered by private database vendors. The descriptive analyses presented in this paragraph are largely based on Eurekahedge data. This approach is in line with previous research and ensures data consistency throughout the dissertation.

Fund of Hedge Fund Industry Size and Growth

2008 and 2009 were certainly testing years for the FoF industry. At the end of 2009, there were an estimated 3,010 FoFs, managing US$440 billion, which represents a decrease of almost 50% since the previous peak (Eurekahedge, 2009c, 2010b). This decline was due mainly to the performance losses of the underlying HFs, as well as to widespread redemptions (Darolles & Vaissié, 2012; Eurekahedge, 2009c, 2010b). Indeed, the Madoff US$50 billion Ponzi-scheme fraud led to a dramatic increase in redemptions (Eurekahedge, 2008).[23] Figure 10 illustrates the development of the FoF industry since 2000.

Figure 10: Development of the Global FoF Industry[24]



Source: Eurekahedge (2009a)

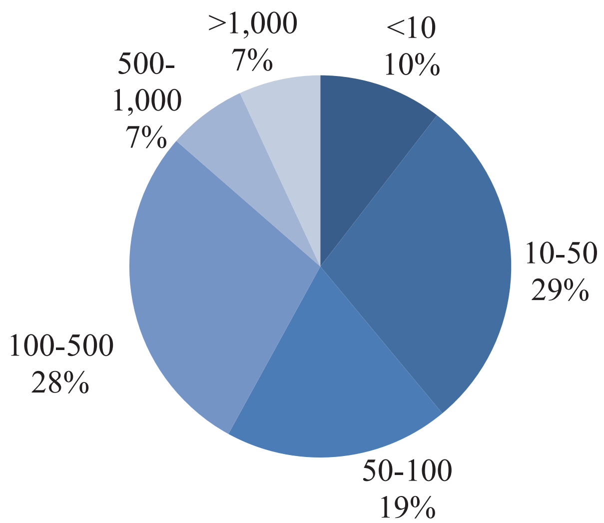
[23] When Bernard Madoff's Ponzi-scheme collapsed, in December 2008, several FoFs were severely hit. As a result, the collapse brought discredit to the entire FoF industry, as their risk management and due diligence had failed to protect their investors from severe losses (Lhabitant & Gregoriou, 2009; Martin, 2009; Stewart, 2008).

[24] Data as reported by Eurekahedge. Please note that not all FoFs publish their AuM. Thus, the sample populations of both lines differ slightly. In June 2009, for instance, there were 2,014 FoFs reporting returns, but only 1,766 FoFs reporting AuM. This includes closed and non-flagship funds.

Fund of Hedge Fund Size

In terms of size, there are considerable disparities within the FoF universe. As Figure 11 illustrates, 10% of FoFs have less than US$100 million in AuM while another 29% have less than US$50 million in AuM. At the other end of the spectrum, there are several very well established funds that manage more than US$1 billion each.[25]

Figure 11: Breakdown of FoF Universe by Fund Size in US$ m (June 2009)[26]



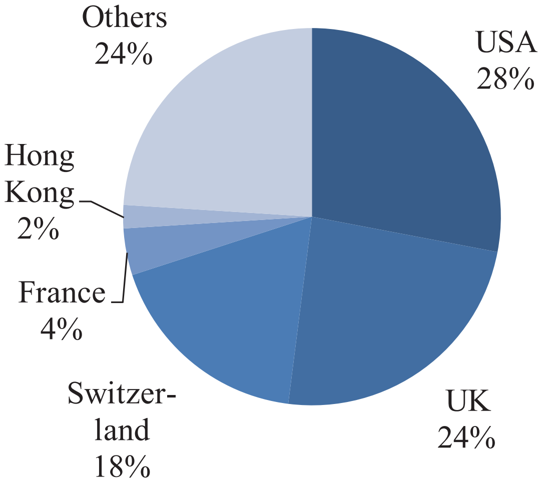
Source: Author's own illustration based on Eurekahedge (2009b)

Fund of Hedge Fund Offices and Investment Geographies

Most FoFs are headquartered in the USA and the UK. Switzerland comes in third with 18% of the global FoF headquarters (Figure 12). In contrast to HFs, 89% of all FoFs are provided with a worldwide investment mandate; thus enabling them to allocate their funds on a global scale with relative ease.

[25] It becomes obvious that, as one would expect, FoFs are on average larger than HFs.
[26] Breakdown of 1,766 FoFs reporting AuM. This includes closed and non-flagship funds.

Figure 12: FoF Assets by Manager Location (2008)



Source: Maslakovic (2009)

Having outlined the heterogeneity of the FoF universe, in terms of fund size, and its homogeneity, in terms of investment geography, it seems appropriate to present an overview of the FoF investment process, which now follows in the next paragraph.

2.3.3 Fund of Hedge Fund Investment Process

There are several descriptions of FoF investment processes in the academic and the practice literature, which are by and large consistent. The following description represents such a standard methodology and is based on a depiction by Lhabitant (2006), except where quoted/annotated:

Investment selection is usually decided on by consulting a HF database. Such databases provide information on a great variety of Individual HFs, such as 'investment strategy', 'AuM', past performance on a monthly basis, etc.

As a first step, this database information is narrowed-down to a selection of HFs that fulfil certain criteria, such as a minimally-acceptable track-record length and a minimally-acceptable size. Other requirements might include specific redemption polices, the use of leveraging, exposure to certain markets, etc. At the end of this first process, the FoF managers are left with a ‘long list’ of potentially investable HFs (Lhabitant, 2006).

The second step usually entails a quantitative analysis. Typically, ratios, such as risk-adjusted performance measures (RAPMs) are calculated to compare a HF’s past absolute and relative performances, as well as its risk-adjusted performance against other HFs with a similar strategy and profile.[27] Such a quantitative analysis is usually supplemented by a qualitative approach. A qualitative analysis usually focuses on marketing presentations, private placement memoranda and discussions with the respective HF managers (Lhabitant, 2006; Koh, 2009).

As a third step, FoF managers usually conduct a ‘due diligence’ analysis, which is a more thorough qualitative analysis that includes site-visits and personal meetings with the HF managers, in order to obtain first-hand, non-public information about their respective funds. The key aspects of a ‘due diligence’ analysis are, typically, the investment strategy, the organization of the HF, the management team, the infrastructure, and the HF decision-making process. These characteristics are usually evaluated by a scorecard system that indicates comparability among different HFs. The final output of this methodology is a ‘short list’ of investable HFs (Lhabitant, 2006).

The fund allocation process within FoFs is normally non-transparent (Gregoriou & Duffy, 2006). It is assumed that both qualitative and quantitative methodologies are applied. Qualitative approaches generally start off from a naive diversification. The FoF managers then adjust the weights of the investable HFs according to their own forecasts on future economic and market conditions. Quantitative approaches usually allocate weights based on mathematical optimizers (Lhabitant, 2006).

[27] As this process relies, essentially, on historical time series, this sort of analysis is often criticized as backward-looking (Moerth, 2007).

2.3.4 Summary

As illustrated in the previous paragraphs, FoFs are defined as investment vehicles that focus on HFs, and which offer valuable benefits over a direct investment in HFs, such as accessibility, liquidity, risk diversification, and professional management. These benefits, however, come at certain costs, such as a second layer of fees, a lack of control, and low returns on the required liquidity buffers.

In general, the FoF universe is not as diverse as the HF universe is. Although there are considerable disparities in size, most FoFs are multi-strategy funds and operate globally, with the USA, the UK, and Switzerland being the preferred locations for FoF headquarters. 2008 and 2009 were very difficult years for the FoF industry, mainly due to the performance losses of the underlying HFs, as well as widespread redemptions.

A typical FoF investment process consists of investment selection and fund allocation. Investment selection is based mainly on qualitative analyses and quantitative criteria like historical performance. Fund allocation is then decided on through a qualitative amendment of a naive diversification approach or by employing an optimization tool.

Following this short overview of FoFs, the following chapter takes a closer look at the special situation of family offices as HF and FoF investors.

2.4 A Suitable Investment Approach for Family Offices

As discussed in the previous chapters, HFs have become a popular investment vehicle and are common means of portfolio diversification. As the risk on an individual HF level tends to be high, however, HF investment is usually conducted in terms of exposure to a well-diversified HF portfolio (Amin & Kat, 2003). FoFs thus seem to be the natural choice for HF investment because they offer valuable benefits over a direct investment in HFs. These are accessibility, liquidity, and professional management. These advantages come at a certain cost, and FoFs charge their investors with a second layer of fees which negatively impacts their performance.[28]

In this context, the special situation of family offices must be pointed out. Family offices are usually potent investors with significant assets under management and a long-term investment horizon. Furthermore, they employ several investment professionals who can provide oversight of potential direct HF investments. Thus, the benefits that FoFs provide compared to a direct investment in HFs, namely accessibility, liquidity, and professional management, are likely to be less advantageous for family offices than for other investors with lesser financial and human resources and shorter investment horizons. In other words, family offices are less likely to appreciate the particular advantages of FoFs than other investors and a direct investment in HFs seems to be preferable from their point of view.

This dissertation aspires to make a worthwhile contribution to the existing academic literature in the field of portfolio management within an ever-increasing HF universe. To the author's best knowledge, there is not a single academic study that is 1:1 applicable to the reality of family office practitioners seeking HF investment. While there are several studies on HF portfolio management, they usually fail to consider several major practical limitations and restrictions.[29] In addition to its contribution to academic literature, this dissertation also aims to enhance the investment management processes of family offices by providing an easy-to-implement and inexpensive-to-operate approach to direct HF investment.

Against such a background, therefore, it now seems appropriate to present a brief review of the fundamental academic literature that is most relevant to this dissertation, which is what the following section of this thesis focuses on.

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[28] See for instance Beckers et al. (2007) and Goetzmann et al. (2004).
[29] A detailed description of the research gap is provided in chapter 3.5 of this dissertation.

3 Literature Review

The academic literature on HFs and portfolio selection is extensive and diverse. This third part of the thesis, therefore, endeavours to provide an overview of the most relevant research studies done in the field.

Specifically, the following chapter (3.1) deals with the theoretical foundations of portfolio selection as laid by Markowitz and Tobin. After that, the theoretical foundations of risk-adjusted performance measurement are revealed (3.2). Then, drawing on these fundamentals, the author provides an overview of recent quantitative approaches to HF selection in academic literature (3.3). Subsequently, several streams of HF research, that are central to this dissertation, are discussed in greater detail (3.4). Finally, the author outlines the research gap perceived and his own research aspirations (3.5).

3.1 Theoretical Foundations of Portfolio Selection

This chapter provides an introduction to portfolio selection. In this context, the author presents the reader with the works of Harry Markowitz (3.1.1) and James Tobin (3.1.2). After that, the author discusses market efficiency in the HF space (3.1.3). Based on these considerations, portfolio selection for HFs is then examined (3.1.4).

3.1.1 Markowitz' Efficient Frontier

Harry Markowitz is widely considered as the father of classical portfolio theory. His major merit lies in the development of a mathematical framework to determine the optimal combination of assets in a portfolio.

Markowitz' approach (1952, 1959) is based on a single period framework.[30] While the return on a risky asset (i) is uncertain, it can still be considered as a random

[30] The considered investment horizon should not be much longer than one year (Spremann, 2003).

variable and be characterized by a probability distribution.[31] The parameters of the probability distribution are the expected value of return (μ_i) and the standard deviation of return (σ_i).[32] Thus, any asset can be described by only two parameters: μ_i and σ_i.[33]

Markowitz argues that the risk of a portfolio of two or more assets does not only depend on the standard deviations of the constituting assets σ_i and σ_j, but also on the covariance of these assets (σ_{ij}). He shows that the risk of a portfolio (σ_P) can be smaller than the risk of the least risky single asset in the portfolio (σ_i). In other words, a combination of assets in a portfolio does not lead to an addition of risks, but rather to a diversification and thus reduction of risk. Such a risk reduction effect can always be observed if the risks of the single assets are not perfectly correlated. Therefore, any investment opportunity must not be considered on its own but in context of the overall portfolio.

Figure 13 illustrates Markowitz' ideas: it shows a risk / return space. The black squares symbolize different assets, each of which is characterized by a particular combination of μ and σ. The inner region in this space, bordered by a hyperbola, includes all portfolios that can theoretically be constructed through a combination of these assets in a portfolio. Due to its characteristic shape, the hyperbola is sometimes called 'Markowitz Bullet'.

Markowitz defines those portfolios as 'efficient' that are not dominated by any other portfolio. A portfolio is dominated if it is possible to construct another portfolio with a higher expected return (R_P) and the same or an even lower standard deviation (σ_P). Therefore, one can say that efficient portfolios reduce risk to the highest extent possible through diversification. All efficient portfolios are located on the upper arm of the hyperbola, the so-called 'efficient frontier'. The left-most point of the

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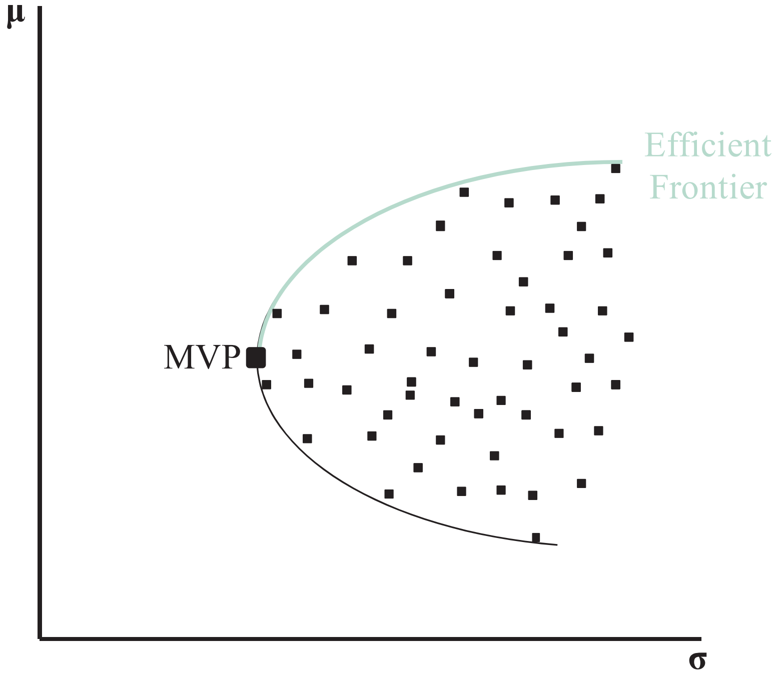
31 It is important to note, that 'return' includes any capital gain during the observation period such as price gains, interest payments, and dividends.

32 In other words, Markowitz defines risk as the deviation of return from the expected value of return.

33 In this context, it must be noted that Markowitz' investment approach is indented for portfolios of stocks and bonds, but not options. As a consequence of this limitation, returns can be considered as normally distributed and it is possible to condense the probability distribution to the parameters risk and return (Spremann, 2003, p. 220).

efficient frontier represents the minimum variance portfolio, labelled 'MVP'. This is the combination of assets that shows the lowest standard deviation.

Figure 13: The 'Markowitz Bullet' and the Efficient Frontier



Source: Author's own illustration based on Spremann (2003)

The efficient frontier can be determined formally as shown by Spremann (2003):[34] First, the number of assets (n) in the portfolio is determined. After that, the portfolio risk (σ_P) is minimized for any given expected portfolio return (R_P).

$$R_P = \sum_{i=1}^{n} w_i \mu_i$$

$$\sigma_P^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{ij} \rightarrow \text{min!}$$

[34] Several analogous descriptions exist in academic and practical literature. The one below is sourced from Spremann (2003).

Moreover, if selling assets short is prohibited, the following conditions must hold with regards to the weights (w_i) of the assets within the portfolio.

$$\sum_{i=1}^{n} w_i = 1$$

$$w_i \geq 0 \quad (i = 1, ..., n)$$

Based on these formulas, a multitude of efficient portfolios can be determined through the variation of R_P. All of these are located on the efficient frontier (Spremann, 2003).

While Markowitz' efficient portfolios lay the foundation of classical portfolio theory, they are hardly used today for the purpose of portfolio optimization. This is because the choice of asset weights under Markowitz' approach finally depends on investor preferences: Every investor will choose to invest in another portfolio on the efficient frontier according to her / his individual risk aversion. Thus, the Markowitz approach does not yield one single allocation that can be universally applied to all investors. Tobin offered an elegant solution to this problem which is discussed in the next paragraph.

3.1.2 Tobin's Separation Theorem

Tobin (1958) amended Markowitz' portfolio theory through the introduction a risk-free asset. Tobin's amendment allows investors not only to invest their capital in risky assets, but also in a risk-free asset that is not subject to price fluctuations. This risk-free asset pays interest at the risk-free rate (r_f) and can be borrowed or lent.

Tobin's approach is, like Markowitz', based on a single period framework. At the beginning of the period, the investor decides to invest a specific part (w) of his capital in a portfolio of risky assets and the rest (1-w) in the risk-free asset. Under these assumptions, the expected return (R) and risk (σ) of the overall portfolio is given by

$$R(w) = r_f + w \cdot (\mu_P - r_f)$$

$$\sigma(w) = w \cdot \sigma_P$$

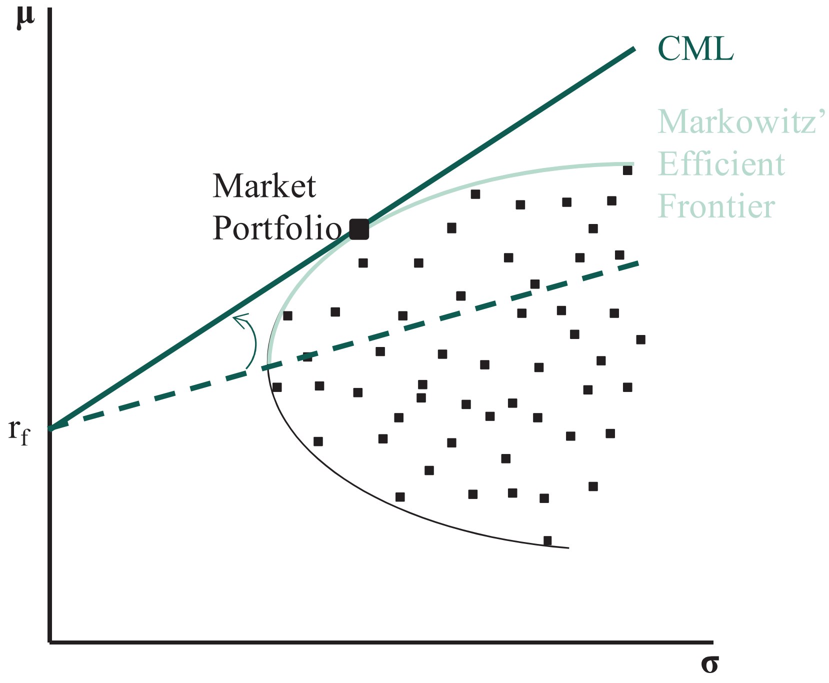
In the risk / expected return space, all returns are located on a straight line with the equation

$$R(w) = r_f + (\mu_P - r_f) / \sigma_P \cdot \sigma(w)$$

The points $(0; r_f)$ and $(\sigma_P; \mu_P)$ are located on this line. The slope of the line depends on the values of r_f, σ_P, and μ_P. While it is possible to construct many different lines that meet these requirements, investors take most interest in the line with the steepest slope. This is due to the fact that a higher slope represents a higher return at the same level of risk; it can be shown that the line with the steepest slope is a tangency to Markowitz' efficient frontier (Spremann, 2003). This tangency is called 'capital market line' (CML). The portfolio of risky assets that is located at the osculation point of the efficient frontier and the CML is called 'market portfolio'. This is illustrated by Figure 14.

According to Tobin (1958), all portfolios that are not located on the CML are dominated since they offer an inferior trade-off between expected return and risk. This is even true for the portfolios that are located on Markowitz' efficient frontier. Thus, they cannot be considered efficient anymore if the possibility of investing in a risk-free asset is given. On the other hand, none of the portfolios on the CML is dominated; thus Tobin considers all of these portfolios as efficient. These efficient portfolios are created by investing a part of the investor's capital in the risk-free asset and the other part in the market portfolio.

Figure 14: Determination of the Market Portfolio[35]



Source: Author's own illustration based on Spremann (2003)

The establishment of the market portfolio requires the knowledge of the risk-free rate as well as assumptions regarding the distributional characteristics of all assets and their covariances. Thus, the market portfolio fundamentally depends on every investor's assumptions regarding these factors; on the other hand, the market portfolio is independent from the investor's risk aversion (Spremann, 2003).

It can be argued that all investors have access to the same information, such as company reports, thus, they form homogeneous expectations (Spremann, 2003). If this is the case, the market portfolio is the same for all investors regardless of their preferences. Thus, an optimal portfolio can be created without any assumptions on the investor's risk aversion required.

[35] The dashed line represents an alternative line satisfying the equation $R(w) = r_f + (\mu_P - r_f) / \sigma_P \cdot \sigma(w)$. However, this line is dominated by the CML which has a steeper slope. All efficient portfolios are located on the CML.

Tobin's major merit is that he separates the task of portfolio selection into two different steps. The first step is the calculation of the market portfolio. This requires the determination of the return distribution parameters as well as the risk-free interest rate. The second step is the determination of the optimum risk exposure for every investor according to her / his risk aversion. This separation of portfolio selection into two different steps is commonly called Tobin separation.

All investors construct their portfolios as follows: They invest one part of their capital into the risk-free asset, the other part is invested in the market portfolio. The weighing of both parts depends on investor preferences. It is important to note that this approach allows for a passive investment style: If an investor holds a risk-free asset and the market portfolio and asset prices change, then the investor holds the new market portfolio (Spremann, 2003).

3.1.3 Market Efficiency in a Hedge Fund Context

Portfolio selection fundamentally relies on the existence of market efficiency. Fama (1970, p. 383) describes markets as efficient "in which prices always fully reflect available information." Fama differentiates between a strong, a semi-strong, and a weak form of market efficiency:

- Strong market efficiency suggests that market prices completely reflect public information (annual reports, company announcements etc.) as well as private information that is exclusively available to some investors.
- Semi-strong market efficiency suggests that market prices completely reflect public but not private information.
- Weak market efficiency implies that market prices completely reflect past price histories.

Strong market efficiency implies that investors process new information instantaneously and correctly. Thus, any new information is instantly reflected in market prices. As a result, active management does not deliver any advantages compared to a buy-and-hold strategy, and investors simply hold the market portfolio.

Semi-strong market efficiency, on the other hand, suggests that market prices do not reflect private information. As a result, insiders have an advantage over other investors and are able to 'beat' the market. In such an environment, competent active management is expected to deliver superior results as compared to a buy-and-hold strategy.

The HF universe is "notorious for its opacity and its subsequently highly asymmetric and incomplete information flow" (Laube et al., 2011, p. 77). HFs' unusual legal structures do not require them to disclose much information (Maxam et al., 2006; Aggarwal & Jorion, 2012) and HF investors, such as FoFs, usually conduct a 'due diligence' analysis that includes site-visits and personal meetings with the HF managers in order to obtain first-hand, non-public information about their respective HFs (Koh, 2009; Lhabitant, 2006). In fact, "information access and control presents one of the key skills for successful asset management in the HF industry" (Laube et al., 2011, p. 77).

Bearing these peculiarities of the HF market in mind, it becomes clear that there is significant private information that is not available to all investors and not reflected in market prices. As a consequence, the HF market must be considered as semi-strongly efficient. In such a market, competent active management is expected to deliver superior results compared to a buy-and-hold strategy. As expected, the overwhelming majority of HF investments are actively managed and passive products like HF ETFs are still of marginal importance.

3.1.4 Portfolio Selection in a Hedge Fund Context

Active management in the HF space can take different forms, and the corresponding portfolio selection can be conducted via optimizers and heuristics. Optimizers manipulate the weightings of a HF basket in order to establish the best possible ratio of risk and return. Heuristics, on the other hand, are quantitative and qualitative procedures that go a long way in reaching a satisfactory albeit not optimal solution.

Despite the theoretical advantages of having an optimised portfolio, the employment of optimizers within the HF space has been subjected to some pertinent criticism. Nawrocki (2000), for instance, argues that the use of portfolio-optimization tools causes a ‘butterfly effect’, suggesting that a relatively minor change in input factors might well lead to significant – and possibly unfavourable – changes in a portfolio’s set-up and, consequently, in its returns. For this very reason, Nawrocki promotes the use of investment heuristics, which, although they might not produce optimal allocations, can certainly provide acceptable results (Nawrocki, 2000).

The potentially devastating consequences of a ‘butterfly effect’ in the HF space are well illustrated in Fang et al. (2008), whose findings are that portfolios that have been formed from a heuristic approach, deliver both, superior raw returns and superior risk-adjusted returns, as compared to portfolios based on optimizers. They ascribe this inferiority of optimizers, by and large, to the ‘butterfly effect’.

While the portfolio selection process in the practice of HF investors is generally not transparent, it is assumed that HF portfolio selection is normally achieved through the employment of heuristics. These heuristics usually entail a quantitative analysis that rests upon risk-adjusted performance measurement. As risk-adjusted performance measurement is at heart of this thesis, the author revisits its theoretical foundations in the next chapter (3.2).

3.2 Theoretical Foundations of Risk-Adjusted Performance Measurement

This chapter provides a brief introduction to risk-adjusted performance measurement. In this context, the Sharpe Ratio is portrayed (3.2.1) and its limitations in the HF space are discussed (3.2.2). Against this background, the author points out the reasons that have led to the emergence of new measures of risk and return in a HF context (3.2.3).

3.2.1 The Sharpe Ratio

William F. Sharpe is widely regarded as one of the fathers of risk-adjusted performance analysis; his work is fundamentally based on Tobin's research. Tobin (1958) states that efficient portfolios are located on the CML. The excess return of these portfolios is proportional to the standard deviation.[36] Thus, an investor who aims to invest her / his capital in just one single portfolio of risky assets plus borrowing or lending at the risk-free rate should select the portfolio "for which the ratio of expected excess return to standard deviation is the highest" (Sharpe, 1998, p. 24). This ratio is named Sharpe Ratio and was introduced by Sharpe (1966).

$$SharpeRatio = (\mu_i - r_f)/\sigma_i$$

i:	Specific portfolio on the CML labelled 'i'
μ_i	expected return of portfolio 'i'
r_f	risk-free interest rate
σ_i	standard deviation of portfolio 'i'

3.2.2 The Sharpe Ratio in a Hedge Fund Context

The Sharpe Ratio is often used as a measure of HF performance (Pedersen & Rudholm-Alfvin, 2003). Thereby, μ_i is usually replaced by an individual HF's historic return and σ_i by the individual HF's historic standard deviation. In such a setting, any investor who aims to hold just one single investment will select the HF with the highest Sharpe Ratio over its peers because it appears to offer the best trade-off between risk and return.[37]

Despite its popularity among practitioners (Pedersen & Rudholm-Alfvin, 2003), such a usage of the Sharpe Ratio for the selection of HFs has been vividly criticized in academic literature.[38] This is mainly due to the fact that the Sharpe Ratio is based

[36] Excess return is defined as expected return minus the risk free rate.

[37] "The use of historic results involves an implicit assumption that the statistics derived from past performance have at least some predictive content for future performance" (Sharpe, 1998, p. 21).

[38] See for instance Brooks and Kat (2002), Lo (2002), and Sharma (2004).

on classical portfolio theory. Thus, it is theoretically dependent on the assumption of normally-distributed returns. In particular, it depends on either or both of the following conditions to be met (Pedersen & Rudholm-Alfvin, 2003):

- Portfolio returns can be characterised completely by the two first moments of the return distribution
- Investors only consider the two first moments of the return distribution

Critics argue that these assumptions do not hold true for the reality of HF investing. This is because HF returns are not normally-distributed and investors tend to strongly dislike negative returns. Both arguments are discussed below.

HFs typically have investment mandates that allow for the use of leverage, short selling, derivatives, and investment in highly illiquid securities (Dor et al., 2006). As a consequence of such techniques, HF returns display performance characteristics that are very different from traditional asset classes (Viebig, 2012; Lambert, 2012; Abdou & Nasereddin, 2011). It has been shown that most HFs' returns do not follow a normal distribution, but show a negative skewness and positive kurtosis as well as positive serial correlation (Abdou & Nasereddin, 2011; Brooks & Kat, 2002; Ding & Shawky, 2007; Lucas & Siegmann, 2008; Mahdavi, 2004).[39] Thus, the Sharpe Ratio seems inadequate to analyze HFs as it is based on the assumption of standard normally-distributed returns.

Moreover, the Sharpe Ratio does not account for typical investor preferences. Several studies indicate that investors strongly dislike negative returns and "would even prefer to partly sacrifice positive returns in order to avoid negative ones; this asymmetric behaviour is not captured by the Sharpe Ratio" (Bacmann & Scholz, 2003, p. 1).[40] Considering both, the distributional patterns of HF returns and investor behaviour, the Sharpe Ratio seems inadequate to analyze HFs.

[39] In other words, many HFs' follow non-symmetrical return distributions with significant tail risks (Abdou & Nasereddin, 2011). This is especially true for HF strategies involving arbitrage or distressed securities (Brooks & Kat, 2002).

[40] Pedersen and Rudholm-Alfvin (2003, p. 156) argue that, "for instance, pension and asset fund managers are typically judged relative to a benchmark and punished more severely when failing to meet target returns (e.g. no bonus, loss of reputation and funds, or even dismissal) than they are rewarded when they beat targets (e.g. proportional bonus)." According to them, this

3.2.3 Alternative Measures of Risk and Return in a Hedge Fund Context

The considerations above have triggered the development of a variety of alternative risk-adjusted performance measures (RAPMs) that account for asymmetrical returns and investor preferences. These RAPMs describe the risk / return profiles of individual HFs and enable investors to judge whether a particular HF has shown a good risk / return relationship compared to its peers in the past. Many of these new RAPMs are based on the Sharpe Ratio and replace the standard deviation in the denominator with a term that takes non-normality of return distributions into account.[41] Current academic discussions on HF performance concentrate on several different RAPMs, but, so far, no single indicator has been found to dominate over the others. Based on such alternative RAPMs, several quantitative investment approaches have been proposed in academic literature. The next chapter (3.3) provides an overview of these approaches.

3.3 Quantitative Approaches to Hedge Fund Selection

In this dissertation, the author strives to make a contribution to the academic literature in the field of portfolio management within a broad universe of HFs, a subject that has been recurrently discussed in academic literature. Several studies have examined the problem of how to identify the best HFs, the 'future winners' and avoid the 'future losers', by using strictly quantitative means. During the last couple of years, several different approaches have been discussed.

Gregoriou and Rouah (2001), for instance, examined a rudimentary HF selection approach. Their strategy involved yearly investment in that particular HF that had delivered the highest returns in the previous year. They discovered that this simple trading strategy was not able to outperform the market.

De Souza and Gokcan (2004) took a different approach. They constructed several portfolios of HF indices based on conditional value at risk (CVaR), an alternative

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incentive system leads to "loss aversion rather than applied mean-variance optimisation" (Pedersen & Rudholm-Alfvin, 2003, p. 156).

[41] The relevant academic research on RAPMs is portrayed in close detail at a later stage in this thesis (paragraph 3.4.2.2.2)

risk measure, and compared them to reference portfolios that were established by a mean-variance optimization. They found that the return distributions of most HF strategy indices did not follow a standard normal distribution. Instead, they displayed significantly negative skewness and unstable correlation patterns. De Souza and Gokcan concluded that portfolio construction based on CVaR was superior to a mean-variance approach as it considered the special statistical characteristics of HF return distributions.

A further interesting approach was made by Alexander and Dimitriu (2005). In their study, HFs were selected according to their abnormal returns, Alpha. In a second step, the portfolio weights were determined based on a constrained minimum variance optimizer. Alexander and Dimitriu showed that these portfolios performed much better than equally weighted portfolios of all HFs in their database or minimum variance portfolios of randomly selected HFs.

Jöhri and Leippold (2006) proposed a strictly quantitative approach based on a broad range of alternative RAPMs. In their model, capital was only invested in those HFs that had shown superior risk-adjusted performance in the past. They found that basing fund allocation on RAPMs, instead of purely return based measures, led to more favourable results in terms of portfolio statistics and decreased portfolio turnover. In a next step, they proposed an equally-weighted 'Combined Indicator' of different RAPMs. They found that portfolios constructed on the basis of such an indicator exhibited very attractive risk-return profiles such as a high Sharpe Ratio and low downside risk measures.

In a further study Gregoriou et al. (2007) investigated a similar HF investment approach. They constructed equal-weights HF portfolios by selecting the HFs with the highest Alphas, Information Ratios, and Sharpe Ratios. The performance of the constructed portfolios was compared to that of real-life FoFs. Gregoriou et al. found that their portfolios greatly outperformed the best FoFs on the basis of Alpha, the Sharpe Ratio, and the Information Ratio. They ascribed this result to the second layer of fees charged by FoFs. They concluded that the extra fees paid to FoFs managers were largely unmerited as it was possible to create portfolios of HFs that were superior to the average FoF by using simple portfolio construction techniques and readily available information.

Fang et al. (2008) developed a heuristic approach to HF investment based on semivariance, an alternative measure for downside risk. They discovered that unlike traditional investment vehicles, HFs seemed to follow return distributions with significant non-normal skewness and kurtosis. Therefore, they judged that mean-variance optimization was not appropriate in the HF space. A further observation was that the utilization of portfolio optimizers in the HF space caused a 'butterfly effect': Small changes in inputs, especially mean returns, caused large changes in the optimal asset weights. They judged that this phenomenon, coupled with the illiquidity of HFs, made optimizers a poor tool in the HF space. Accordingly, they showed that their newly developed heuristic approach was able to construct portfolios with higher returns, lower risk, and more diversification compared to portfolios constructed on the basis of mean-variance and mean-semivariance optimizers.

The studies above illustrate that it is possible to construct excellent portfolios of HFs using simple construction techniques and readily available information. This dissertation strives to develop a practically-relevant HF investment approach that is strictly quantitative, fully transparent and based on existing academic literature. Therefore, it seems sensible to closely review the different streams of research that are central to this endeavour. This includes academic works on data preparation, investment selection, fund allocation, performance assessment, and performance persistence. The author examines the key literature in this field in the next chapter (3.4).

3.4 Overview of Relevant Streams of Research

In recent years, manifold aspects of HF and FoF investment have been covered by academic research. It therefore seems imperative to limit the scope of the literature examined to those areas that are central to this dissertation, namely *data preparation, investment selection, fund allocation, performance assessment, and performance persistence*. Each of these subjects is briefly described below. For the reason of clarity, these topics are discussed in the same order as outlined in the methodological overview provided by Figure 1.[42]

Data preparation (3.4.1): All major HF databases are affected by a number of biases. In essence, such biases result in an overestimation of returns and an underestimation of risk (Lhabitant, 2004). As any quantitative investment heuristic is necessarily based on, and tested against, one of these databases, it seems natural to assume that it will unavoidably be affected by such biases. An understanding of these biases is, therefore, a pre-requisite.[43]

Investment selection (3.4.2): Several studies have investigated the correlations between certain HF features such as HF size, HF age, and HF returns.[44] The significance of these studies is straight forward: If any characteristics have been shown to be correlated with an above-average performance, this could be adequately captured in an investment heuristic.[45] Thus, it is imperative to consider the literature on this matter.[46]

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42 Digits in brackets point to the respective chapters.

43 In this context, the author presents the key research in the field. This includes works by Malkiel (1995), Brown et al. (1999), Liang (2000), W. Fung and Hsieh (2000), Amin and Kat (2003), Kouwenberg (2003), Ibbotson et al. (2011), and Grecu et al. (2007), and Ibbotson et al. (2011).

44 HF size is usually measured in AuM. HF age is normally defined as time since incorporation and measured as the length of track record.

45 If, for instance, smaller HFs perform better than larger ones, an investment heuristic can exploit this fact by restricting the investible HF universe to small funds.

46 This includes works by Edwards and Caglayan’s (2001), Howell (2001), Brown et al. (2001), H. Fung et al. (2002), Amenc and Martellini (2003), Gregoriou and Rouah (2003), Kazemi and Schneeweis (2003), Hedges (2003), Herzberg and Mozes (2003), Harri and Brorsen (2004), Getmansky (2004), Ammann and Moerth (2005), Moerth (2007), and Boyson (2008, 2010), Lahiri et al. (2011), Mozes and Orchard (2012).

While HF size and age play an important role in the investment selection process, academics and practitioners also advocate the use of RAPMs. Several RAPMs are debated in the current academic discussion. However, not a single indicator has been shown to dominate the others. It, therefore, seems worthwhile to take a closer look at the most prominent RAPMs.[47]

Fund allocation (3.4.3): This thesis takes a clear-cut equal-weights approach to the problem of fund allocation. Against this background, the most relevant literature is pointed out.[48]

Performance assessment (3.4.4): The dissertation at hand relies on a straightforward performance assessment methodology: Portfolios generated by the new approach are benchmarked against equally-weighted HF and FoF indices. This is a common procedure in academic research.[49]

Performance persistence (3.4.5): Any investment heuristic based on past performance can only succeed if HF returns display a sufficient level of performance persistence. Thus, revisiting this field of literature is a further pre-requisite for this dissertation.[50]

These areas of the literature are discussed in the next paragraphs. To illustrate the significance that previous research has for this thesis, the following paragraphs are divided into two sections: The first one, entitled 'Academic Literature', summarizes

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[47] In this context, the benchmark research on RAPMs is presented. This includes works by Sortino and van der Meer (1991), Young (1991), Burke (1994), Kestner (1996), Sortino, van der Meer, and Plantinga (1999), Dowd (2000), Koh, Lee, and Fai (2002), Shadwick and Keating (2002), Lo (2002), Gueyie and Gregoriou (2003), Brooks and Kat (2003), Kaplan and Knowles (2004), Agarwal and Naik (2004), Sharma (2004), Eling and Schuhmacher (2007), Ingersoll, Spiegel, Goetzmann, and Welch (2007), Ornelas et al. (2009), and Nguyen-Thi-Thanh (2010).

[48] This includes studies by Park and Staum (1998), Henker (1998), Nawrocki (2000), Amin and Kat (2003), Lhabitant and Learned (2004), Lhabitant and Laporte (2006), and Fang et al. (2008).

[49] In this context, several studies are discussed. This includes Lhabitant and Learned (2004), Moerth (2005), Alexander and Dimitriu (2005), and Gregoriou et al. (2007).

[50] Benchmark research on performance persistence includes works by Agarwal and Naik (2000a), Barès et al. (2003), Harri and Brorsen (2004), Baquero et al. (2005), Caglayan and Edwards (2001), Herzberg and Mozes (2003), Brown and Goetzmann (2003), Kouwenberg (2003), Kat and Menexe (2003), De Souza and Gokcan (2004b), Capocci and Hübner (2004), Capocci et al. (2005), Kosowski et al. (2007), Moerth (2007), Manser and Schmid (2009), Pätäri and Tolvanen (2009), Eling (2009), Jagannathan et al. (2010).

the key line followed, so far, in the literature. The second part, headlined ‘Critical Evaluation and Relevance for Dissertation’, highlights the direct impact this literature has on the development of an investment heuristic. A brief summary (3.4.6) of the relevant literature is then presented, and this is followed by an outline of the research gap perceived and the author’s aspirations regarding his research (3.5).[51]

3.4.1 Data Preparation

All HF databases are affected by a number of biases which, in turn, affect the calculation of risk and return measures (Hutson et al., 2006). As any empirical academic work in the HF space is unavoidably subject to these biases, they should not be neglected. Common biases include the ‘self-selection bias’, the ‘instant history bias’, and the ‘survivorship bias’. The benchmark literature on these biases is now briefly discussed.[52]

3.4.1.1 Relevant Academic Literature

There is no obligation for HFs to report their returns. Rather, HFs voluntary report their performance in several databases to attract capital (Grecu et al., 2007; Agarwal et al., 2011). Thus, a ‘self-selection bias’ arises as only HFs with acceptable performances decide to report their returns (Bollen & Pool, 2009); On the other hand, other highly successful HFs may well decide not to report if they have already reached their target size and do not wish to attract further capital (Géhin, 2004; Kouwenberg, 2003). Both of these effects, however, are rather difficult to quantify. W. Fung and Hsieh (2000) estimate that these biases are negligible.[53]

[51] Tables F1-F5 in Appendix F provide short overviews of the previous academic works that are of major relevance for this dissertation. This is to ensure full transparency and enable the reader to set this dissertation into the context of existing research.

[52] Table F1 in Appendix F provides short overviews of the relevant academic articles on this topic. Key research includes works by Malkiel (1995), Brown et al. (1999), Liang (2000), W. Fung and Hsieh (2000), Amin and Kat (2003), Kouwenberg (2003), Ibbotson et al. (2011), and Grecu et al. (2007).

[53] Another study by Ackermann et al. (1999) conclude that the self-selection bias and the survivorship bias cancel each other out.

When HFs register with a database, they are given a chance to backfill their previous returns, and whilst successful HFs might well seize such an opportunity, the poorer HF track-records are most likely not backfilled (Géhin, 2006). This phenomenon is usually referred to as the 'instant history bias'. Ibbotson et al. (2011) estimate the instant history bias to be around 4% per year.

All HF databases are necessarily affected by the 'survivorship bias', as they report information on operating ('alive') HFs, whereas, liquidated ('dead') HFs cease to report at a certain point (W. Fung & Hsieh, 2004; Malkiel, 1995). Consequently, cross-sections of HF databases only consist of 'alive' funds. Therefore, the performance is overstated. Brown et al. (1999), Liang (2000), and W. Fung and Hsieh (2000) estimate the survivorship bias of HFs as ca. 1.5%-3% per year. In addition to that, Amin and Kat (2003) further find that the survivorship bias imposes "a downward bias in the standard deviation, an upward bias in the skewness, and a downward bias in the kurtosis" (Géhin, 2004, p. 6).[54]

3.4.1.2 Critical Evaluation and Relevance to this Dissertation

The three data biases introduced above have a direct impact on the data preparation methodology applied in this thesis. As illustrated in the previous paragraph, the self-selection bias seems to be negligible. The instant history bias on the other hand is supposed to be of considerable importance. Thus, the investment heuristic developed in this dissertation only considers HFs for investment after their database registration date, so that backfilled information does not adulterate the data.[55] Finally, in order to prevent survivorship biases, this thesis does not carry-out any cross-sectional analyses of the HF universe, but rather, considers only the performances of portfolios that are comprised of both, moribund and alive HFs, during certain investment periods.

[54] Skewness is a measure of the asymmetry of the return distribution around the mean. Positive (negative) skewness indicates a distribution with a fat right (left) tail. Kurtosis is a measure of the 'peakness' of the return distribution. A positive (negative) kurtosis indicates a relatively peaked (flat) distribution compared to the standard normal distribution.

[55] The author will, however, allow for the calculation of RAPMs on the basis of back-filled information. This solution greatly increases the number of investible HFs in this study, by preventing the back-fill bias from interfering with portfolio's performance. This point will be further elaborated on in the next part (4) of this dissertation.

3.4.2 Investment Selection

Industry practitioners usually consult a HF database before taking investment decisions. As a first step, the HF universe in this database is narrowed-down to a selection of HFs that fulfil certain criteria, such as a minimally-acceptable track-record length and a minimally-acceptable size. At the end of this process, investors are then left with a 'long list' of potentially investable HFs. The second step usually entails a quantitative analysis where RAPMs are calculated to assess HFs' risk-adjusted performance. At the end of this second step, investors are left with a 'short list' of the most promising investable HFs.

In correspondence with these two steps, this chapter is divided into two distinct sections. The first part (3.4.2.1) examines HF size and age and their impact on performance while the second part (3.4.2.2) reviews the wide variety of RAPMs that are currently under debate. This is followed by a short summary of the findings (3.4.2.3).

3.4.2.1 Investment Selection ─ HF Characteristics

HF returns are supposedly affected by a number of individual HF characteristics, but of all their imaginable features their size and their age is what has attracted most attention in the literature. What now follows, is a review of the most relevant studies done on these features, outlined in chronological order, according to their publication dates.[56]

3.4.2.1.1 Relevant Academic Literature

Several studies examine the supposed link between HF size and HF performance. Edwards and Caglayan (2001) investigate HF performance with the help of a factor model. Their study shows that HF returns tend to increase along with HF size,

[56] Table F2 in Appendix F provides short overviews of the relevant academic articles on this topic. Key research includes works by Edwards and Caglayan's (2001), Howell (2001), Brown et al. (2001), H. Fung et al. (2002), Amenc and Martellini (2003), Gregoriou and Rouah (2003), Kazemi and Schneeweis (2003), Hedges (2003), Herzberg and Mozes (2003), Harri and Brorsen (2004), Getmansky (2004), Ammann and Moerth (2005), Moerth (2007), and Boyson (2008, 2010).

although not in the same proportion. H. Fung et al. (2002) discover in an analysis of 115 HFs pursuing equity-based strategies that HF size is consistently related to return performance with larger HFs outperforming smaller ones. Amenc and Martellini (2003) also study the influence of several HF characteristics on performance with the help of various variants of the CAPM a factor model. They discover that larger HFs have excess returns that exceed those of smaller ones.

On the other hand, Gregoriou and Rouah (2003), who analyze the risk-adjusted performance of smaller and larger HFs, find no evidence that HF performance is related to HF size.[57] Kazemi and Schneeweis (2003), who measure HF performance using a stochastic discount factor approach, arrive at a similar conclusion. Hedges, who compares the performance of several portfolios consisting of differently sized HFs, however, goes even further and discovers a negative relation between HF size and performance (2003). This finding is supported by two studies that investigate HF performance persistence, namely Herzberg and Mozes (2003) and Harri and Brorsen (2004) who find that there is a strong negative relation between HF capitalization and returns.

Getmansky (2004), who analyzes HF survival, argues that successful HFs attract more capital, thereby outgrowing their peers. He finds a positive and concave relationship between HF size and HF performance. His findings indicate that there is an optimal HF size, which, if exceeded, adversely affects HF return levels, which can no longer be sustained.

Ammann and Moerth (2005), who study the impact of capital inflows into the HF industry, also find evidence of a negative relationship between HF size and returns. In their study, HFs of less than US$100 million AuM show a better performance than their larger peers. However, they also discover that extremely small HFs with AuM of below US$1 million underperform on average.[58] Mozes and Orchard (2012) find larger HFs to be more prone to closure and liquidity issues. Furthermore, they discover that larger HFs tend to generate less Alpha than their

[57] Gregoriou (2003), however, points out that HF size has a positive effect on HF life expectancy.
[58] They attribute this underperformance to the higher total expense ratios of small funds.

smaller peers since the significant capital inflows received by successful HFs tend to erode their Alphas over time (Mozes & Orchard, 2012).

The question of whether there is a relationship between HF performance and HF age has also been examined in academic literature. Howell (2001) compares portfolios consisting of HFs of different ages. He shows that on average younger HFs, with track records below three years, outperform older ones with longer track records.[59] Brown et al. (2001), who investigate HF risk in light of managerial career concerns, arrive at the same conclusion. Herzberg and Mozes (2003) further quantify the difference in returns between younger and older HFs. They show that HFs of an age below 3 years display annual returns that are 3-4% higher than those of older HFs. Boyson (2008, 2010), who studies HF performance persistence and managerial career concerns, also confirms that younger funds outperform their older peers. Indeed, in her study (2008), she shows how a portfolio of small young HFs with prior good performance outperforms a portfolio of large, old HFs with prior poor performance by almost 10 percent per year. Lahiri et al. (2011) demonstrate that the risk of failure increases considerably with HF age.

3.4.2.1.2 Critical Evaluation and Relevance to this Dissertation

The analysis of correlations between individual HF characteristics and their performances has a straightforward relevance for this dissertation, given that, if there is sufficient academic literature that shows that certain HF features are significantly correlated with an above-average performance, this could be adequately captured by an investment heuristic.

In general terms, however, it can be said that the academic literature on the relationships between HF characteristics and their performance delivers a mixed picture. One possible explanation for such disparity may be that the many studies carried-out are based on different types of HF samples and calculated over different periods of time. However, if one concentrates exclusively on the latest studies done on topic, the picture immediately brightens up, as the most recent studies

[59] However, he also shows that younger HFs are more likely to be liquidated (Howell, 2001).

unanimously indicate a clear negative relationship between HF size and performance. The same is true for the relationship between the length of HF track-records and their performance.

In line with these findings, the model proposed in this dissertation concentrates on comparatively small HFs, of between US$1 million and US$100 million in AuM.[60] Furthermore, only those HFs with comparatively short track-records of up to 36 months qualify for investment.[61]

After discussing the impact of HF size and HF age, the second column of investment selection, that is RAPMs, is discussed in the next section (3.4.2.2).

3.4.2.2 Investment Selection ─ Risk-Adjusted Performance Measures

This dissertation develops an investment heuristic based on a variety of alternative RAPMs. The use of such measures for the evaluation of HFs was triggered by the special statistical properties of HF returns. This is illustrated in the next section by pointing out the limitations of the Sharpe Ratio within the HF space.[62]

3.4.2.2.1 The Sharpe Ratio and its Limitations within the Hedge Fund Space

In the context of their quantitative analyses, financial analysts rely heavily on risk-adjusted performance measures (RAPMs) to decide on their selection of the available investment funds (Eling & Schuhmacher, 2007). Such indicators measure the relationship between performance and risk. The most prominent RAPM is the

[60] Amman and Moerth (2005) indicate that performance drops considerably if the HF AuM either fall short of, or exceed, these values.

[61] The minimum length of the required track record is 24 months; This is necessary to be able to calculate reliable RAPM values.

[62] Table F3 in Appendix F provides short overviews of the relevant academic articles on this topic. Key research includes works by Sortino and van der Meer (1991), Young (1991), Burke (1994), Kestner (1996), Sortino et al. (1999), Dowd (2000), Koh et al. (2002), Shadwick and Keating (2002), Lo (2002), Gueyie and Gregoriou (2003), Brooks and Kat (2003), Kaplan and Knowles (2004), Agarwal and Naik (2004), Sharma (2004), Eling and Schuhmacher (2007), Ingersoll et al. (2007), Ornelas et al. (2009), and Nguyen-Thi-Thanh (2010).

Sharpe Ratio, which expresses the relationship between the excess returns and the standard deviation of a fund during a given period.

$$Sharpe\ Ratio_i = \frac{r_i^d - r_f}{\sigma_i}$$

i: specific HF labelled ‘i’

T: number of observations in observation period

$r_{i1},\ldots, r_{iT}$ monthly historical returns (1,...,T) during the observation period

r_i^d average monthly historical return of HF_i during observation period

$r_i^d = (r_{i1} + \ldots + r_{iT})/T$

r_f risk-free monthly interest rate

σ_i standard deviation of the monthly returns of HF_i during observation period

$\sigma_i = (((r_{i1} - r_i^d)^2 + \ldots + (r_{iT} - r_i^d)^2)/(T - 1))^{0.5}$

Although widely used among practitioners (Pedersen & Rudholm-Alfvin, 2003), the Sharpe Ratio has been heavily criticized as non-adequate tool within the HF space. Most of the critique focuses on the special properties of HF performance distributions.

HFs typically have investment mandates that allow for the use of leverage, short selling, derivatives and investment in highly illiquid securities (Dor et al., 2006). As a consequence of such techniques, HF returns display performance characteristics that are very different from traditional asset classes. It has been shown that most HFs’ returns do not follow a normal distribution, but rather show a negative skewness and positive kurtosis as well as positive serial correlation (Abdou & Nasereddin, 2011, Brooks & Kat, 2002; Ding & Shawky, 2007; Lucas & Siegmann, 2008; Mahdavi, 2004).[63]

Considering these characteristics, the Sharpe Ratio seems inadequate for the analysis of HFs as it is based on the assumption of standard normally-distributed

[63] In other words, many HFs’ follow non-symmetrical return distributions with significant tail risks. This is especially true for strategies that involve arbitrage or distressed securities (Brooks & Kat, 2002).

returns. By ignoring the distributions' 3rd and 4th moments, the Sharpe Ratio tends to underestimate inherent HF risk (Brooks & Kat, 2002). Likewise, Lo (2002) illustrates that the Sharpe Ratio of HFs can be overstated by as much as 65 percent and Sharma (2004) shows that HF performance rankings based on the Sharpe Ratio can be very misleading, which makes it a rather poor choice of tool for HF selection. Furthermore, risk-averse investors "strongly dislike negative returns [...] and would even prefer to partly sacrifice positive returns in order to avoid negative ones", this common behaviour is also neglected by the Sharpe Ratio (Bacmann & Scholz, 2003, p. 1). Such observations have motivated a variety of alternative RAPMs for use within the HF space.

In the next section (3.4.2.2.2), the author examines the most relevant academic literature on RAPMs. After that, the author critically reviews the relevance of these measures for the dissertation at hand (3.4.2.2.3)

3.4.2.2.2 Relevant Academic Literature

Current academic discussions on HF performance concentrate on several performance indicators, but, so far, not a single indicator has been shown to dominate over the others. It seems worthwhile, therefore, to take a closer look at the most prominent of these measures. All of the RAPMs that play a central role in this thesis can be clustered into four groups, i.e., 'Lower Partial Moment', 'Draw-down', 'Value at Risk'-based, and 'Other RAPMs'.

- Lower partial moment (LPM)-based RAPMs include Omega, the Sortino Ratio, Kappa 3, the Upside Potential Ratio, and Excess Return on Probability of Shortfall (ERoPS).
- Drawdown-based RAPMs comprise of the Calmar, Sterling, and Burke Ratios.
- Value at Risk (VaR)-based RAPMs include Excess Return on Value at Risk (ERoVaR), the Conditional Sharpe Ratio, and the Modified Sharpe Ratio.
- Other RAPMs consist of the D-Ratio, the Hurst Ratio, and the Manipulation-proof Performance Measure (MPPM).

Eling and Schuhmacher (2007) offer an excellent overview of most LPM-, drawdown-, and VaR-based RAPMs. Thus, the three following sections are closely based on their explanations.[64] In addition to that, several further measures that are not touched upon by Eling and Schuhmacher but nevertheless relevant in this dissertation are discussed.[65]

Lower Partial Moment (LPM)-based RAPMs

As portrayed by Eling and Schuhmacher (2007), lower partial moments (LPMs) define risk as the negative deviations of the returns from a fixed minimum acceptable return τ.[66] The LPM of the order n for a certain HF_i is calculated as

$$LPM_{ni}(\tau) = \frac{1}{T}\sum_{t=1}^{T} max\ [\tau - r_{it}, 0]^n$$

In contrast to the standard deviation, LPMs do not consider positive but only negative deviations of returns from a fixed minimum acceptable return (Eling & Schuhmacher, 2007). Thus, from an investor's point of view, they may be considered a better risk measure. Different weights are attributed to the deviations from the minimum acceptable through the selection of 'n'. It is supposed that the more risk-averse the investor is, the higher the selection of 'n'. Eling and Schuhmacher (2007) show that the LPMs of the order 1, 2, 3 are used for

- Omega[67] (n = 1) (Shadwick & Keating, 2002),
- Sortino Ratio (n = 2) (Sortino & van der Meer, 1991),
- Kappa 3 (n = 3) (Kaplan & Knowles, 2004).

64 The following portrayal of the Sharpe Ratio, Omega, the Sortino Ratio, Kappa 3, the Upside Potential, Calmar, Sterling, and Burke Ratios, Excess Return on Value at Risk (ERoVaR), the Conditional Sharpe and Modified Sharpe Ratios are explicitly based on the work of Eling and Schuhmacher (2007).

65 This includes Excess Return on Probablility of Shortfall (ERoPS), the Manipulation-proof Performance Measure (MPPM), the D-Ratio, and the Hurst Ratio.

66 Theta (τ) is usually zero, the risk-free rate or average return.

67 Although the definition of Omega, as it is presented in this thesis, is not identical to the original definition by Shadwick and Keating (2002), it does, however, provide an equivalent that is more easily interpreted (Eling & Schuhmacher, 2007).

$$Omega_i = \frac{r_i^d - \tau}{LPM_{1i}(\tau)} + 1$$

$$Sortino\ Ratio_i = \frac{r_i^d - \tau}{\sqrt[2]{LPM_{2i}(\tau)}}$$

$$Kappa\ 3_i = \frac{r_i^d - \tau}{\sqrt[3]{LPM_{3i}(\tau)}}$$

The RAPMs listed above calculate the excess return by deducting the minimum acceptable return from the average return during the observation period. Alternatively, it is possible to calculate excess return by the means of a higher partial moment (HPM) that measures positive deviations from the minimum acceptable return τ (Eling & Schuhmacher, 2007). The authors portray that the Upside Potential Ratio (Sortino, van der Meer, & Plantinga, 1999) combines the HPM (n=1) and the LPM (n=2) into a single RAPM.

$$Upside\ Potential\ Ratio_i = \frac{HPM_{1i}(\tau)}{\sqrt[2]{LPM_{2i}(\tau)}}$$

Another straightforward related RAPM is the 'Excess Return on Probability of Shortfall' (ERoPS). The denominator of this RAPM simply reflects the probability that returns fall short of the minimum acceptable return τ (Pedersen & Rudholm-Alfvin, 2003).

$$ERoPS_i = \frac{r_i^d - \tau}{Probability[\tau - r_{it} < 0]}$$

In summary, therefore, it can be concluded that most LPM-based RAPMs account for the asymmetry of HF return distributions by replacing the standard deviation with a downside deviation defining risk as 'bad volatility' (Géhin, 2004).

Drawdown-based RAPMs

Drawdown-based measures are very common among practitioners (Koh, 2009). The drawdown of a HF is measured as the experienced loss during the observation period. 'MD' stands for 'maximum drawdown'. MD_{i1} denotes the lowest return of a HF_i during the observation period, MD_{i2} is the second lowest return, etc. Eling and Schuhmacher (2007) illustrate that several RAPMs are based on the concept of maximum drawdown:

- Calmar Ratio (Young, 1991),
- Sterling Ratio (Kestner, 1996),
- Burke Ratio (Burke, 1994).

The Calmar Ratio has maximum drawdown in the denominator, the Sterling Ratio uses an average of the N largest drawdowns, and the Burke Ratio measures risk as a type of variance above the N largest drawdowns (Eling & Schuhmacher, 2007).

$$Calmar\ Ratio_i = \frac{r_i^d - r_f}{-MD_{i1}}$$

$$Sterling\ Ratio_i = \frac{r_i^d - r_f}{\frac{1}{N}\sum_{j=1}^{N} -MD_{ij}}$$

$$Burke\ Ratio_i = \frac{r_i^d - r_f}{\sqrt[2]{\sum_{j=1}^{N} MD_{ij}^2}}$$

In summary, therefore, one can state that drawdown-based RAPMs account for the asymmetry in HF return-distributions by replacing the standard deviation of the Sharpe Ratio with a drawdown function in order to offer a better representation of risk.

Value at Risk (VaR)-based RAPMs

Value at risk (VaR)-based RAPMs have also been discussed in a HF context. Value at risk (VaR_i) is defined as the worst loss that can occur under normal market conditions over a specified time-horizon (Giamouridis & Ntoula, 2009). It describes the possible loss of a HF_i, which is not exceeded with a given probability of 1-α during the observation period (Eling & Schuhmacher, 2007). Value at risk is calculated as $VaR_i = -(r_i^d + z_\alpha * \sigma_i)$ with z_α denoting the α-quantile of the standard normal distribution (Eling, 2008).

A further topic that is regularly debated in academic literature is the expected loss under the condition that the VaR is exceeded; this conditional value at risk (CVaR) is described by $CVaR_i = E[-r_{it} \mid r_{it} \leq -VaR_i]$ (Eling & Schuhmacher, 2007). Moreover, as HF returns do not follow standard normal distributions, it is advantageous to use the Cornish-Fisher expansion to include skewness and kurtosis in the VaR. As portrayed by Eling and Schuhmacher (2007), the modified value at risk based on the Cornish-Fisher expansion is calculated as $MVaR_i = -(r_i^d + \sigma_i*(z_\alpha + (z_\alpha^2-1) * S_i/6 + (z_\alpha^3-3*z_\alpha)*E_i/24 - (2*z_\alpha^3 - 5*z_\alpha)*S_i^2/36))$, with S_i denoting the skewness and E_i the denoting the kurtosis for HF_i (Favre & Galeano, 2002). As shown by Eling and Schuhmacher (2007), several RAPMs operate on the basis of VaR, CVaR, and MVaR:

- Excess return on Value at Risk (Dowd, 2000),
- Conditional Sharpe Ratio (Agarwal & Naik, 2004),
- Modified Sharpe Ratio (Gueyie & Gregoriou, 2003).

$$Excess\ Return\ on\ Value\ at\ Risk_i = \frac{r_i^d - r_f}{VAR_i}$$

$$Conditional\ Sharpe\ Ratio_i = \frac{r_i^d - r_f}{CVAR_i}$$

$$Modified\ Sharpe\ Ratio_i = \frac{r_i^d - r_f}{CVAR_i}$$

In summary then, it can be stated that VaR-based RAPMs replace the standard deviation of the Sharpe Ratio with a VaR, CVaR or MVaR. While VaR operates under the assumption of normally-distributed returns (López de Prado & Peijan, 2004), CVaR and MVaR are both apt to operate in an environment of non-normally distributed returns.

Other RAPMs

In addition to the RAPMs discussed above, this thesis also considers three less common measures: The D-Ratio, the Hurst Ratio, and the Manipulation-proof Performance Measure (MPPM).

The D-Ratio, discussed by Koh et al. (2002), is a simple way of comparing the value and frequency of a HF's positive and negative returns.

$$D - Ratio_i = \frac{number\ of\ negative\ returns\ times\ their\ value}{number\ of\ positive\ returns\ times\ their\ value}$$

The D-Ratio does not require any assumptions regarding the underlying distribution and captures skewness in returns; it may be used as a proxy for HF risk with D = 0 representing a HF with positive-only returns, and D = infinity representing a HF with no positive returns (Koh et al., 2002).

The Hurst Ratio is another RAPM discussed by Koh, et al. (2002). It is defined as

$$Hurst\ Ratio_i = \frac{\log\left(r_i^{max} - r_i^{min}\right)/S_i}{(\log(\Delta t) - \log(a))}$$

with r_i^{max} and r_i^{min} representing the minimum and maximum returns of HF_i during the observation period; Δt is the lapse of time between observations, 'a' is a constant term that is negligible for observation periods that are shorter than five years (Koh et al., 2002). The authors illustrate that a Hurst Ratio between 0 and 0.5 means that HF_i's returns tend to fluctuate randomly, but eventually converge to a stable value over time. With a Hurst Ratio of around 0.5, performance is regarded as totally random and Hurst Ratios between 0.5 and 1 indicate that returns are persistent (Koh et al., 2002).

Ingersoll et al. (2007) show that several RAPMs discussed in the academic literature could be manipulated by a HF in order to achieve a higher ranking and thus attract greater inflows of capital. As a solution to this problem they suggest a Manipulation-proof Performance Measure (MPPM) that cannot be easily 'gamed'. The MPPM can be characterized as a weighted average of a utility-like function; ρ represents a risk-penalizing coefficient, which is usually set between ρ = 2 and ρ = 4 (Ingersoll et al., 2007).

$$MPPM_i = \frac{1}{(1-\rho)\Delta t} ln\left(\frac{1}{T}\sum_{t=1}^{T}\left(\frac{(1+r_{it})}{(1+r_f)}\right)^{1-\rho}\right)$$

In summarizing the previous paragraphs, therefore, it can be stated that HFs have non-normal return distributions. Thus, the popular Sharpe Ratio is probably not the most accurate measure to apply within the HF space, as it assumes normality in returns. In the quest for a more accurate way of measuring risk and performance, several RAPMs have been discussed in academic literature. Many of these are based on the Sharpe Ratio and they replace the risk term in the denominator with a term that takes non-normality of return distributions into account.

Does the Choice of RAPM Matter?

In the academic discussion of RAPMs, Eling and Schuhmacher's study (2007) attracted a high level of attention. Eling and Schuhmacher test different RAPMs against a sample of 2,763 HFs. They rank HFs according to their RAPM values and find that the HF rankings established by these RAPMs are highly correlated. They conclude that the choice of RAPM is not critical to the evaluation of HFs and that the Sharpe Ratio, despite its theoretical shortcomings, is generally adequate. This finding is confirmed by a follow-up study (Eling et al., 2011). Moreover, Eling (2008) broadens this analysis to mutual funds. He concludes that the Sharpe Ratio is not only an adequate RAPM for the analysis of HFs, but also for mutual funds investing in stocks, bonds, and real estate, as well as FoFs, and commodity pool operators (Eling, 2008).

In contrast to Eling and Schuhmacher, however, other studies argue that the choice of RAPM does play a critical role. Ornelas et al. (2009) apply several RAPMs to the ranking of US mutual funds. While they discover high ranking correlations for the majority of tested RAPMs, they show considerably lower correlations for some other RAPMs, such as the MPPM. Their robustness checks further show that several RAPMs are highly sensitive to parameter changes. Consequently, they conclude that the choice of RAPM is actually an important factor in mutual fund selection (Ornelas et al., 2009).

Nguyen-Thi-Thanh (2010) voices her concern that Eling and Schumacher draw their conclusion just on the basis of observed correlations between HF rankings. She argues that the mere existence of correlations does not sufficiently prove that these rankings are actually consistent. In her study, Nguyen-Thi-Thanh tests different RAPMs against a sample of 149 HFs. Despite strong positive correlations between HF rankings established by different RAPMs, she observes significant modifications in the rankings in absolute terms. While few HFs actually maintain their initial positions, many are subject to a considerable increase or decrease in position. Consequently, Nguyen-Thi-Thanh concludes that the choice of RAPM is crucial for the evaluation and the selection of HFs.

3.4.2.2.3 Critical Evaluation and Relevance to this Dissertation

As illustrated in the previous paragraphs, several RAPMs have been discussed in academic literature. However, while HF rankings established by such measures are highly correlated as shown by Eling and Schuhmacher (2007), the ranking of individual HFs in absolute terms can differ considerably from RAPM to RAPM (Nguyen-Thi-Thanh, 2010). While there are strong positive correlations between HF rankings established by different RAPMs, Nguyen-Thi-Thanh notices considerable variations in absolute terms: Only few HFs actually stay in the same place while many suffer a noteworthy rise or drop in their ranking positions. If one considers that most family offices are invested exclusively in 10 HFs (Preqin, 2009), although they select their investments from among a universe of several thousand HFs (Eurekahedge, 2009c), the choice of RAPM is very likely to play a significant role in HF evaluation and selection.

This dissertation develops a fully-quantitative HF investment methodology that is based on RAPMs. Since no single generally-accepted best RAPM has yet emerged from academic literature, this dissertation draws on a wide range of RAPMs and tests them under close-to-practice conditions. In particular, all the measures previously elaborated on in this paragraph are tested.[68]

3.4.2.3 Investment Selection – Summary

The dissertation at hand employs an investment selection process that comprises of two steps. Firstly, attractive HFs are determined based on their size and age. Secondly, RAPMs are calculated to identify the most promising HFs.

The latest studies done on HF characteristics indicate a clear negative relationship between HF size and performance. The same is true for the relationship between HF age and performance. To account for these findings, the model proposed in this dissertation concentrates on comparatively small HFs, of between US$1 million and US$100 million in AuM. Furthermore, only those HFs with comparatively short track-records of up to 36 months qualify for investment.

Several RAPMs are currently under academic debate. These RAPMs tend to rank HFs differently and are therefore very likely to play a significant role in HF evaluation and investment selection. None of these RAPMs, however, has been

[68] This includes:

- LPM-based measures (Omega, the Sortino Ratio, Kappa 3, the Upside Potential Ratio, ERoPS),
- Drawdown-based measures (the Calmar, Sterling, and Burke Ratios),
- VAR-based measures (Excess Return on Value at Risk, the Conditional Sharpe Ratio, the Modified Sharpe Ratio), and
- other measures (the Sharpe Ratio, the D-Ratio, the Hurst Ratio, and the MPPM).

shown to dominate over the others. Since no single generally-accepted best RAPM has yet emerged, this dissertation puts a wide range of RAPMs to the test.[69]

After this review of investment selection, the academic literature on fund allocation is assessed in the next paragraph (3.4.3).

3.4.3 Fund Allocation

Fund allocation in the HF space can be conducted via optimizers and heuristics. The employment of optimizers, however, has been subjected pertinent criticism as illustrated in chapter 3.1.4. The main concern lies in the fact that optimizers tend to cause a 'butterfly effect', which means that minor changes in input factors might cause significant – and possibly unfavourable – changes in fund allocation (Nawrocki, 2000). This is well illustrated by Fang et al. (2008), who find that portfolios formed from a heuristic approach, deliver both, superior raw returns and superior risk-adjusted returns, as compared to portfolios based on optimizers.

In addition to the above findings, it should be pointed out that academic works on fund allocation typically neglect the minimum-investment requirements faced by practitioners. Considering, however, that many HFs impose rather high minimum-investment requirements, some as high as US$1 million, this may well impose constraints on the fund allocation process for many smaller family offices. As this dissertation explicitly assumes the role of a small family office, with c. US$10 million in AuM available for HF investment, portfolio allocation based on an optimizer might well result in a poorly-diversified portfolio with a high concentration of risk. As the investment method proposed in this dissertation is based exclusively on a quantitative analysis and, thus, does not consider any

[69] This includes:
- LPM-based measures (Omega, the Sortino Ratio, Kappa 3, the Upside Potential Ratio, ERoPS),
- Drawdown-based measures (the Calmar, Sterling, and Burke Ratios),
- VAR-based measures (Excess Return on Value at Risk, the Conditional Sharpe Ratio, the Modified Sharpe Ratio), and
- other measures (the Sharpe Ratio, the D-Ratio, the Hurst Ratio, and the MPPM).

qualitative risk reduction methods, such as ‘due diligence’, a high concentration of risk could well be fatal.

For the reasons portrayed above, this thesis takes a straightforward equal-weights approach to the problem of fund allocation. In fact many practitioners take the equal-weights approach as a starting point for fund allocation and adjust the weights of their portfolios according to their own forecasts of future economic and market conditions (Lhabitant, 2006). Furthermore, while equally-weighted portfolios are not very sophisticated, the methodology usually delivers satisfactory and even superior results, as compared to the use of optimizers (Lhabitant, 2006).

This raises the question of the optimal number of HFs in such a portfolio. The relevant academic literature that tackles this question is presented in the next section.[70]

3.4.3.1 Relevant Academic Literature

Starting off from naive diversification, several academic studies have attempted to figure-out the optimal number of HFs for a FoF portfolio. As Lhabitant (2006) points out, the optimal number of HFs in an equally-weighted portfolio is probably rather small, which is why HFs should never be considered as individual securities on their own; in fact, every HF is already a diversified portfolio itself, as it contains several securities (Lhabitant, 2006).

Park and Staum (1998) reason that there are diminishing marginal risk benefits in adding HFs to a portfolio. This finding is supported by Amin and Kat (2003), as well as by Lhabitant and Learned (2004). Both studies conclude that raising the number of HFs in a portfolio decreases volatility and other risk measures. On the other hand, however, it also leads to an increased correlation with major market indices, as different HF strategies nullify one another. These studies conclude that

[70] This includes works by Park and Staum (1998), Henker (1998), Nawrocki (2000), Amin and Kat (2003), Lhabitant and Learned (2004), and Lhabitant and Laporte (2006).

most diversification benefits are captured with a portfolio of 5 to 15 HFs, and a follow-up study by Lhabitant and Laporte (2006) echoes such findings.

Lhabitant (2006) also states that an increase in the number of HFs has negative impacts on overall portfolio performance, the reason being that all HF managers charge performance fees; a portfolio consisting of a winning HF and a losing one will end up paying performance fees to one of the managers, although the overall performance will be zero. Furthermore, this effect increases with an increasing number of HFs in a portfolio as a more diversified portfolio is more likely to include more poor performers (Lhabitant, 2006). Summarizing these findings, it can be assumed that the optimum number of HFs in an equally-weighted portfolio is probably around 10.[71]

3.4.3.2 Critical Evaluation and Relevance to this Dissertation

The pervious paragraph focused on the fund allocation in academic literature. There seems to be unanimous consent among researchers that most diversification benefits can be obtained with just 10 HFs in an equally-weighted portfolio. Thus, in keeping with the previous literature on the subject, a portfolio formed under the heuristic proposed will consist of not more than 10 HFs at any given time.

3.4.4 Performance Assessment

In this dissertation, the author strives to develop a strictly quantitative approach to HF investment. To find out whether this new investment approach is sensible, a meaningful performance assessment methodology is indispensable. Several

[71] Interestingly, this academic finding seems to be in line with the practice of many family offices; a survey of North American family offices found that they were typically invested in 10 different HFs or FoFs (Preqin, 2009b). In this context it should be mentioned that real-life FoFs are, on average, invested in approximately 30 HFs (Eurekahedge, 2009b). While this may be an indication of 'overdiversification', it may also be due to limited investment opportunity in small HFs: As the majority of HFs are comparatively small, this may necessitate larger FoFs to invest their capital into a large number of different HFs. Since this thesis aims at the development of an approach tailored to family offices with ca. US$10 million in AuM available for HF investment, this effect is reasonably ignored in the development of the proposed investment approach.

different approaches have been applied in academic literature and are revisited in the next section.

3.4.4.1 Relevant Academic Literature

A straightforward performance assessment methodology is used by Lhabitant and Learned (2004). The authors investigate the diversification effects in portfolios of HFs. To this end, they create numerous equally-weighted HF portfolios. In a next step, they determine the first four statistical moments of these portfolios as well as other risk measures[72] and compare them.

A further interesting approach is made by Alexander and Dimitriu (2005). In their study, HFs are selected according to their abnormal returns, Alpha. In a second step, the portfolio weights are determined based on a minimum variance optimizer. Alexander and Dimitriu benchmark these portfolios inter alia against equally-weighted portfolios of all HFs in their database. Moerth (2005) maintains that "asset-weighted returns are suitable to derive average returns of HF investors while equally-weighted returns measure the returns of the average HF" (Moerth, 2005, p. 26).

Jöhri and Leippold (2006) propose a quantitative investment approach based on RAPMs. In their model, capital is only invested in HFs that have shown superior risk-adjusted performance in the past. In order to evaluate the portfolios constructed on the basis of their approach, they calculate the first four statistical moments of these portfolios as well as Alpha and compare them with the benchmark index.

In a further study Gregoriou et al. (2007) construct equal-weights HF portfolios by selecting the HFs with the highest Alphas, Information Ratios, and Sharpe Ratios. The performance of the constructed portfolios is compared to real-life FoFs.

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72 This includes, for instance, Value-at-Risk (VaR) and maximum drawdown (MD).

3.4.4.2 Critical Evaluation and Relevance to this Dissertation

The dissertation at hand suggests an innovative approach to HF investment. To evaluate this approach, the author draws on several performance assessment methodologies put forward in academic literature: Portfolios generated by the new approach are benchmarked against equally-weighted HF and FoF indices. In this context, the author calculates the first four statistical moments of the newly constructed portfolios and the two benchmarks in order to compare them side-by-side. In addition to that, the robustness of the approach is tested by varying the input parameters critical to portfolio construction in order to uncover the sensitivities of the proposed approach to parameter changes.

3.4.5 Performance Persistence

As discussed earlier in this dissertation, many HF investors base their investment decisions on the evaluation of past performance data. Such methodologies, however, assume a certain degree of persistence in individual HF returns. Unsurprisingly, performance persistence is one of the key research areas in the HF space, with many studies having been published on the topic. This paragraph analyzes the capacious literature that this field has motivated.[73]

3.4.5.1 Relevant Academic Literature

As the literature on HF performance persistence is quite sizeable, and for the sake of simplicity, the previous research has been clustered, according to the lengths of the periods analyzed, thus ensuring easier readability. The clusters are:

- short term performance persistence (1-6 months),
- medium term performance persistence (around 12 months), and
- long term performance persistence (24 months and beyond)

[73] This includes works by Agarwal and Naik (2000a), Barès et al. (2003), Harri and Brorsen (2004), Baquero et al. (2005), Caglayan and Edwards (2001), Herzberg and Mozes (2003), Brown and Goetzmann (2003), Kouwenberg (2003), Kat and Menexe (2003), De Souza and Gokcan (2004b), Capocci and Hübner (2004), Capocci, et al. (2005), Kosowski et al. (2007), Moerth (2007), Manser and Schmid (2009), Pätäri and Tolvanen (2009), Eling (2009), Jagannathan et al. (2010).

The relevant articles are presented largely in chronological order, considering the years of their publication.

Short Term Performance Persistence (1-6 Months)

Several studies have investigated the short-term performance persistence of HFs. Agarwal and Naik (2000a) examine short term performance persistence in the Appraisal Ratios and the excess returns of HFs. Their tests show significant persistence in pre-fee and post-fee returns for both directional and non-directional investment strategies over a quarterly period (Géhin, 2004).

Barès et al. (2003) find return persistence over the one and three-months time-horizons. Such findings are supported by Harri and Brorsen's (2004) study, whose calculations indicate significant performance persistence for most investment strategies over one-to-three-month horizons.[74]

Baquero et al. (2005) analyze HF performance persistence over a quarterly period and find strong evidence of performance persistence particularly in the best-performing HFs. Moreover, they observe strong persistence of risk-adjusted relative returns. Eling's study (2009) also shows that performance persistence exists on a time-horizon of up to 6 months.

Medium Term Performance Persistence (around 12 Months)

Agarwal and Naik (2000a) extend their analysis to a 12 months period; they find that the extent of return persistence clearly decreases with the longer observation period. Caglayan and Edwards (2001) investigate the existence of outperformance as well as underperformance persistence for HFs and FoFs over a 12 months period. In essence, they discover significant performance persistence.

In contrast to these studies, neither Herzberg and Mozes (2003) nor Brown and Goetzmann (2003) find performance persistence over an annual horizon. The same

[74] For longer horizons, however, the significance decreases rapidly.

is true for Capocci and Hübner (2004) as well as the follow-up study (Capocci et al., 2005). While they find no evidence of performance persistence for the best and worst performing funds, they discover limited evidence of performance persistence among average performers in 'bull markets'.

Harri and Brorsen (2004) on the other hand, examine HF and FoF return persistence and arrive at a different result. They discover significance performance persistence for most investment strategies. The strongest significance is observed for market neural HFs and FoFs. Baquero et al. (2005) observe performance persistence in annual returns. Furthermore, Kosowski et al. (2007) discover that top HF performance persists at annual horizons. Manser and Schmid (2009) examine the persistence of reported and risk-adjusted returns for equity long/short HFs. While they find only limited persistence of reported returns, they find annual performance persistence based on RAPMs. They further observe that HFs with significant risk-adjusted returns show less exposure to the market, high raw returns, and low volatility. Pätäri and Tolvanen (2009) show that the extent of performance persistence depends on HF strategies and the performance metric employed. They find that model-free performance metrics (such as the Sharpe Ratio) are more sensitive to detecting performance persistence than models (Pätäri & Tolvanen, 2009).

Long Term Performance Persistence (around 24 Months and beyond)

Caglayan and Edwards (2001) extend their analysis of HF and FoF return persistence to a two-year horizon. Again, they discover significant performance persistence. The same is true for Harri and Brorsen (2004). Kouwenberg (2003) discovers performance persistence on the basis of Alpha and the Sharpe Ratio for most HFs over a 36-months horizon. HFs that focus on emerging markets or specific sectors, however, show no performance persistence.

Kat and Menexe (2003) discover no evidence of long-term performance persistence at the individual HF level nor at the investment strategy level. Their study indicates, however, performance persistence for FoFs and HFs with an emerging market focus. Furthermore, it reveals evidence of persistence in HF return distribution skewness and kurtosis. De Souza and Gokcan (2004b) analyze return and Sharpe Ratio persistence over a two and three year period: For most of the HF strategies examined, however, they find no significant evidence of performance persistence.

Moerth (2007), on the other hand, conducts "an analysis of long-term performance persistence of up to 60 months" (Moerth, 2007, p. 4). Using a variety of performance measures, he finds strong evidence of significant performance persistence. Jagannathan et al. (2010) also discover significant performance persistence among successful funds but little evidence of performance persistence among unsuccessful ones over a three year time-horizon.

3.4.5.2 Critical Evaluation and Relevance to this Dissertation

In general terms, therefore, it can be stated that academic literature on HF performance persistence portrays a rather mixed picture. While the vast majority of studies agrees on the existence of short term performance persistence, there is considerable disagreement with regard to longer horizons. One possible explanation for this dissent may be that these studies are based on different HF samples and time periods. Eling (2009), for instance, concludes that previous controversial results are probably due to methodological differences and biases in the data.

If one concentrates on the more recent studies[75] done in the field, however, the picture brightens up. Newer studies unanimously indicate that there is performance persistence with an annual horizon and even beyond that. Furthermore, research shows that RAPMs are better tools for the detection of performance persistence than raw returns or factor models (Manser & Schmid, 2009; Pätäri & Tolvanen, 2009).

This dissertation develops a quantitative investment methodology on the basis of RAPMs. Such an approach, however, is fundamentally dependent on the existence of performance persistence. As performance persistence appears to be strongest over short-term horizons, frequent portfolio reallocation seems to be advisable to

[75] (2007 and beyond)

ensure that this feature is achieved. On the other hand, such frequent reallocation comes at the expense of increased transaction costs, which might well erode the relative benefits achieved. To demonstrate this problem more clearly, this dissertation constructs and evaluates a variety of portfolios, some of which are reallocated quite frequently, (every 6 months), while others are characterized by medium-term holding periods, (of 12 or 18 months), and others are based on long-term holding periods (of 24 months).

In the following paragraph, after reviewing the most relevant literature on the topic, a brief summary is presented and the relevance of such literature to this dissertation is explained.

3.4.6 Summary

The academic literature published on the topic of HFs is capacious and diverse, but the studies that are most relevant to this particular dissertation are the ones that focus on *data preparation, investment selection, fund allocation, performance assessment, and performance persistence*.

The academic literature on *data preparation* clearly shows that all major HF databases are subject to biases. In essence, such biases cause an overestimation of returns and an underestimation of risk. In order to avoid the 'survivorship bias', this thesis does not comprise cross-sections of the HF universe. Instead, it considers the performance of portfolios comprising moribund as well as alive HFs. Moreover, to evade the 'instant-history bias', this thesis only considers HFs after their registration with a database.

The most recent studies in the field of *investment selection* indicate a clear negative relationship between HF size and performance. The same is true for the relationship between the length of a HF's track record and its performance. To take advantage of these findings, the investment approach proposed in this dissertation concentrates on comparatively small HFs, of between US$1 million and US$100 million in

AuM.[76] Furthermore, only HFs with a comparatively short track record of up to 36 months are considered for investment.[77]

In the context of *investment selection,* several RAPMs have been discussed in the academic literature. The most prominent measurements are based on lower partial moments, drawdown, and value at risk. While the HF rankings established by these measures are highly correlated, the ranking of individual HFs in absolute terms may differ considerably. Since no previous research has been able to demonstrate that any single RAPM dominates over the others, this dissertation draws on a wide range of RAPMs and tests them under close-to-practice conditions.

The *fund allocation* process within family offices is assumed to consider qualitative and quantitative aspects. Mathematical optimizers are not quite apt for the daily practice of family offices, which have to consider the high minimum investment sizes that most HFs require. Moreover, such optimization tools can trigger a detrimental butterfly effect. The fund allocation mechanism proposed in this thesis, therefore, is based on equally-weighted portfolios. As such, each portfolio examined here consists of no more than 10 HFs.

In order to conduct a *performance assessment* of the investment approach put forward in this dissertation, the author uses a straightforward methodology. The newly-formed portfolios are benchmarked against equally-weighted HF and FoF indices. In this context, the author calculates the first four statistical moments of the newly constructed portfolios and the two benchmarks and compares them side-by-side. In addition, a sensitivity analysis is performed: The author varies the input parameters critical to portfolio construction in order to uncover the sensitivities of the proposed approach to parameter changes.

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76 Amman and Moerth (2005) indicate that performance drops considerably if HF AuM fall short of or exceed these values.

77 Howell (2001), Brown et al. (2001), and Herzberg and Mozes (2003) indicate that HFs with track record below 36-months considerably outperform their older peers. The minimum required track record will be 24 months; this is necessary to calculate the RAPM values.

As previously mentioned, the academic literature published on the topic of HF *performance persistence* portrays a rather mixed picture. While the vast majority of studies agree on the existence of short-term performance persistence, there is considerable disagreement regarding longer horizons. The most recent studies, however, indicate that there is performance persistence over an annual horizon, and even beyond that. Frequently reshuffled portfolios are likely to take advantage of the presence of performance persistence better than buy-and-hold portfolios. At the same time, however, frequent reallocations may affect performance negatively, so this dissertation evaluates portfolios that are reallocated over different horizons (6, 12, 18 and 24 months).

Following this short summary of the academic literature and its implications for this dissertation, the following chapter outlines the need for a different route into HF investment.

3.5 Research Gap & Research Aspiration

This dissertation explicitly assumes the viewpoint of a family office that seeks investment in a well-diversified portfolio of HFs. Despite the capacious amount of literature published on HFs, there is – to the best of the author's knowledge – not a single academic study that considers the major practical restrictions that family office practitioners must face. The most important of these are the HF lock-up periods, HF minimum-investment requirements, and the transaction costs.

In addition to these shortcomings, several academic studies investigate HF performance at the level of HF indices and not at the individual fund level. As a result, these studies are not based on the precise universe of investable HFs that is most relevant for practitioners. Furthermore, there is very little academic literature that considers the 2007 - 2009 crisis, which had a particularly devastating effect on the HF industry.[78] These facts are illustrated by the tables presented below, which highlight a selection of the benchmark research and demonstrate the perceived shortcomings from a family office practitioner's perspective.

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[78] HF AuM have dropped by almost 25% during this period (Eurekahedge, 2009c).

Table 1: Selection of Literature ─ Performance Persistence

Author(s) (Year)	Database(s)	Number of Funds/ Indices	Investi-gation Period	2007-09 Crisis	Indivi-dual HF Data[79]	Lock-up Peri-ods[80]	Min. Inv. Re-quire-ments[81]	Trans-action Costs
Abdou & Nasereddin (2011)	CISDM	n.a.	2000-2005	×	✓	×	×	×
Agarwal, Daniel, & Naik (2009)	CISDM, HFR, MSCI, TASS	7,535	1994-2002	×	✓	×	×	×
Agarwal & Naik (2000a)	HFR	746	1982-1998	×	✓	×	×	×
Agarwal & Naik (2000b)	HFR	167	1995-1998	×	✓	×	×	×
Amenc, El Bied, & Martellini (2003)	CSFB/ Tremont	9	1994-2000	×	×	×	×	✓
Baquero, Horst, & Verbeek (2005)	TASS	1,797	1994-2000	×	✓	×	×	×
Barès, Gibson, & Gyger (2003)	FRM	4,934	1992-2000	×	✓	×	×	×
Boyson (2008)	TASS	1,659	1994-2000	×	✓	×	×	×
Brown & Goetzmann (2003)	TASS	1,295	1992-1998	×	✓	×	×	×
Brown, Goetzmann, & Ibbotson (1999)	US OF Directory	399	1989-1995	×	✓	×	×	×
Capocci, Corhay, & Hübner (2005)	CISDM, HFR, TASS	2,894	1994-2002	×	✓	×	×	×
Capocci & Hübner (2004)	HFR, MAR	2,796	1988-1995	×	✓	×	×	×
De Souza & Gokcan (2004b)	HFR	314	1997-2002	×	✓	×	×	×

79 as opposed to index data
80 at individual HF level
81 at individual HF level

Table 1: Selection of Literature ─ Performance Persistence (Continued)

Author(s) (Year)	Database(s)	Number of Funds/ Indices	Investi-gation Period	2007-09 Crisis	Indivi-dual HF Data[82]	Lock-up Peri-ods[83]	Min. Inv. Re-quire-ments[84]	Trans-action Costs
Edwards & Caglayan (2001)	MAR	1,665	1990-1998	✗	✓	✗	✗	✗
Eling (2009)	CISDM	4,314	1996-2005	✗	✓	✗	✗	✗
Harri & Brorsen (2004)	LaPorte	1,209	1977-1998	✗	✓	✗	✗	✗
Herzberg & Mozes (2003)	Hedge-Fund.net, Altvest, Spring Mountain Capital	3,300	1995-2001	✗	✓	✗	✗	✗
Jagannathan, Malakhov, & Novikov (2010)	HFR	2,141	1996-2003	✗	✓	✓	✗	✗
Kat & Menexe (2003)	TASS	324	1994-2001	✗	✓	✗	✗	✗
Koh, Koh, & Teo (2003)	Eurekahegde, Asia-Hedge	3,810 (Asian funds)	1999-2003	✗	✓	✗	✗	✗
Kosowski, Naik, & Teo (2007)	TASS, HFR, CISDM, MSCI	9,338	1990-2002	✗	✓	✗	✗	✗
Kouwenberg (2003)	Zurich (MAR)	2,614	1995-2000	✗	✓	✗	✗	✗
Malkiel & Saha (2005)	TASS	2,065	1996-2003	✗	✓	✗	✗	✗

✓ Accounts for restriction ✗ Does not account for restriction

Source: Author's own illustration, Eling (2009)

[82] as opposed to index data
[83] at individual HF level
[84] at individual HF level

Table 2: Selection of Literature ─ Portfolio Selection

Author(s) (Year)	Database(s)	Number of Funds/ Indices	Investi-gation Period	2007-09 Crisis	Indivi-dual HF Data[85]	Lock-up Peri-ods[86]	Min. Inv. Re-quire-ments[87]	Trans-action Costs
Alexander & Dimitriu (2005)	HFR	282	1990-2003	×	✓	×	×	×
Bergh & van Rensburg (2008)	CSFB/ Tremont	14	1994-2004	×	×	×	×	×
Carretta & Mattarocci (2005)	Hedge Index, Tremont, TASS, Hedgefund.net	556	1993-2003	×	✓	×	×	×
Davies, Kat, & Lu (2009)	Tremont, TASS	2,183	1994-2001	×	✓	×	×	×
De Souza & Gokcan (2004a)	HFR	8	1990-2002	×	×	×	×	×
Eling & Schuhmacher (2007)	Ehedge	2,763	1985-2004	×	✓	×	×	×
Fang, Phoon, & Xiang (2008)	Eurekahedge (Asian funds)	70	2000-2004	×	✓	×	×	×
Giamouridis & Vrontos (2007)	HFR	8	1990-2005	×	×	×	×	×
Glaffig (2006)	CSFB/ Tremont	11	1994-2004	×	×	×	×	×
Gregoriou, Hübner, Papageorgiou, & Douglas Rouah (2007)	HFR	2,300	1995-2003	×	✓	×	×	×
Gregoriou & Rouah (2001)	Zurich, LaPorte	n/a	1988-1999	×	✓	×	×	×
Hakamada, Takahashi, & Yamamoto (2007)	Eurekahedge (Asian funds)	108	2002-2005	×	✓	×	×	×

[85] as opposed to index data
[86] at individual HF level
[87] at individual HF level

Table 2: Selection of Literature ─ Portfolio Selection (Continued)

Author(s) (Year)	Database(s)	Number of Funds/ Indices	Investi-gation Period	2007-09 Crisis	Indivi-dual HF Data[88]	Lock-up Peri-ods[89]	Min. Inv. Re-quire-ments[90]	Trans-action Costs
Jöhri & Leippold (2006)	TASS	3,130	1994-2005	×	✓	×	×	×
Kaiser, Schweizer, & Wu (2008)	HFI, Absolute Return, Eurekahedge	9	1996-2006	×	×	×	×	×
Krokhmal, Uryasev, & Zrazhevsky (2002)	Foundation for Managed Derivatives Research	301	1995-2001	×	✓	×	×	×
Lamm (2003)	HFR, CSFB/ Tremont	10	1990-2002	×	×	×	×	×
Nguyen-Thi-Thanh (2010)	CISDM	149	2000-2005	×	✓	×	×	×

✓ Accounts for restriction × Does not account for restriction

Source: Author's own illustration

These tables clearly illustrate that existing academic research in the field is not 1:1 applicable to the reality of family office HF investing, since it fails to consider significant practical restrictions. In this dissertation, the author seeks to develop a practically-relevant investment approach in an effort to bridge the research gap. The new investment approach is strictly quantitative, fully transparent, based on existing academic literature, and tested against a relevant sample of HFs in a close-to-practice environment. The approach proposed here also considers the major practical restrictions that investors face, such as lock-up periods, minimum-investment requirements, transaction costs, and buy and sell lags.

[88] as opposed to index data
[89] at individual HF level
[90] at individual HF level

With the presentation of this new approach, the author strives to make a distinctive contribution to academic literature in the field of fund allocation. At the same time, he aims to enhance investment management of family offices by providing a heuristic that is easy to implement and to operate. The proposed heuristic is outlined in detail in the following section.

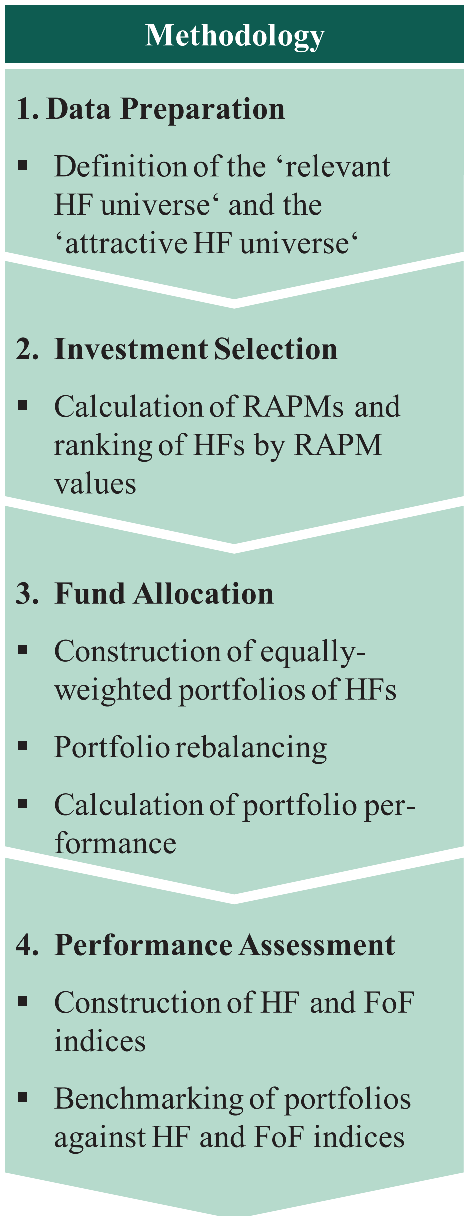
4 Empirical Analysis

This section of the dissertation is presented in two basic parts. The first part outlines the methodology applied in this empirical study (4.1) and the second part discusses the findings (4.2).

4.1 Research Design

This dissertation aims at developing a fully-transparent, strictly quantitative portfolio management heuristic that is specifically targeted at family offices. The heuristic is developed in several steps.

Figure 15: Research Design



Source: Author's own illustration

The first step concerns the dataset. The author defines the 'relevant HF universe' as one which excludes HFs that are irrelevant to this thesis. Through the selection of the most promising HFs for investment, the 'attractive HF universe' is then established. The second step is to calculate a variety of different RAPMs for all HFs in the 'attractive HF universe'; The HFs are ranked, from best to worst, according to their RAPM values. In total, 23 different rankings are established by employing 23 different RAPMs. Moreover, these different rankings are merged into one single equally-weighted ranking, the so-called 'Combined Indicator' ranking. In a third step, 23 equally-weighted portfolios are constructed, one for each RAPM ranking. Furthermore, an equally-weighted 'Combined Indicator' portfolio is created. These portfolios are subsequently reallocated periodically throughout the observation period. This dissertation evaluates portfolios of four different holding periods (of 6, 12, 18 and 24 months, respectively), and the author calculates the performance of each of these portfolios. In a forth step, the performance of the constructed portfolios is assessed against the relevant benchmark indices, which involves a comparison of various risk and return characteristics.[91] This section also presents a detailed sensitivity analysis of the 'Combined Indicator' portfolio.

The following paragraphs outline this methodology in closer detail. First, there is a brief outline of the data set and the method employed for data preparation (4.1.1), investment selection (4.1.2), and fund allocation (4.1.3). This is then followed by an introduction to the sort of performance assessment that is employed in this thesis (4.1.4). Finally, a short summary of the research design is presented (4.1.5).

4.1.1 Data Set and Data Preparation

This dissertation is based on the Eurekahedge Global HF database and the Eurekahedge FoF database.[92] These databases report monthly returns and AuM data on an individual fund level. Moreover, they include detailed fund characteristics, such as the investment strategy, the investment geography, lock-up periods, and the minimum-investment requirements of the respective funds.

The data preparation process includes three steps, the first being the setting of the observation period. In the second step, the author defines the fund universe that is relevant to this dissertation by narrowing-down a standard HF data sample. In the third step, the so-called 'attractive fund universe' is established by selecting the most promising HFs, based on their size and age.

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91 The constructed portfolios are measured against two different benchmarks: an equally-weighted index of HFs in the 'relevant HFs universe' and an equally-weighted index of FoFs in the 'relevant FoFs universe'. These indices are constructed based on the Eurekahedge Global HF and the Eurekahedge FoF databases. Paragraph 4.1.4 provides a detailed overview of the benchmarking process.

92 Eurekahedge, based in Singapore, is a data vendor in the alternative investments space and one of the world's largest providers of HF data.

Definition of the Observation Period

The Eurekahedge Global HF and FoF databases contain fund returns and AuM track records dating back to 1988. It is important to note, however, that the earliest registration date of funds with the databases is August 2004. As a matter of fact, any information before that point in time must have been backfilled and is thus subject to the instant-history bias. Moreover, HFs, which registered with the database after that point in time, were also given the opportunity to backfill their previous returns and AuM giving further rise to the same bias.[93]

In order to prevent the instant-history bias from eroding the data sample of this dissertation, the author only considers HFs for investment after their listing date with the database. Thus, the observation period of this dissertation ranges from August 2004 to June 2009. Any extension of the observation period prior to August 2004 would make the data sample subject to the instant history bias and is thus neglected.

Definition of the Relevant HF and FoF Universes

Previous literature in the field of HF performance persistence clearly shows that the explanatory power of any study is largely depended on the underlying data sample. In contrast to several previous studies, this dissertation narrows down the dataset considerably in order to portray as accurately as possible the relevant HF universe that practitioners face.

The underlying Eurekahegde Global HF database contains 8,249 'dead' and 'alive' HFs.[94] Unfortunately, not all of these HFs report their returns. After removing the non-reporting funds from the sample, there are 7,288 left. Furthermore, the database includes different versions of several HFs. These are for most part on-shore/off-shore, accumulating/distributing and different currency versions of essentially the same HF. The author removes such duplicate funds by concentrating on the fund with the highest AuM, the so-called flagship fund. After this procedure, 5,171 HFs

[93] While successful HFs are expected to seize this opportunity, bad track records are most likely not backfilled (Géhin, 2006).

[94] As of November 2009

are left. In the following step, all closed HFs are removed.[95] This is why these HFs are not part of the investable fund universe from an investors perspective. After this process 4,816 HFs are left. These funds constitute the 'relevant HF universe' from a practitioner's point of view. A corresponding procedure is applied to the Eurekahedege FoF database in order to define a 'relevant FoF universe' of 1,710 funds. Figure 16 illustrates the process. The relevant HF and FoF universes play a further important role in the performance assessment since they are used for the calculation of benchmark indices (4.1.4).[96]

Figure 16: Confinement of the Relevant HF and FoF Universe[97]

Eurekahedge Global HF Database	
8,249	**Global HFs**
7,288	Reporting returns
5,171	Flagship
4,816	Open
4,816	**Relevant HFs**

Eurekahedge FoF Database	
3,248	**Global FoFs**
3,139	Reporting returns
1,811	Flagship
1,710	Open
1,710	**Relevant FoFs**

Source: Author's own illustration

Definition of the Attractive HF Universe

The 'relevant HF universe' as described above represents an enumeration of all HFs that are theoretically investable. In the next step, the author narrows down this group even further to those HFs that the previous literature has identified as the most attractive for investment. These HFs constitute the 'attractive HF universe'.

More recent research in the field of HF characteristics unanimously indicates a clear negative relationship between HF size and performance. The same is true for the

95 Unfortunately, the Eurekahedge databases only include the current open/closed status of a specific fund. As historic information is not available, the author assumes that open funds have always been open and closed funds have always been closed. This, however, is a simplification and is only applied because of the lack of more accurate information.

96 The constructed portfolios are measured against two different benchmarks: an equally-weighted index of HFs in the 'relevant HFs universe' and an equally-weighted index of FoFs in the 'relevant FoFs universe'. Paragraph 4.1.4 provides a more detailed overview of this process.

97 Includes dead as well as alive funds.

relationship between the length of HF track records and their performance. To account for these findings, the proposed investment heuristic only considers comparatively small HFs, of between US$1 million and US$100 million in AuM.[98] Furthermore, only those HFs qualify for investment that have track records of 36 months or less.[99] Finally, all those HFs that do not report their returns for more than two consecutive months are not considered eligible for investment.

This 'attractive HF universe' serves as the basis for the proposed investment heuristic.[100] In a further step, the author strives to identify the most promising HFs of the 'attractive HF universe' with the help of RAPMs. This procedure is elaborated in the next paragraph.

4.1.2 Investment Selection

This dissertation proposes an entirely quantitative investment selection approach that relies heavily on RAPMs. These indicators are used to identify the HFs with the best risk / return profiles within the 'attractive HF universe'. Since no single RAPM has been shown to dominate over the others in the previous academic literature, this dissertation draws on a broad range of RAPMs. On the whole, 23 different RAPMs are calculated for each individual HF included in the 'attractive HF universe'. These 23 RAPMs are comprised of five LPM-based RAPMs[101], three drawdown-based RAPMs[102], three VAR-based RAPMs[103], and four further RAPMs[104]; the remaining

[98] Amman and Moerth (2005) indicate that performance drops considerably if HF AuM fall short of or exceed these values.

[99] Howell (2001), Brown et al. (2001), and Herzberg and Mozes (2003) indicate that HFs with track records of 36-months and below considerably outperform their older peers. The minimum required track record will be 24 months; this is necessary to calculate the RAPM values.

[100] It is important to note that the size of the 'attractive HF universe' fluctuates across the observation period. If, for instance, a 24-months-old HF in this universe expands its AuM from US$90 million to US$110 million within 6 months, it will no longer be considered for investment anymore, because it has become too large. If, however, AuM drop below US$100 million 6 months later, it will once more be included in the 'attractive HF universe'.

[101] Omega, the Sortino Ratio, Kappa 3, the Upside Potential Ratio, and Excess Return on Probability of Shortfall (ERoPS)

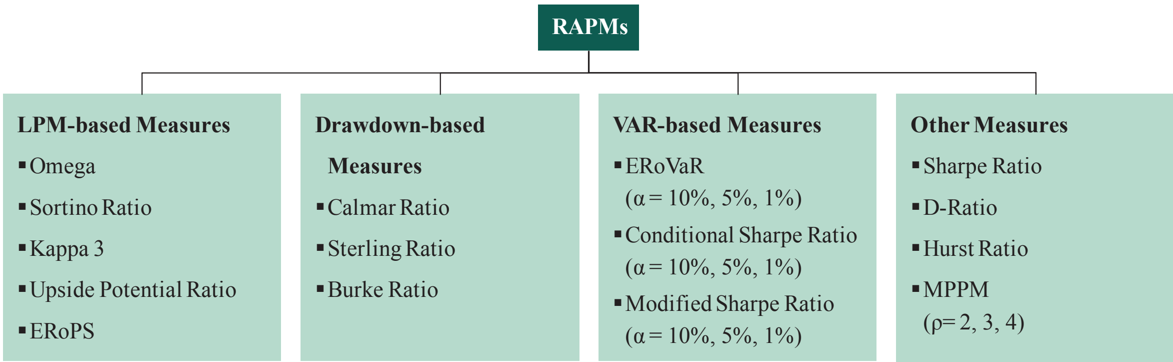
[102] The Calmar, Sterling, and Burke Ratios

[103] Excess Return on Value at Risk (ERoVaR), the Conditional Sharpe Ratio, and the Modified Sharpe Ratio

[104] The D-Ratio, the Hurst Ratio, and the Manipulation-proof Performance Measure (MPPM)

RAPMs constitute variants of the VAR-based RAPMs and the MPPM inasmuch as they feature different key parameters. Figure 17 provides an overview.

Figure 17: Risk-adjusted Performance Measures (RAPMs)



Source: Author's own illustration

The computation of these RAPMs is based essentially on the historical post-fee returns reported by the individual HFs within the 'attractive HF universe'. Furthermore, several parameters have to be fixed. These include the length of the in-sample period ($r_{i1},\ldots, r_{iT}$), the risk free rate (r_f), the minimum acceptable return (τ), the number of largest drawdowns considered as per the Sterling and Burke Ratios, the significance level for VaR-based RAPMs (α), and the risk-penalizing coefficient of the MPPM (ρ).

The author sets the length of the in-sample period at 24 months.[105] The risk-free rate is defined as the interest on a US T-Bill.[106] Furthermore, the minimum acceptable return is set as equal to the risk-free rate.[107] For the Sterling and Burke Ratios, the author considers the three largest drawdowns during any in-sample period.[108] In the

[105] In general, in-sample periods should be as short as possible to capture performance persistence but long enough to deliver reliable estimates. In the HF space, there is no single generally-used in-sample period. In the light of previous studies, such as Jöhri and Leippold's (2006), an in-sample period of 24-months appears sensible.

[106] This selection of the risk-free rate is a common choice in academic literature.

[107] τ is usually zero, the risk-free rate or average return; previous research has shown that these different choices of τ by and large deliver equivalent results (Eling & Schuhmacher, 2007).

[108] The choice of N is arbitrary. In the light of previous studies, such as Eling and Schuhmacher's (2007), a value of N = 3 seems reasonable.

case of VAR-based measures, three different significance levels, specifically α = 1%, 5%, and 10% are tested.[109] Similarly, the MPPM is calculated under three different risk-penalizing coefficients ρ = 2, 3, 4.[110] Finally, this dissertation employs a buy and sell lag of three months.[111]

On the whole, 23 different RAPMs are calculated for each individual HF in the 'attractive HF universe'. Based on these RAPMs, the author builds 23 different portfolios. Each portfolio invests in the 10 best HFs under one certain RAPM.[112] This results in 23 different portfolios; each of them consists of 10 HFs and is based on one specific RAPM. This process is illustrated in Figure 18. In this context, it must be noted that HF selection is not based on the absolute value of an RAPM, but rather on the ranking of HFs established by an RAPM: All HFs in the 'attractive HF universe' are ranked from best to worst under a certain RAPM and only the top 10 HFs are considered for investment.[113]

Correspondingly, a 'Combined Indicator' portfolio is created: The different HF rankings established by the 23 RAPMs are merged into one single equally-weighted ranking.[114] The author then builds a 'Combined Indicator' portfolio consisting of the 10 HFs with the highest 'Combined Indicator' values.

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[109] Significance levels of 1%, 5%, and 10% are standard in academic literature.

[110] This selection of the risk-penalizing coefficient is common in previous research on the MPPM (Ingersoll et al., 2007).

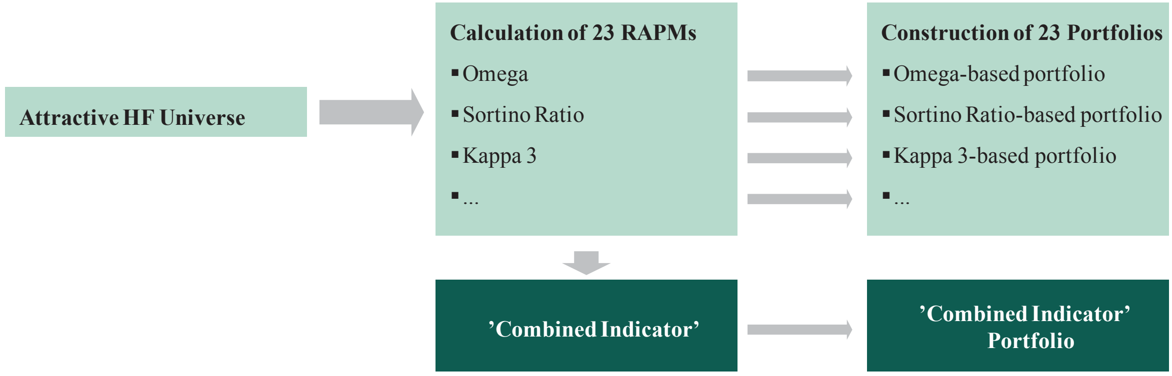
[111] While the choice of this buy and sell lag might be considered arbitrary, it certainly seems to be a sensible and conservative assumption.

[112] The first portfolio invests in the 10 HFs with the best 'Omega' values, the second portfolio invests in the 10 HFs with the best 'Sortino Ratios' etc. All portfolios consist of 10 HFs because previous research shows that most diversification benefits in a HF portfolio are captured by 10 equally-weighted HFs; see for instance Park and Staum (1998), Henker (1998), Amin and Kat (2003), Lhabitant and Learned (2004), and Lhabitant and Laporte (2006).

[113] This procedure is based on a study by Alexander and Dimitriu (2006), which examines the performance of portfolios when the fund selection is based on the rank of a HF's Alpha rather than the value of Alpha. The study finds that ranking HFs according to their Alpha is an efficient HF selection process.

[114] This procedure is based on a study by Jöhri and Leippold (2006).

Figure 18: Construction of Portfolios Based on RAPMs



Source: Author's own illustration

As RAPMs tend to fluctuate over time, the portfolio construction process is reiterated on a rolling basis throughout the observation period. This procedure is elaborated on in the next paragraph.

4.1.3 Fund Allocation and Portfolio Reallocation

This dissertation is based on a series of out-of-sample tests. As discussed in the previous paragraph, the RAPMs for all HFs within the 'attractive HF universe' are calculated based on a 24-month in-sample period. The HFs are then ranked according to their RAPM-values with the top HFs qualifying for investment. As RAPMs seem to capture HF performance persistence best over a short term, frequent portfolio reallocation seems to be desirable in order to achieve high returns. In the presence of transaction costs, however, the increased costs of such frequent reallocations may deplete this advantage. In order to account for this problem, this dissertation constructs and evaluates a variety of portfolios, specifically, portfolios that are rebased every 6, 12, 18, and 24 months during the observation period.[115]

[115] The author assumes portfolio reallocation to occur either on June 30^{th} or December 31^{th}. While the choice of these dates might seem arbitrary, most smaller HFs are not open to new investors year-round, but rather accept capital inflows only on key dates such as end of quarter etc. Portfolio reshufflings on June 30^{th} or December 31^{th} correspond to most of these key dates.

In total, this thesis simulates 92 portfolios. This is the result of analyzing 23 different RAPMs over 4 different holding periods.[116] Each portfolio represents a unique combination of one of the 23 RAPMs and a specific holding period of 6, 12, 18, or 24 months.

This dissertation takes a straightforward approach to fund allocation within these portfolios. Considering the high minimum investment amounts that most HFs require, it seems appropriate from a family office practitioner's point of view to strictly limit the number of individual investments. Previous research indicates that the majority of diversification benefits are captured with a naively-diversified portfolio of just 10 HFs.[117] Thus, the 92 simulated portfolios presented here as well as the 'Combined Indicator' portfolio are invested in no more than 10 HFs at any given time during the observation period. At the beginning of each period, an equal share of disposable capital is allocated to each HF selected. These weights are not adjusted throughout the respective period.

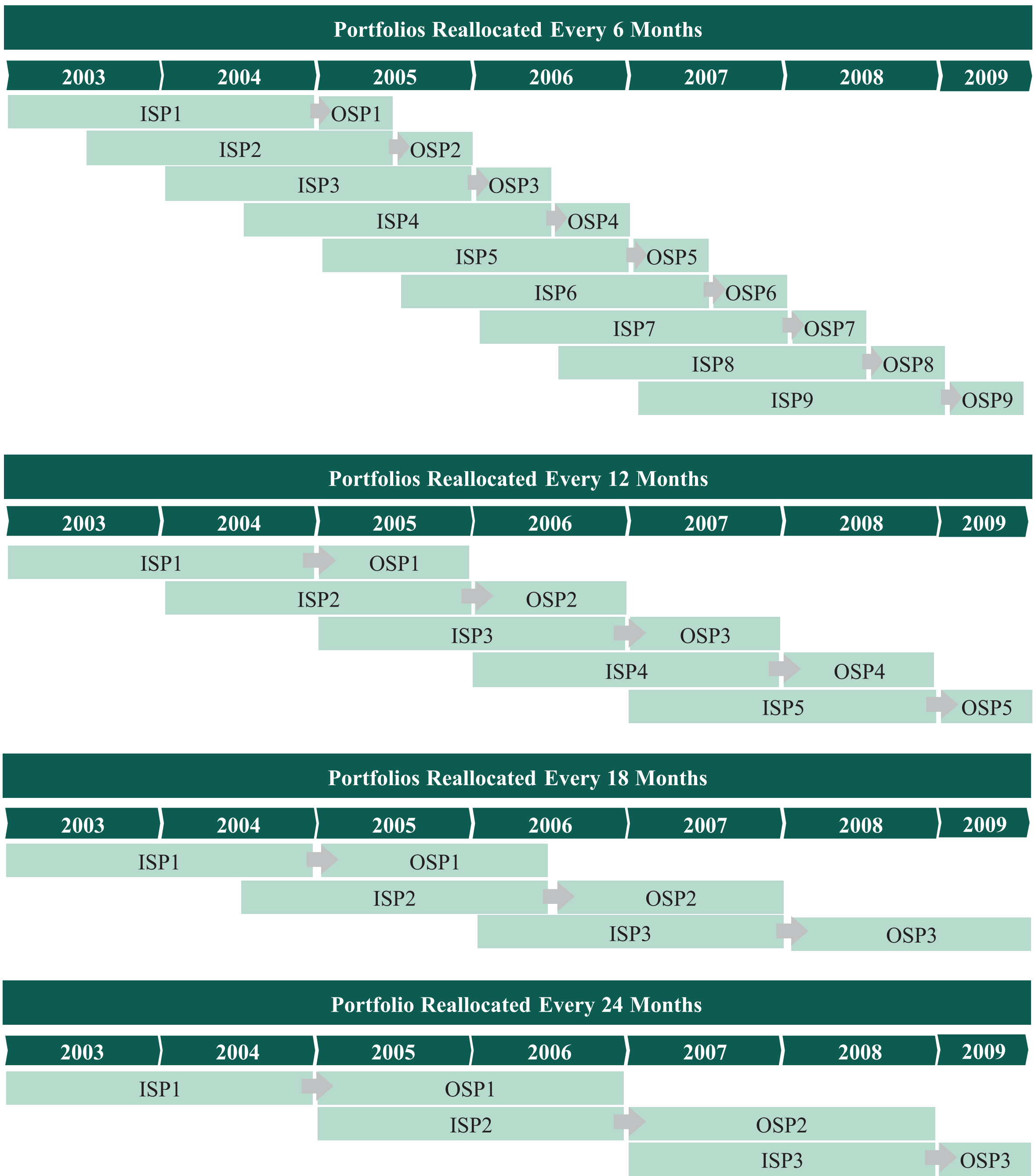
Figure 19 illustrates this process: In a first step, the 10 most promising HFs under each of the 23 different RAPMs are identified based on their size, age, and their risk-adjusted performance during in-sample period 1 (ISP1). Then, at the beginning of out-of-sample period 1 (OSP1), the investor forms 23 equally-weighted portfolios of these HFs. The performance of these portfolios is tracked on a monthly basis throughout OSP1. As the individual HFs generate different returns in the course of OSP1, portfolio weights tend to deviate during this period. At the end of OSP1, all HFs are sold irrespective of their performance. Then, the investor buys in new portfolios of HFs with the best RAPM values based on their size, age, and their risk-adjusted performance during in-sample period 2 (ISP2) which corresponds to OSP1. To this end, 23 new equally-weighted portfolios based on the 23 different RAPMs are formed at the beginning of out-of-sample period 2 (OSP2). Again,

[116] It is noteworthy that the size of the investable 'attractive HF universe' is different for these four holding periods. This is due to the different lock-up periods at individual HF levels. A portfolio that is reallocated every 6 months will only be able to invest in HFs with a lock-up period of up to 6 months. Another portfolio that is reallocated every 12 months may also include HFs with a lock-up period of between 6 and 12 months. In other words, the longer the holding period is, the larger the size of the investable 'attractive HF universe' will be.

[117] See for instance Park and Staum (1998), Henker (1998), Amin and Kat (2003), Lhabitant and Learned (2004), and Lhabitant and Laporte (2006).

portfolio performance is tracked on a monthly basis and all HFs are sold at the end of OSP2. This process is reiterated until the end of the observation period in June 2009.

Figure 19: Illustrative Overview of Portfolio Reallocations[118]



ISP: In-sample period

OSP: out-of-sample period

Source: Author's own illustration

[118] As RAPMs seem to capture HF performance persistence best over a short term, frequent portfolio reallocation seems to be desirable to be able to capture this feature. On the other hand, such frequent reallocation comes at the expense of high transaction costs, which may easily erode the benefits. In order to account for this problem, this dissertation constructs and evaluates a variety of portfolios. Specifically, portfolios that are rebased every 6, 12, 18, and 24 months during the observation period are tested here.

After this examination of the fund allocation and portfolio reallocation process, the performance assessment methodology applied in this dissertation is now outlined in the following paragraph.

4.1.4 Performance Assessment

The evaluation comprises of two different parts: a benchmarking analysis and a sensitivity analysis. In the benchmarking analysis, the author calculates the first four statistical moments of the 92 constructed portfolios, the 'Combined Indicator portfolio', and the two benchmarks in order to compare them side-by-side. The sensitivity analysis is also straightforward: In order to uncover the sensitivities of the proposed 'Combined Indicator' approach to parameter changes, the author digresses from the base case of the foregoing analysis by varying the critical input parameters. Both analyses are described in closer detail below.

4.1.4.1 Benchmarking Analysis

The performances of all of the 92 portfolios constructed and the 'Combined Indicator' portfolio is tracked on a monthly basis.[119] These portfolios are measured against two different benchmarks: an equally-weighted index of HFs in the 'relevant HFs universe' and an equally-weighted index of FoFs in the 'relevant FoFs universe'.[120] This comparison, using both benchmarks, addresses different questions.

[119] In order to facilitate the evaluation of these portfolios, they are all denoted in US$. By defining the US$ as the base currency, a maximum comparability with international academic literature is ensured. It is noteworthy, that the specification of a base currency inevitably affects the reported performance because the returns of foreign-currency HFs must be converted into US$. As such, overall returns are inevitably subject to exchange rate fluctuations. It must be pointed out, however, that, in this exercise, foreign-currency-denominated HF returns are only converted into US$ for performance assessment purposes; RAPM calculation and, thus, investment selection is based entirely on HF returns in their base currencies.

[120] In order to avoid a survivorship bias, these benchmarks include 'moribund' / 'dead' as well as 'alive' funds. Furthermore, they are reallocated after the same holding periods as the portfolios that are benchmarked against them.

Benchmarking against an Equally-weighted Index of Relevant HFs

The comparison of these 92 portfolios against the 'relevant HF universe' is aimed at answering the question of whether the methodology proposed is capable of selecting superior funds from the 'relevant HF universe'. If such is the case, the portfolios constructed here should surpass the benchmark.

Benchmarking against an Equally-weighted Index of Relevant FoFs

The comparison of the 92 portfolios and the 'Combined Indicator' portfolio against the 'relevant FoF universe' is aimed at answering the question of whether the methodology proposed here produces portfolios that are superior to real-life FoFs. If such is the case, the constructed portfolios should surpass the benchmark with regard to their risk / return characteristics.

In this context, it must be stressed that FoFs offer valuable benefits over a direct investment in HFs in the form of accessibility, liquidity, and professional management. These advantages come at a certain cost, and FoFs charge their investors with a second layer of fees which negatively impacts their performance. As the portfolio management approach developed here offers none of the aforementioned benefits that FoFs provide, benchmarking against FoFs is not a like-with-like comparison and thus included for reference only.

4.1.4.2 Sensitivity Analysis

This dissertation proposes a portfolio management approach that is essentially based on a 'Combined Indicator' that consists of several different RAPMs. The approach is focused on investment in comparatively small and young HFs because these have been identified as particularly attractive for investment by previous academic research.[121] In order to evaluate whether such a focus is prudent, it is necessary to test the suggested investment approach against these two parameters.

[121] See for instance Howell (2001), Brown et al. (2001), Herzberg and Mozes (2003), Hedges (2003), Harri and Brorsen (2004), Getmansky (2004), Ammann and Moerth (2005), and Boyson (2008, 2010).

At the same time, it must be stressed that the empirical study presented here is fundamentally based on a number of assumptions related to parameter choice. These assumptions include the level of transaction costs, performance fees, management fees, liquidity buffers and asset recovery rates. The necessity to test the investment approach presented here for its sensitivity towards these parameters is outlined below:

- Transaction costs include operating expenses and pre-sale charges, as well as other costs incurred. Academic approaches to HF portfolio management typically ignore the effect of transaction costs. For the lack of reliable information, the author assumes transactions costs of 5% of the total investment volume to incur every time that the portfolio is reallocated.[122] In order to account for this imponderability, different scenarios are tested in the sensitivity analysis.

- It is not a commonly-accepted industry practice for family offices to charge their clients with performance fees; thus, these fees are ignored in the base case of the analysis. Still, in order to cover for all possible compensation schemes, the author considers performance fees in the sensitivity analysis.

- Family offices charge their clients with management fees that range from 0.25% to 1.50% of AuM annually (FOX, 2011; Silverman, 2008). The author assumes annual management fees to stand at 1%, which is a rather conservative assumption. Nevertheless, it appears sensible to test the performance of the presented investment approach in different scenarios.

- FoFs usually have flexible redemption policies. In order to provide such liquidity, all FoFs have liquidity buffers, which are characterized, naturally, by very low returns. Family offices on the other hand strive to preserve and grow their clients' assets in the long run. Thus, they have a long-term investment horizon and do not need to provide the same liquidity as FoFs. Therefore, the investment approach

[122] A transaction costs estimate of 5% is in line with the assumptions of a previous study by Amenc et al. (2003). In the context of this dissertation, a 5% estimate seems to be very high: A hypothetical family office with HF investments of US$10 million would incur transaction costs of around US$1 million just for reallocating its portfolio twice a year.

presented in this study does not take liquidity buffers into consideration. Still, for the reason of completeness, the author includes liquidity buffers in the sensitivity analysis.

- Although asset recovery rates are typically ignored in previous academic research, they play a critical role. Academics usually assume that HFs going out of business can recover 100% of their AuM at the point of liquidation. This, however, may not always be the case as many HFs are active in illiquid markets. If these HFs are liquidated, investors may lose a considerable share of their AuM. While an asset recovery of 100% represents the base case, the impact of less favourable assumptions is tested in the sensitivity analysis.

As shown above, a sensitivity analysis for the listed factors is required in order to evaluate whether the proposed investment approach is sensible even if the underlying parameters were different, i.e. less favourable than assumed. The sensitivity analysis itself is straightforward: The author digresses from the base case of the foregoing analysis by varying the critical input parameters[123] one at a time. Then the 'Combined Indicator' portfolio and the two benchmarks are compared side-by-side. This procedure helps to assess how sensitive the proposed investment approach is to the parameter changes.

After this elaboration of the performance assessment procedure, the following paragraph is dedicated to summarizing the entire research design.

4.1.5 Summary of Research Design and Overview of Relevant Parameters

In the previous paragraphs, a detailed research design for the development and evaluation of a purely quantitative HF investment approach specifically targeted at the situation of family offices has been described. The methodology proposed here involves several steps and is summarized in Figure 20.

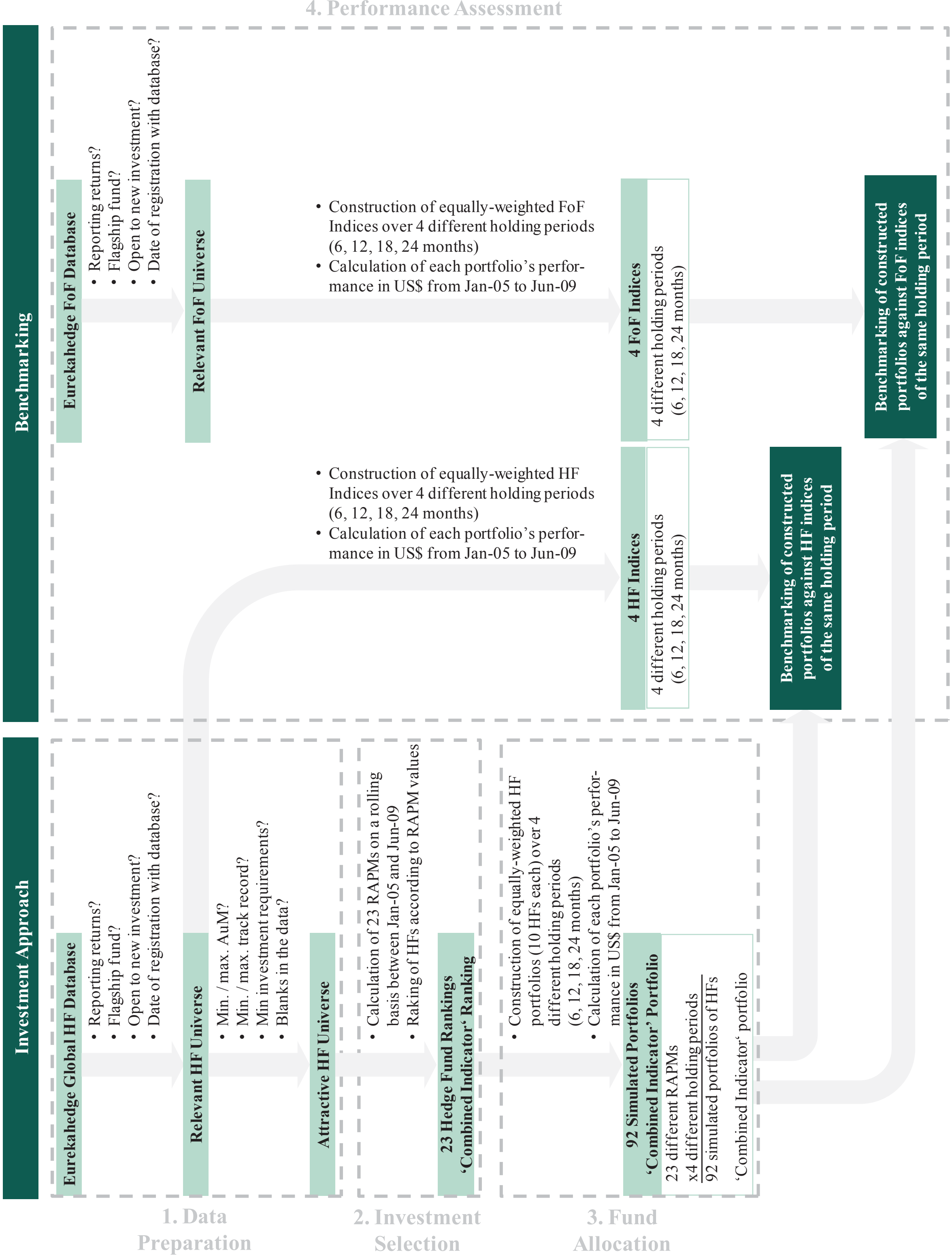
[123] Specifically, HF size, HF age, the level of transaction costs, performance fees, management fees, liquidity buffers, and asset recovery rates.

Starting off from the Eurekahedge Global HF database, the 'relevant HF universe' is established by ignoring all HFs that do not report returns, non-flagship funds, and any funds that are closed to new investment. The most promising HFs are then selected, based on their size, their age, and their reporting discipline, which results in the 'attractive HF universe'. At this stage, 23 different RAPMs are calculated on a rolling basis for all the HFs in the 'attractive HF universe'. For every RAPM, a HF ranking, from 'best' to 'worst', is established, resulting in a short-list of the 10 most attractive HFs under each RAPM.[124] The next step involves fund allocation and portfolio reallocation. On the whole, 92 equally-weighted portfolios of 10 HFs each are constructed. This is why there are 23 different RAPMs analyzed over 4 different holding periods.[125] Each portfolio represents a unique combination of one of the 23 RAPMs and a specific holding period of 6, 12, 18, or 24 months. Finally, there is a performance assessment, in which the 92 constructed portfolios are compared to an equally-weighted HF index and an equally-weighted FoF index. Moreover, all 23 RAPMs are merged into a 'Combined Indicator' and a 'Combined Indicator' portfolio of 10 HFs is established. This portfolio, as well, is benchmarked against to an equally-weighted HF index and an equally-weighted FoF index and its sensitivity to parameter changes is tested.

[124] These short-lists change periodically, of course, in line with the underlying HF rankings.

[125] It is noteworthy that the size of the investable 'attractive HF universe' is different for these four holding periods. This is due to the different lock-up periods at individual HF levels. A portfolio that is reallocated every 6 months will only be able to invest in HFs with a lock-up period of up to 6 months. Another portfolio that is reallocated every 12 months may also include HFs with a lock-up period of between 6 and 12 months. In other words, the longer the holding period is, the larger the size of the investable 'attractive HF universe' will be.

Figure 20: Systematic Overview of Research Design (Simplified)



Source: Author's own illustration

Now that the research design has been summarized, it seems appropriate to revisit the most important input parameters of this dissertation. Table 3 provides an overview of the key parameters and gives a detailed reasoning for each item.

Table 3: Overview of the Relevant Parameters

Investment Selection

Item / Parameter	Resolution / Value	Explanation / Reasoning
Length of in-sample period	24 months	In general, in-sample periods should be as short as possible to capture performance persistence, yet long enough to deliver reliable estimates. In the HF space, there is no single generally-used in-sample period. In the light of previous studies, such as Jöhri and Leippold's (2006), 24 months appear reasonable.
Buy and sell lag	3 months	The choice of a buy and sell lag is certainly arbitrary. In the light of previous studies, such as Jöhri and Leippold's (2006), three months seem to be a sensible and conservative assumption.
Risk-free rate (r_f)	Interest on US T-Bill of same maturity	This selection of the risk-free rate is a common choice in academic literature.
Minimum acceptable return (τ)	Risk-free rate (r_f)	τ is usually zero, the risk-free rate or average return; previous research has shown that these different choices of τ by and large deliver equivalent results (Eling & Schuhmacher, 2007).
Number of considered largest drawdowns (N)	3	The choice of N is arbitrary. In the light of previous studies, such as Eling and Schuhmacher's (2007), a value of N = 3 seems reasonable.
Significance level of VAR-based RAPMs (α)	1%, 5%, 10%	Significance levels of 1%, 5%, and 10% are standard in academic literature.
Risk-penalizing coefficient (ρ) of the MPPM	2, 3, 4	This selection of the risk-penalizing coefficient is common in previous research on the MPPM (Ingersoll et al., 2007).

Fund Allocation & Portfolio Reallocation

Item / Parameter	Resolution / Value	Explanation / Reasoning
Length of out-of-sample period	6, 12, 18, 24 months	Whilst frequent portfolio reallocation is considered superior for the capitation of performance persistence, it comes at the cost of an increase in the total transaction costs incurred. This study therefore compares holding periods of several different lengths.
Initial size of simulated portfolios	US$10 million	This thesis explicitly takes the role of a small family office, and whilst the choice of the initial fund size is certainly arbitrary, a fund size of US$10 million for HF investment appears to be a rather conservative assumption. This is because most family offices are estimated have AuM in excess of US$100 million of which they invest 12%-14% in HFs (Amit et al., 2008; FOX, 2011; Preqin, 2009; Silverman, 2008).
Number of HFs in portfolio	10	Previous research shows that most diversification benefits in a HF portfolio are captured by 10 equally-weighted funds.[126]
Reference currency	US$	In order to ensure maximum academic comparability of this dissertation, the reference currency of all simulated portfolios is US$.
Transaction costs	5%	For the lack of reliable information, the author assumes transactions costs of 5% of the total investment volume to incur every time that the portfolio is reallocated.[127]
Management fees	1% on AuM annually	Family offices charge their clients with management fees that range from 0.25% to 1.50% of AuM annually (FOX, 2011; Silverman, 2008). The author assumes annual management fees to be at 1% which is a rather conservative assumption.

[126] See for instance Park and Staum (1998), Henker (1998), Amin and Kat (2003), Lhabitant and Learned (2004), and Lhabitant and Laporte (2006). Interestingly, this academic finding seems to be in line with the practice of many family offices; a recent survey of North American family offices found that they were typically invested in 10 different HFs or FoFs (Preqin, 2009).

[127] Transactions costs include operating expenses as well as pre-sales charges and other costs incurred. A transaction costs estimate of 5% is in line with the assumptions of a previous study by Amenc et al. (2003). In the context of this dissertation, however, a 5% estimate seems to be very high.

Benchmarks

Item / Parameter	Resolution / Value	Explanation / Reasoning
Benchmarks	Equally-weighted indices of all relevant HFs and FoFs	Benchmarking against the ‘relevant HF universe’ is used to answer the question of whether the proposed methodology is capable of selecting superior funds from the ‘relevant HF universe’. Benchmarking against the ‘relevant FoF universe’ is employed to answer the question of whether the proposed methodology produces portfolios that are superior to real-life FoFs.[128]

Source: Author’s own illustration

Having thus outlined the research design and the selection procedure for all the parameters that are relevant to this dissertation, the following paragraph presents the key findings of this study.

[128] In this context, it must be stressed that FoFs offer valuable benefits over a direct investment in HFs. These are accessibility, liquidity, and professional management. These advantages come at a certain cost and FoFs charge their investors with a second layer of fees which negatively impacts their performance. As the portfolio management approach developed here offers none of the aforementioned benefits that FoFs provide, benchmarking against FoFs is not a like-with-like comparison and thus included for reference only.

4.2 Evaluation and Findings

This thesis takes a strictly quantitative approach to HF investment. As shown in the previous chapter, the author constructs several different HF portfolios, each of which is comprised of the highest ranking HFs under a specific RAPM. These portfolios are reallocated regularly. The performance of each of these portfolios is tracked on a monthly basis and their fundamental return statistics are measured against an equally-weighted index of all investable HFs in the database, i.e., the so-called 'relevant HF universe' and an equally-weighted index of all investable FoFs in the data base, i.e., the so-called 'relevant FoF universe'. This process is presented in several steps. First, the constructed portfolios are benchmarked against an equally-weighted HF index (4.2.1), then against an equally-weighted FoF index (4.2.2). In a next step, the fundamental return statistics of the 'Combined Indicator' portfolio and the results of the sensitivity analysis are presented (4.2.3). This is followed by a short summary of the results (4.2.4).

4.2.1 Performance Benchmarking against HF Index

This paragraph focuses on the benchmarking of the HF portfolios that were constructed against an equally-weighted index of relevant HFs. The aim of this comparison is to verify whether the methodology proposed in this thesis is capable of selecting superior funds from the 'relevant HF universe'. If this is the case, the constructed portfolios should clearly outperform the benchmark during the observation period.

The following pages present a detailed comparison of portfolios based on the 23 RAPMs. All portfolios are denoted in US$ and are reallocated every 6 months.[129] For the sake of brevity, the portfolios with longer holding periods (12, 18, 24 months) are not discussed at this point. However, their key statistics can be observed in Appendix E (Tables E6-E8).

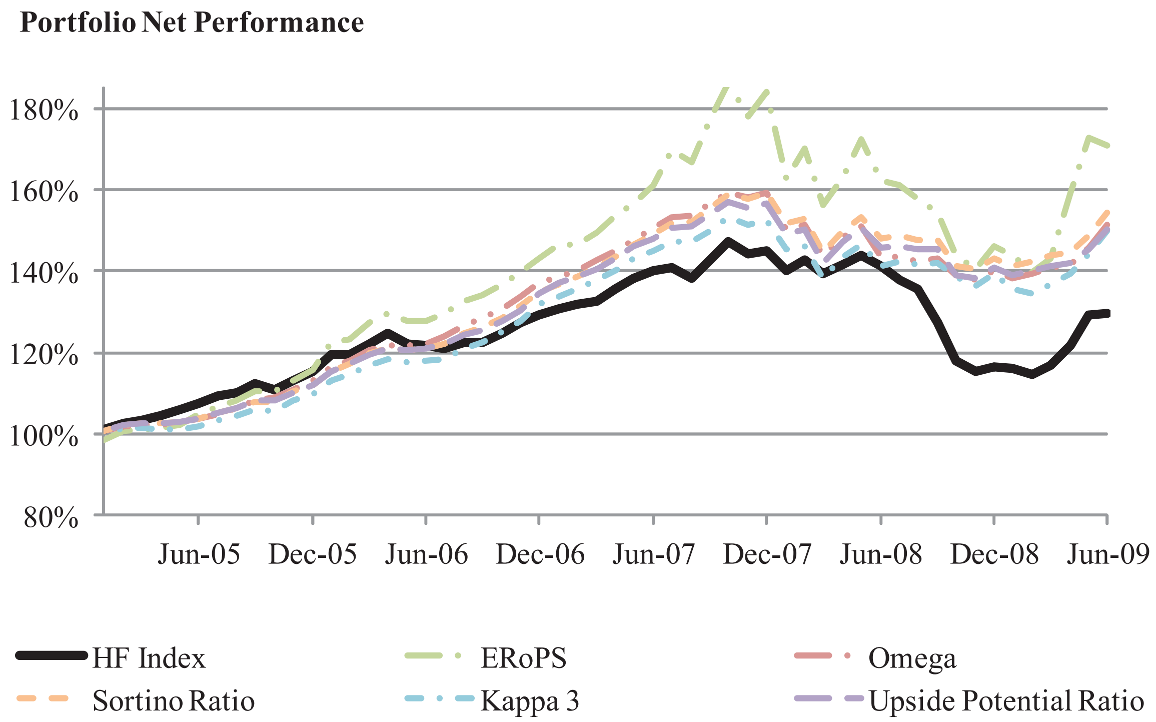
[129] Portfolio reallocation is assumed to occur on June 30th and December 31st every year. While the choice of these dates might seem arbitrary, most smaller HFs are not permanently open to new investment, but rather accept capital inflows only on key dates, such as 'end of month', 'end of quarter', etc. Portfolio reallocations on June 30th or December 31th correspond to such key dates.

To ensure maximum transparency, the presentation of the 23 portfolios is grouped into four parts: First, lower partial moment (LPM)-based portfolios are discussed (4.2.1.1). This is followed by an overview of the drawdown-based (4.2.1.2) and the 'Value at Risk' (VaR)-based portfolios (4.2.1.3). Subsequently, there is a discussion on the portfolios that are based on other RAPMs (4.2.1.4). Finally, the findings are summarized (4.2.1.5)

4.2.1.1 Lower Partial Moment (LPM)-based RAPMs

LPM-based RAPMs include Omega, the Sortino Ratio, Kappa 3, the Upside Potential Ratio, and Excess Return on Probability of Shortfall (ERoPS). Between January 2005 and June 2009, portfolios based on each of these measures clearly outperform the HF index on a net return basis. As Figure 21 shows, all of the portfolios constructed are characterized by a higher monthly net return and most are characterized by a lower standard deviation than is indicated by this benchmark. However, some portfolios display a lower skewness and a higher kurtosis. All of the constructed portfolios, but the ERoPS portfolio, seem to be correlated in the 'bull market' from 2005 to 2007 as well as in the 'bear market' from 2007 up to early 2009 when all of these portfolios outwear the crisis much better than the HF index proposes.

Figure 21: Benchmarking ─ Lower Partial Moment (LPM)-based RAPMs[130]



	CMGR of Net Returns	Standard Deviation	Skewness	Kurtosis
HF Index	0.48%	2.33%	(1.01)	2.49
ERoPS	1.00%	3.89%	(0.64)	2.01
Omega	0.77%	1.85%	(1.89)	4.39
Sortino Ratio	0.81%	1.86%	(1.63)	3.36
Kappa 3	0.75%	1.91%	(1.26)	2.08
Upside Potential Ratio	0.76%	1.83%	(1.67)	3.48

Source: Author's own illustration based on Eurekahedge (2009c)

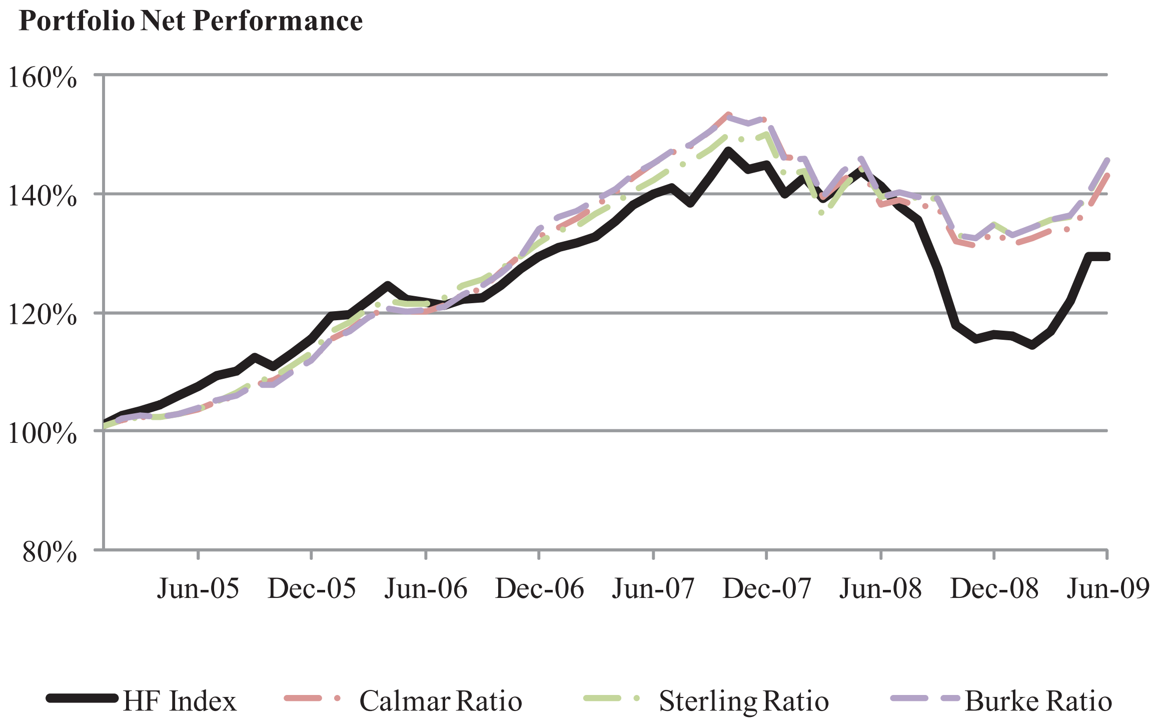
4.2.1.2 Drawdown-based RAPMs

Drawdown-based RAPMs include the Calmar, Sterling, and Burke Ratios. All portfolios dominate the HF index on a net return basis throughout most of the observation period. Furthermore, these portfolios seem to be highly correlated in the 'bull market' from 2005 to 2007, as well as in the 'bear market' from 2007 to early 2009. As in the case of several LPM-based RAPMs, these portfolios are

130 Pre application of management fees and transaction costs. Portfolios reallocated every 6 months.

characterized by higher monthly returns and lower standard deviations, as well as lower 3^{rd} and higher 4^{th} moments (Figure 22).

Figure 22: Benchmarking – Drawdown-based RAPMs[131]



	CMGR of Net Returns	Standard Deviation	Skewness	Kurtosis
HF Index	0.48%	2.33%	(1.01)	2.49
Calmar Ratio	0.67%	1.73%	(1.62)	3.21
Sterling Ratio	0.70%	1.78%	(1.71)	3.96
Burke Ratio	0.70%	1.80%	(1.54)	3.13

Source: Author's own illustration based on Eurekahedge (2009c)

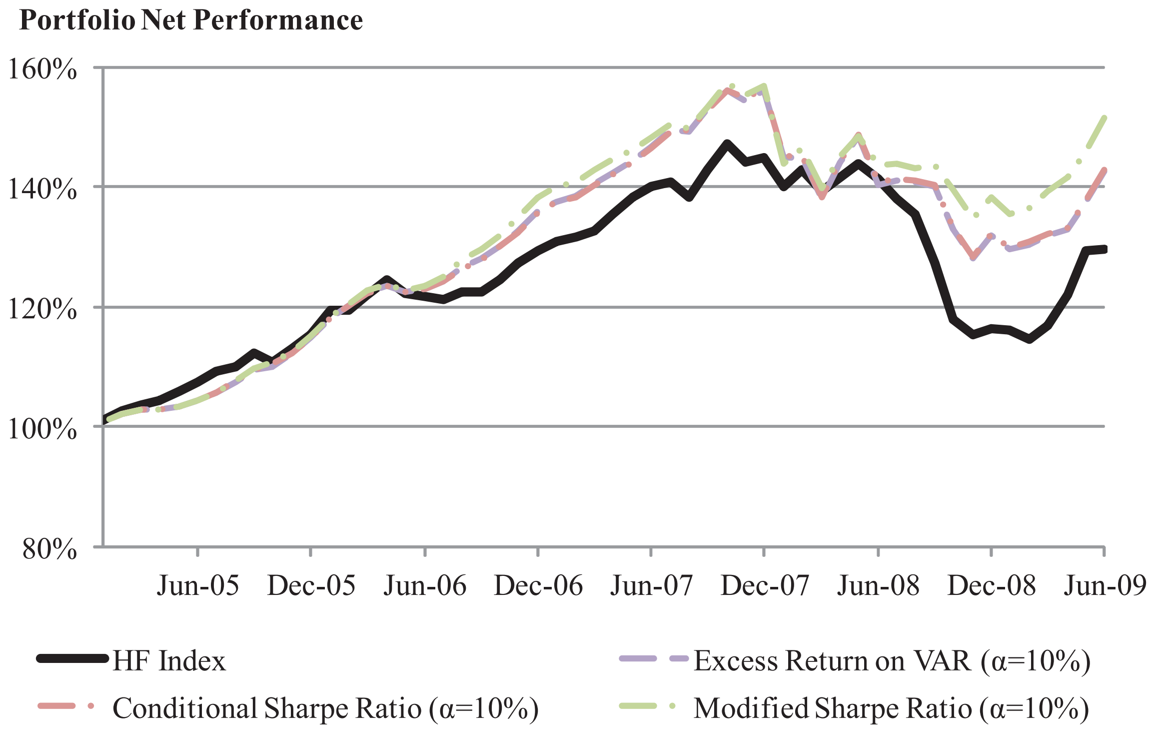
4.2.1.3 Value at risk (VAR)-based RAPMs

Value at risk (VAR)-based RAPMs include Excess Return on Value at Risk (ERoVaR), the Conditional Sharpe Ratio, and the Modified Sharpe Ratio. Between January 2005 and June 2009, all portfolios that were constructed clearly outperform

[131] Pre application of management fees and transaction costs. Portfolios reallocated every 6 months.

the HF index on a net return basis.[132] As Figure 23 illustrates, these portfolios are characterized by higher average monthly returns and lower standard deviations when compared to the benchmark. However, they display a lower skewness and higher kurtosis. All of the portfolios tested appear to be highly correlated. This is especially true during the ‘bull market’ from 2005 to 2007.

Figure 23: Benchmarking ─ Value at Risk (VaR)-based RAPMs[133]



	CMGR of Net Returns	Standard Deviation	Skewness	Kurtosis
HF Index	0.48%	2.33%	(1.01)	2.49
Excess Return on VAR (α=10%)	0.66%	2.24%	(1.71)	3.44
Conditional Sharpe Ratio (α=10%)	0.66%	2.23%	(1.75)	3.63
Modified Sharpe Ratio (α=10%)	0.77%	2.13%	(2.05)	5.87

Source: Author’s own illustration based on Eurekahedge (2009c)

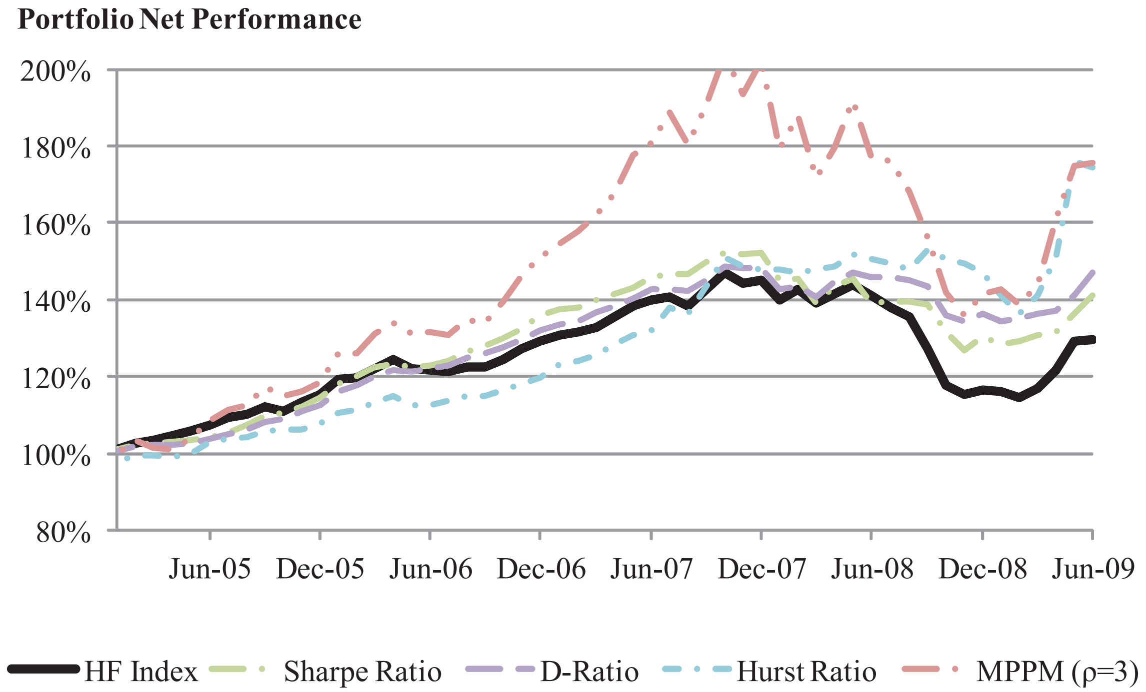
132 For the reason of clarity, not all ERoVAR, Conditional Sharpe Ratio, Modified Sharpe Ratio portfolios are shown in Figure 23. However, their fundamental net return statistics are shown in Table E5 in Appendix E.

133 Pre application of management fees and transaction costs. Portfolios reallocated every 6 months.

4.2.1.4 Other RAPMs

Other RAPMs include the Sharpe, the D-, and the Hurst Ratios, as well as the Manipulation-proof Performance Measure (MPPM). Portfolios that are based on any of these measures show very different patterns of behaviour during the observation period. The MPPM-based portfolio colossally outperforms the benchmark in the 'bull market', from 2005 to 2007. However, it also generates substantial losses in the following 'bear market'. The MPPM-based portfolio is characterized by a high standard deviation, combined with a moderate skewness and kurtosis. In contrast, the Sharpe Ratio and the D-Ratio-based portfolios generate moderate but steady returns throughout the observation period. These portfolios also show lower standard deviations and less favourable 3^{rd} and 4^{th} moments than the benchmark. The Hurst Ratio, on the other hand, is characterized by higher 1^{st}, 2^{nd}, 3^{rd}, and 4^{th} moments than the benchmark implies.

Figure 24: Benchmarking ─ Other RAPMs[134]



	CMGR of Net Returns	Standard Deviation	Skewness	Kurtosis
HF Index	0.48%	2.33%	(1.01)	2.49
Sharpe Ratio	0.64%	1.94%	(1.54)	2.51
D-Ratio	0.72%	1.56%	(1.49)	4.53
Hurst Ratio	1.04%	2.98%	2.73	12.83
MPPM (ρ=3)	1.05%	4.67%	(0.67)	0.50

Source: Author's own illustration based on Eurekahedge (2009c)

4.2.1.5 Summary of Performance Benchmarking against Hedge Fund Index

Table 4 recapitulates the findings of the benchmarking process against the HF index. The table highlights the fundamental statistics of the 23 portfolios tested, all of which outperform the HF index between January 2005 and June 2009 on a net return basis.[135] At the same time, most of these portfolios are characterized by lower standard deviations than this benchmark proposes. However, the high net returns

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[134] Pre application of management fees and transaction costs. Portfolios reallocated every 6 months.

[135] The portfolios shown here are reallocated every 6 months, on June 30 and December 31. Similar tables showing the corresponding results for longer observation periods (12, 18, 24 months) are shown in Appendix E (Tables E6-E8).

and low standard deviations displayed by most of these portfolios are partly outweighed by a clearly negative skewness and a high kurtosis. Drawing on these findings, there seems to be evidence that the proposed methodology, which is based exclusively on the analysis of historical data, may indeed be capable of selecting superior HFs from a broad universe of investment choices.

It now seems logical to verify whether the proposed methodology is truly able to produce superior results in the case of real-life FoFs. This is achieved in the next chapter.

Table 4: Fundamental Portfolio Return Statistics (January 2005 - June 2009)[136]
Portfolios Reallocated Every 6 Months

	CMGR of Net Returns	Standard Deviation	Skewness	Kurtosis
HF Index	**0.48%**	**2.33%**	**(1.01)**	**2.49**
Lower Partial Momements (LPM)-Based RAPMs				
ERoPS	1.00%	3.89%	(0.64)	2.01
Omega	0.77%	1.85%	(1.89)	4.39
Sortino Ratio	0.81%	1.86%	(1.63)	3.36
Kappa 3	0.75%	1.91%	(1.26)	2.08
Upside Potential Ratio	0.76%	1.83%	(1.67)	3.48
Drawdown (DD)-Based RAPMs				
Calmar Ratio	0.67%	1.73%	(1.62)	3.21
Sterling Ratio	0.70%	1.78%	(1.71)	3.96
Burke Ratio	0.70%	1.80%	(1.54)	3.13
Value at Risk (VAR)-Based RAPMs				
Excess Return on VAR (α=1%)	0.66%	2.22%	(1.77)	3.71
Excess Return on VAR (α=5%)	0.66%	2.23%	(1.75)	3.63
Excess Return on VAR (α=10%)	0.66%	2.24%	(1.71)	3.44
Conditional Sharpe Ratio (α=1%)	0.68%	2.19%	(1.76)	3.71
Conditional Sharpe Ratio (α=5%)	0.66%	2.22%	(1.77)	3.71
Conditional Sharpe Ratio (α=10%)	0.66%	2.23%	(1.75)	3.63
Modified Sharpe Ratio (α=1%)	0.51%	2.31%	(1.63)	3.50
Modified Sharpe Ratio (α=5%)	0.74%	1.92%	(1.75)	5.52
Modified Sharpe Ratio (α=10%)	0.77%	2.13%	(2.05)	5.87
Other RAPMs				
Sharpe Ratio	0.64%	1.94%	(1.54)	2.51
D-Ratio	0.72%	1.56%	(1.49)	4.53
Hurst Ratio	1.04%	2.98%	2.73	12.83
MPPM (ρ=2)	0.99%	4.70%	(0.66)	0.29
MPPM (ρ=3)	1.05%	4.67%	(0.67)	0.50
MPPM (ρ=4)	0.94%	4.78%	(0.47)	0.58

Source: Author's own illustration based on Eurekahedge (2009c)

[136] Pre application of management fees and transaction costs. The portfolios shown here are reallocated every 6 months, on June 30 and December 31.

4.2.2 Performance Benchmarking against Funds of Hedge Funds Index

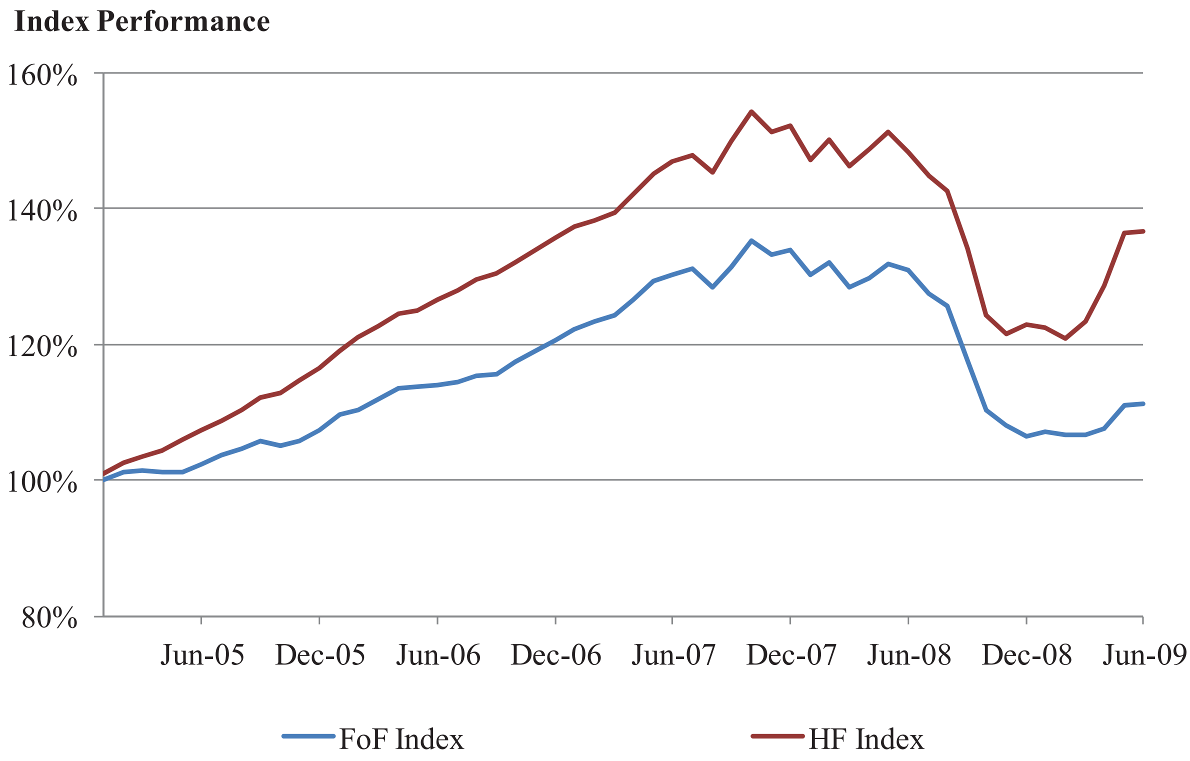
The comparison between the constructed HF portfolios and the index of relevant FoFs is to answer the question of whether the proposed methodology provides superior portfolios to real-life FoFs. If such is the case, the constructed portfolios should outperform the benchmark.

Figure 25 shows a comparison between two indices: an equally-weighted index of HFs in the 'relevant HF universe' and an equally-weighted index of FoFs in the 'relevant FoF universe'.[137] Given that FoFs are nothing more than investment vehicles that consist of several HFs, the FoF index, by and large, mirrors the movements of the HF index. It is striking, however, that throughout the entire observation period, the FoF index is dominated by the HF index. In other words, investors would have been better off if they had bought the average HF instead of the average FoF.

This pronounced difference in performance must be put into context: FoFs offer valuable benefits over a direct investment in HFs. These are accessibility, liquidity, and professional management. These advantages come at a certain cost, specifically a second layer of fees, which negatively impacts FoF performance. Furthermore, it must be stressed that the FoF index is per se negatively affected by transaction costs whereas the HF index is not.

[137] The indices shown here are reallocated every 6 months, on June 30 and December 31.

Figure 25: HF Index vs. FoF Index



Source: Author's own illustration based on Eurekahedge (2009b, 2009c)

Thus, in order to achieve better comparability between the constructed HF portfolios and the FoF index, it is necessary to apply hypothetical transaction costs and hypothetical management fees to the constructed portfolios. The author assumes fully variable transaction costs of 5% of the total investment volume and hypothetical management fees of 1% on AuM annually. The resulting portfolios are then benchmarked against an equally-weighted index of FoFs in the 'relevant FoF universe'. The results of this benchmarking are illustrated below.[138] Table 5 shows a comparison of the compound monthly growth rate of net returns on all 92 portfolios. The red shaded fields indicate that the relevant portfolios have underperformed an equally-weighted FoF portfolio of the same holding period, the green shaded fields indicate that the benchmark has been outperformed. It is noteworthy that all of the portfolios with a 6-month holding period and most of the portfolios with a 12-month

[138] Still, it must be stressed that the portfolio management approach developed here offers none of the aforementioned benefits that FoFs provide, specifically accessibility, liquidity, and professional management. Therefore, benchmarking against the FoF index cannot be considered as a like-with-like comparison and is included for reference only.

or 18-months holding period underperform their relative benchmark portfolios. This is due mainly to the presence of high transaction costs.[139] On the other hand, the best results for most RAPMs are obtained by reallocating the portfolios every two years. It seems sensible, therefore, to examine these portfolios more closely. Table 6 shows the fundamental statistics of all the portfolios with a 24-month holding period after hypothetical transaction costs, and management fees have been applied.[140]

[139] A transaction costs estimate of 5% is in line with the assumptions of a previous study by Amenc et al. (2003). Portfolio reallocation every 6 months means that the transaction costs of 5% fall due twice a year. None of the portfolios tested can compensate for such a high level of costs.

[140] Similar tables that show the results that correspond to shorter observation periods (6, 12, and 18 months, respectively) can be seen in Appendix E (Tables E9-E12).

Table 5: Net Return CMGR of Constructed Portfolios[141]

	Holding Period			
	6 Months	12 Months	18 Months	24 Months
FoF Index	**0.21%**	**0.16%**	**0.19%**	**0.20%**
HF Index (Post Costs & Fees)	**(0.53%)**	**(0.11%)**	**0.09%**	**0.19%**
Lower Partial Momements (LPM)-Based RAPMs				
ERoPS	(0.02%)	0.13%	0.30%	0.03%
Omega	(0.25%)	(0.06%)	0.27%	0.49%
Sortino Ratio	(0.21%)	(0.10%)	0.27%	0.38%
Kappa 3	(0.27%)	(0.23%)	0.12%	0.12%
Upside Potential Ratio	(0.26%)	(0.15%)	0.11%	0.52%
Drawdown (DD)-Based RAPMs				
Calmar Ratio	(0.35%)	(0.17%)	0.07%	0.33%
Sterling Ratio	(0.32%)	(0.21%)	0.03%	0.41%
Burke Ratio	(0.32%)	(0.23%)	0.12%	0.31%
Value at Risk (VAR)-Based RAPMs				
Excess Return on VAR (α=1%)	(0.36%)	(0.16%)	0.16%	0.42%
Excess Return on VAR (α=5%)	(0.35%)	(0.16%)	0.16%	0.45%
Excess Return on VAR (α=10%)	(0.36%)	(0.27%)	0.17%	0.45%
Conditional Sharpe Ratio (α=1%)	(0.34%)	(0.16%)	0.16%	0.42%
Conditional Sharpe Ratio (α=5%)	(0.36%)	(0.16%)	0.16%	0.42%
Conditional Sharpe Ratio (α=10%)	(0.35%)	(0.16%)	0.16%	0.42%
Modified Sharpe Ratio (α=1%)	(0.50%)	(0.18%)	0.22%	0.13%
Modified Sharpe Ratio (α=5%)	(0.28%)	(0.16%)	0.28%	0.44%
Modified Sharpe Ratio (α=10%)	(0.25%)	(0.20%)	0.27%	0.42%
Other RAPMs				
Sharpe Ratio	(0.38%)	0.02%	0.35%	0.42%
D-Ratio	(0.30%)	(0.00%)	0.27%	0.39%
Hurst Ratio	0.02%	0.30%	0.03%	0.42%
MPPM (ρ=2)	(0.03%)	0.32%	0.34%	(0.07%)
MPPM (ρ=3)	0.03%	0.29%	0.32%	0.09%
MPPM (ρ=4)	(0.08%)	0.20%	0.12%	0.16%

Outperforms equally-weighted HF and FoF portfolios of the same holding period
Underperforms equally-weighted HF and FoF portfolios of the same holding period

Source: Author's own illustration based on Eurekahedge (2009b, 2009c)

[141] Post application of hypothetical management fees and transaction costs. 'CMGR' stands for 'compound monthly growth rate'.

Table 6: Fundamental Portfolio Return Statistics (January 2005 - June 2009)[142]
Portfolios Reallocated Every 24 Months

	CMGR of Net Returns	Standard Deviation	Skew-ness	Kurtosis	Higher Return And Lower Risk
FoF Index	**0.20%**	**1.86%**	**(1.72)**	**3.94**	**-**
HF Index (Post Costs & Fees)	**0.19%**	**2.20%**	**(1.30)**	**3.79**	**-**
Lower Partial Momements (LPM)-Based RAPMs					
ERoPS	0.03%	2.81%	(1.70)	4.16	×
Omega	0.49%	0.92%	0.13	1.73	✓
Sortino Ratio	0.38%	1.41%	(1.13)	2.34	✓
Kappa 3	0.12%	1.83%	(1.16)	2.60	×
Upside Potential Ratio	0.52%	1.13%	0.40	0.89	✓
Drawdown (DD)-Based RAPMs					
Calmar Ratio	0.33%	1.17%	(0.74)	2.06	✓
Sterling Ratio	0.41%	0.97%	(0.19)	1.81	✓
Burke Ratio	0.31%	1.22%	(0.59)	1.54	✓
Value at Risk (VAR)-Based RAPMs					
Excess Return on VAR (α=1%)	0.42%	0.68%	(0.11)	0.36	✓
Excess Return on VAR (α=5%)	0.45%	0.86%	0.06	1.32	✓
Excess Return on VAR (α=10%)	0.45%	0.86%	0.06	1.32	✓
Conditional Sharpe Ratio (α=1%)	0.42%	0.68%	(0.11)	0.36	✓
Conditional Sharpe Ratio (α=5%)	0.42%	0.68%	(0.11)	0.36	✓
Conditional Sharpe Ratio (α=10%)	0.42%	0.68%	(0.11)	0.36	✓
Modified Sharpe Ratio (α=1%)	0.13%	1.73%	(1.42)	3.93	×
Modified Sharpe Ratio (α=5%)	0.44%	0.74%	(0.19)	(0.26)	✓
Modified Sharpe Ratio (α=10%)	0.42%	0.68%	(0.13)	0.39	✓
Other RAPMs					
Sharpe Ratio	0.42%	0.68%	(0.11)	0.36	✓
D-Ratio	0.39%	0.81%	(1.17)	2.32	✓
Hurst Ratio	0.42%	4.24%	1.35	4.58	×
MPPM (ρ=2)	(0.07%)	4.60%	(1.78)	6.06	×
MPPM (ρ=3)	0.09%	4.77%	(1.45)	5.86	×
MPPM (ρ=4)	0.16%	4.85%	(1.34)	5.62	×

Better than equally-weighted HF and FoF portfolios
Worse than equally-weighted HF and FoF portfolios

Source: Author's own illustration based on Eurekahedge (2009b, 2009c)

[142] Post application of hypothetical management fees and transaction costs. 'CMGR' stands for 'compound monthly growth rate'.

The benchmarking process against the FoF index over a 24-months holding period provides, in essence, three major results: First, that most constructed portfolios deliver superior risk / return profiles as compared to their benchmarks; secondly, that portfolios constructed under the assumption of symmetrical return distributions do not perform noticeably worse than those based on more sophisticated measures; and thirdly, that the MPPM seems to be an inadequate tool to capture medium or long-term performance persistence. These three results are discussed below.

It is possible to 'beat' the average FoF drawing on historical data

Table 6 shows the fundamental statistics of the 23 portfolios tested under a 24-months holding period; 17 of these outperform the investable FoF index between January 2005 and June 2009 on a net return basis. Strikingly, 16 out of 23 portfolios show higher net returns along with a lower standard deviation and more attractive 3rd and 4th moments (Table 6). Therefore, they clearly dominate their benchmarks on a risk / return basis. Thus, there seems to be evidence that the proposed methodology is indeed capable of constructing portfolios superior to the average real-life FoF under close-to-reality assumptions.[143]

Symmetrical RAPMs are capable of producing superior HF portfolios

Most HFs' returns do not follow a normal distribution, but show a negative skewness and positive kurtosis. Considering these characteristics, the Sharpe Ratio and ERoVaR should be inadequate to analyze HFs as both RAPMs are based on the assumption of standard normally-distributed returns. Interestingly, portfolios based on both measures are absolutely capable of outperforming the benchmark over the observation period.

[143] Again, it must be stressed that the portfolio management approach developed here does not provide the same benefits as FoFs, specifically accessibility, liquidity, and professional management. Therefore, benchmarking against the FoF index must not be considered as a like-with-like comparison and is included for reference only.

MPPM may be inadequate to capture long-term performance persistence

The MPPM plays a special role when compared to other RAPMs. MPPM-based portfolios, that are rebased every 6 months, deliver high net returns when compared to their peers. Over a 24-months holding period, however, the MPPM-based portfolios clearly underperform their peers. This fact is further illustrated by Table 7, which compares the net returns of the MPPM-based portfolios across all holding periods without hypothetical transaction costs and management fees. This gives reason to assume that the MPPM-based portfolios may not be able to capture performance persistence in the long run to the same extend as in the short run.

Table 7: Net Return CMGR of Constructed MPPM Portfolios
Pre Hypothetical Transaction Costs and Management Fees

	6 Months	12 Months	18 Months	24 Months
MPPM (ρ=2)	0.99%	0.92%	0.80%	0.32%
MPPM (ρ=3)	1.05%	0.89%	0.78%	0.48%
MPPM (ρ=4)	0.94%	0.80%	0.58%	0.55%

Source: Author's own illustration based on Eurekahedge (2009c)

After it has been shown that a variety of RAPMs discussed in this thesis are actually capable of producing results superior the average FoF under close-to-reality assumptions, the author now analyzes the performance of the 'Combined Indicator' portfolio in the next chapter.

4.2.3 The 'Combined Indicator' Portfolio

This dissertation proposes a portfolio management approach that is essentially based on several different RAPMs. These different RAPMs are calculated for each HF in the 'attractive HF universe' in order to identify the most promising HFs with the best risk / return characteristics. The HF rankings established by the different RAPMs can be merged into one single equally-weighted ranking, the so-called 'Combined Indicator' ranking.[144] Based on this ranking, a 'Combined Indicator' portfolio is created. This equally-weighted portfolio comprises of the 10 HFs with the highest 'Combined Indicator' values. This portfolio is reallocated periodically and is benchmarked and assessed against an equal-weights index of HFs and an equal-weights index of FoFs in order to assess its performance. The comparison of the 'Combined Indicator' portfolio against the HF index is to answer the question of whether the proposed methodology is capable of selecting superior HFs from the 'attractive HFs universe'. The comparison against the FoF index is to answer the question of whether the proposed methodology is superior to real-life FoFs.[145]

Figure 26 highlights the portfolio performance of both indices and the portfolio constructed under the new approach from January 2005 to June 2009. The figure displays two different variants of the 'Combined Indicator' (CI) portfolio which are named 'aggressive' and 'conservative'. The 'aggressive' portfolio variant draws on all HFs in the 'attractive HF universe'. In contrast, the 'conservative' portfolio variant exclusively contains HFs that describe their trading strategy as 'market-neutral'. It can be seen that both of these 'Combined Indicator' portfolio variants clearly outperform the HF index and the FoF index at the end of the observation period. A further result is that the 'aggressive' portfolio and the HF index seem to be somewhat correlated in the 'bull market' from 2005 - 2007. During this period, the 'conservative' portfolio shows a clearly noticeable relative underperformance.

[144] This procedure is based on a study by Jöhri and Leippold (2006).

[145] Still, it must be stressed that the portfolio management approach developed here offers none of the aforementioned benefits that FoFs provide, specifically accessibility, liquidity, and professional management. Therefore, benchmarking against the FoF index cannot be considered as a like-with-like comparison and is included for reference only.

On the other hand, the performance of both 'Combined Indicator' portfolio variants in the bear market of 2007 - 2009 is clearly superior to that of the HF index.[146]

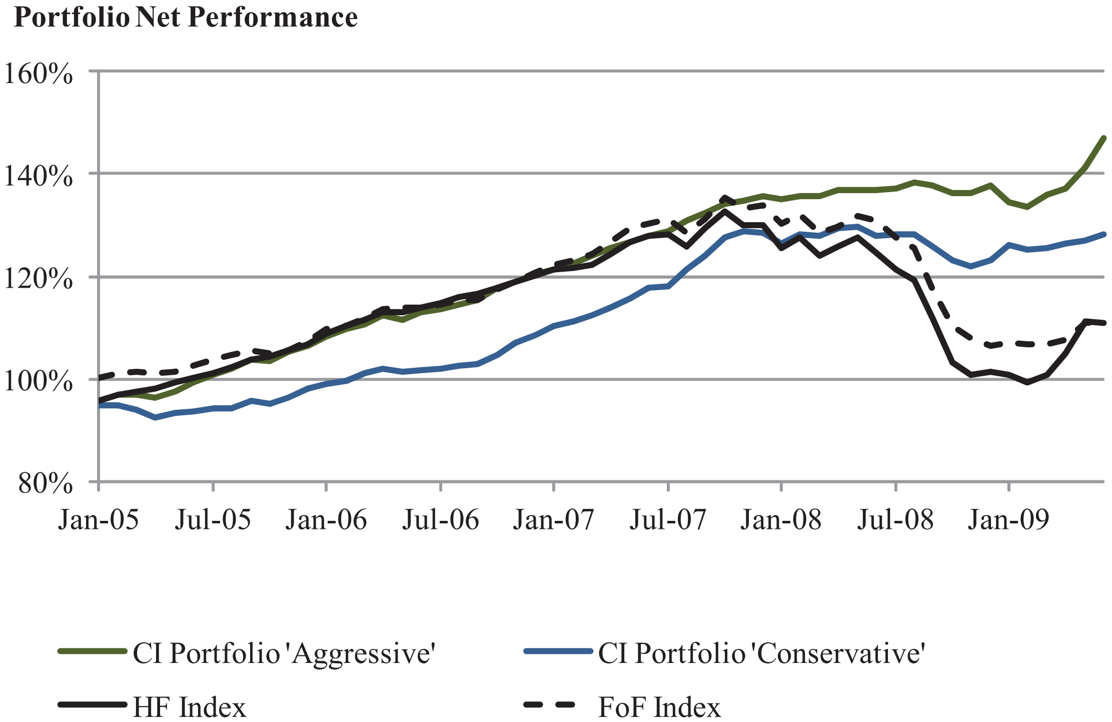
Figure 26 also shows the fundamental statistics of the two 'Combined Indicator' portfolio variants and the indices. It is evident that both constructed portfolios are characterized by higher monthly average returns than the two indices. At the same time they display lower standard deviations than their benchmarks. Moreover, they show a higher skewness, and a lower kurtosis than the two indices. Thus, the two 'Combined' Indicator portfolio variants clearly dominate their benchmarks on a risk / return basis. These results imply that the proposed methodology is capable of successfully selecting superior HFs from the 'relevant HF universe'.

A comparison of the fundamental return statistics between both 'Combined Indicator' portfolio variants is further revealing. The 'Combined Indicator - Aggressive' portfolio is characterized by considerably higher average returns and dominates throughout the observation period. The 'Combined Indicator - Conservative' portfolio, on the other hand, shows a similar standard deviation of returns, a similar skewness, and a considerably lower kurtosis. In other words, it displays an inferior return but a partly superior risk profile.

Drawing on these findings, there seems to be evidence that the proposed methodology is indeed capable of selecting superior HFs from a broad universe of investment choices.

[146] These results may imply that the 'Combined Indicator' in itself tends to favour HFs with a lower market risk over their peers – which leads to an outperformance of both 'Combined Indicator' portfolio variants over the benchmarks.

Figure 26: Performance of 'Combined Indicator' Portfolio[147]



	CMGR of Net Returns	Standard Deviation	Skewness	Kurtosis
HF Index	0.19%	2.20%	(1.30)	3.79
FoF Index	0.20%	1.86%	(1.72)	3.94
CI Portfolio 'Aggressive'	0.72%	1.00%	(0.11)	2.08
CI Portfolio 'Conservative'	0.46%	1.14%	(0.35)	(0.03)

Source: Author's own illustration based on Eurekahedge (2009b, 2009c)

4.2.4 'Combined Indicator' Portfolio – Sensitivity Analysis

This dissertation proposes a portfolio management approach that is essentially based on a 'Combined Indicator' that consists of several different RAPMs. Naturally, such an approach is dependent on the estimation of several different input factors. As shown in chapters 4.1.4.2 and 4.1.5 of this thesis, the author estimated the level of transaction costs, performance fees, management fees, liquidity buffers, and asset recovery rates. As the results of an empirical study can potentially fluctuate with parameter choice, a sensitivity analysis for these factors is necessary in order to

[147] Post application of hypothetical management fees and transaction costs. 'CMGR' stands for 'compound monthly growth rate'.

evaluate whether the proposed investment approach is sensible even if the underlying parameters were different, i.e., less favourable, than assumed. The following sections, therefore, present a detailed sensitivity analysis of the 'Combined Indicator' portfolio. Different transaction costs (4.2.4.1), performance fees (4.2.4.2), management fees (4.2.4.3), liquidity buffers (4.2.4.4), and asset recovery rates (4.2.4.5) are simulated in order to assess how sensitive the proposed investment approach reacts to the parameter changes.

Furthermore, it must be stressed that the investment approach presented here is focused on comparatively small and young HFs because these have been identified as particularly attractive for investment by previous academic research.[148] In order to evaluate whether such a focus is prudent, the author takes a closer look at the relationship between HF size and returns (4.2.4.6) and the relationship between HF age and returns (4.2.4.7).

The sensitivity analysis itself is straightforward: The author digresses from the base case of the foregoing analysis by varying the critical input parameters one at a time. Then he compares the 'Combined Indicator' portfolio and the two benchmarks side-by-side.[149] For the reason of clarity, only the 'Combined Indicator – Aggressive' portfolio is subject to the analysis. An analogous examination of the 'Combined Indicator – Conservative' portfolio mirrors the findings and does not provide additional insights.

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[148] See for instance Howell (2001), Brown et al. (2001), Herzberg and Mozes (2003), Hedges (2003), Harri and Brorsen (2004), Getmansky (2004), Ammann and Moerth (2005), and Boyson (2008, 2010).

[149] The foregoing analysis (part 4.2.3) of this dissertation presents the base case of the sensitivity analysis. The author sets the length of the out-of-sample period at 24 months. Furthermore, fully variable transaction costs of 5% of AuM are assumed to incur every time that the portfolio is reallocated. The base case features no performance fees. Management fees are assumed to stand at 1% of AuM per year. The base case does not consider liquidity buffers; asset recovery rates are set at 100%.

4.2.4.1 Transaction Costs

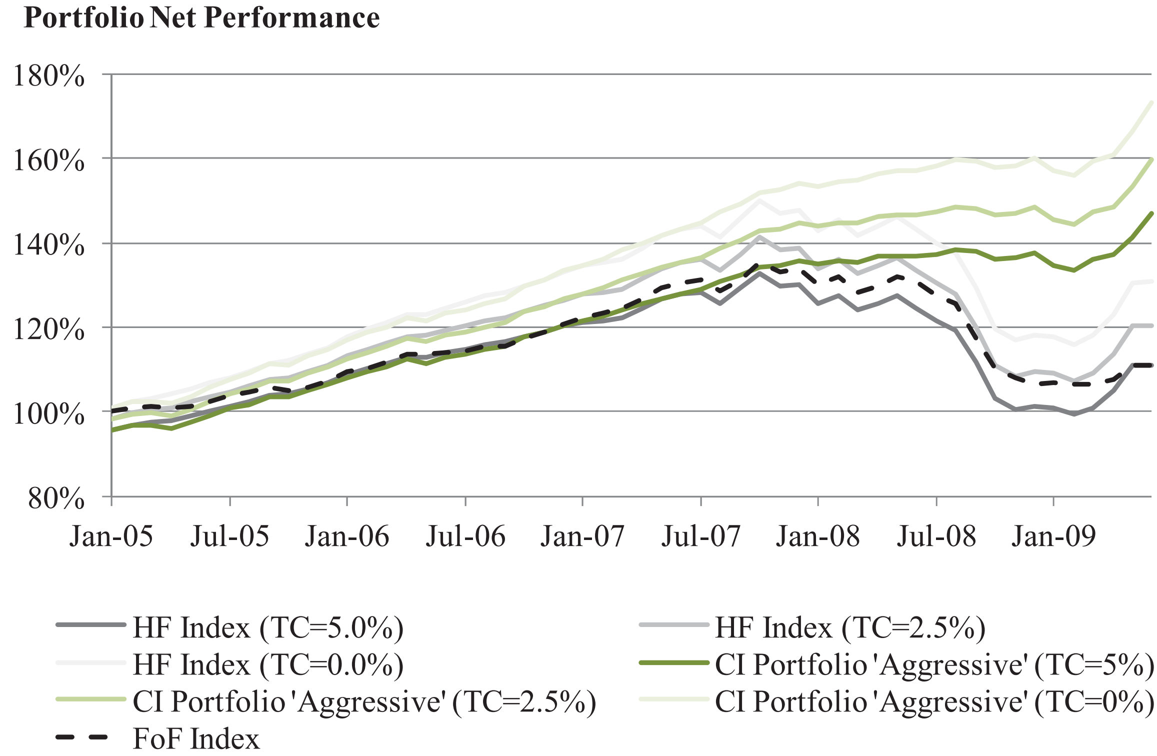
Transaction costs (TC) include operating expenses and pre-sale charges as well as other costs incurred. Academic approaches to HF portfolio management typically ignore the effect of transaction costs. In the base case, the author estimated transactions costs of 5% of AuM to incur every time that the portfolio is reallocated. As this estimate appears very conservative, different scenarios are evaluated here.[150] Specifically, the author compares three different settings with TC = 0%, TC = 2.5%, and TC = 5% transaction costs. These costs are assumed to incur up-front.[151]

Figure 27 illustrates that the proposed investment approach is highly sensitive to transaction costs. At the end of the observation period, the 'Combined Indicator' portfolio exhibits AuM that are 26% higher in the most favourable (TC = 0%) than in the most unfavourable (TC = 5%) scenario. Still, even under the assumption of the most detrimental transaction costs, the 'Combined Indicator' portfolio is able to perform in line with the benchmark indices in the 'bull market' and outperform them in the 'bear market'.

[150] While transaction costs of 5% are in line with the assumptions of a previous study by Amenc et al. (2003), this estimate seems to be very high in the context of this dissertation.

[151] This is, for instance, evidenced in the different axis intercepts in Figure 27.

Figure 27: Sensitivity Analysis – Transaction Costs[152]



Source: Author's own illustration based on Eurekahedge (2009b, 2009c)

4.2.4.2 Performance Fees

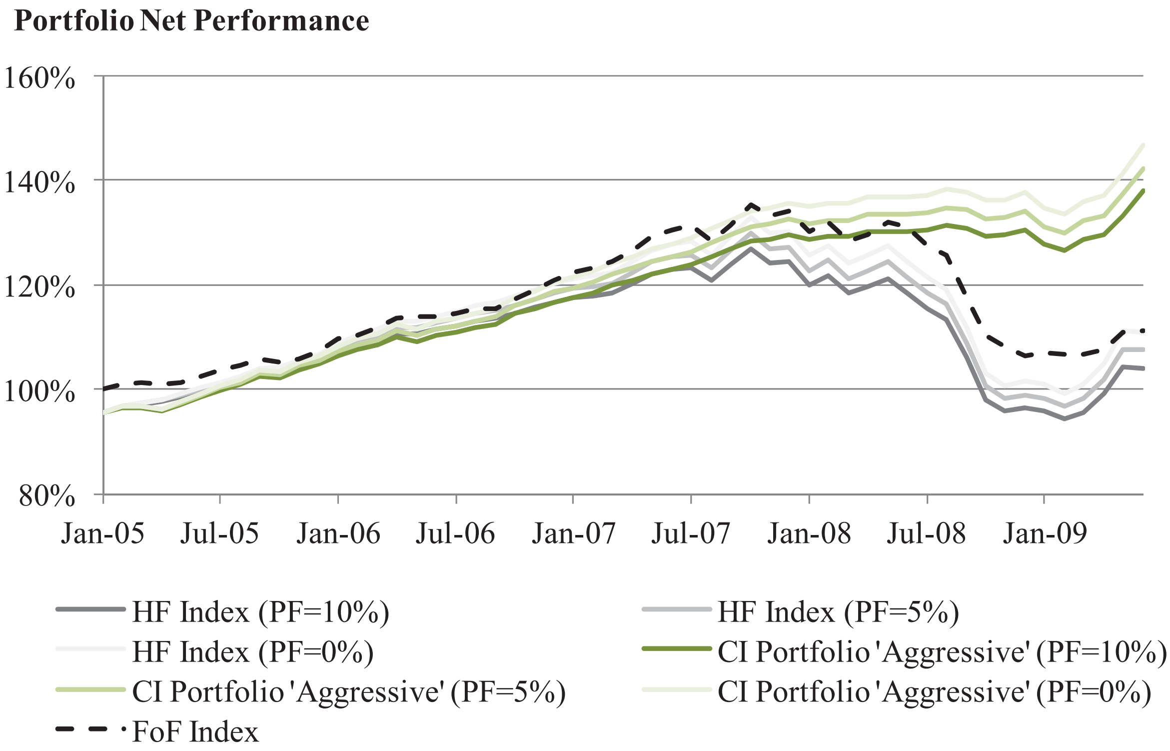
It is not a commonly-accepted industry practice for family offices to charge their clients with performance fees (PF); therefore, these fees are ignored in the base case of the analysis. Still, in order to cover for all possible compensation schemes, these fees are considered here. The different scenarios of performance fees tested are geared to FoF compensation levels. FoFs typically charge performance fees in the range of 5-10% annually (Eurekahedge, 2009b); classically, these fees fall due once or twice a year. In order to present conservative sensitivity estimates, the author assumes that performance fees fall due on a monthly basis. Furthermore, in order to account for the worst possible case, there is no provision for a hurdle rate or a high-water-mark.[153] Figure 28 shows the results. The suggested approach seems to be

[152] Post application of hypothetical management fees and transaction costs.

[153] Several FoFs employ a hurdle rate and/or a high-water-mark in order to mitigate principal agent conflicts. The hurdle rate indicates the minimum performance that must be achieved in order to charge performance-related fees (Gregoriou & Duffy, 2006; Lhabitant, 2006). The high-water-

only modestly affected by the presence of performance fees and still outperforms its benchmarks over the observation period.

Figure 28: Sensitivity Analysis ─ Performance Fees[154]



Source: Author's own illustration based on Eurekahedge (2009b, 2009c)

4.2.4.3 Management Fees

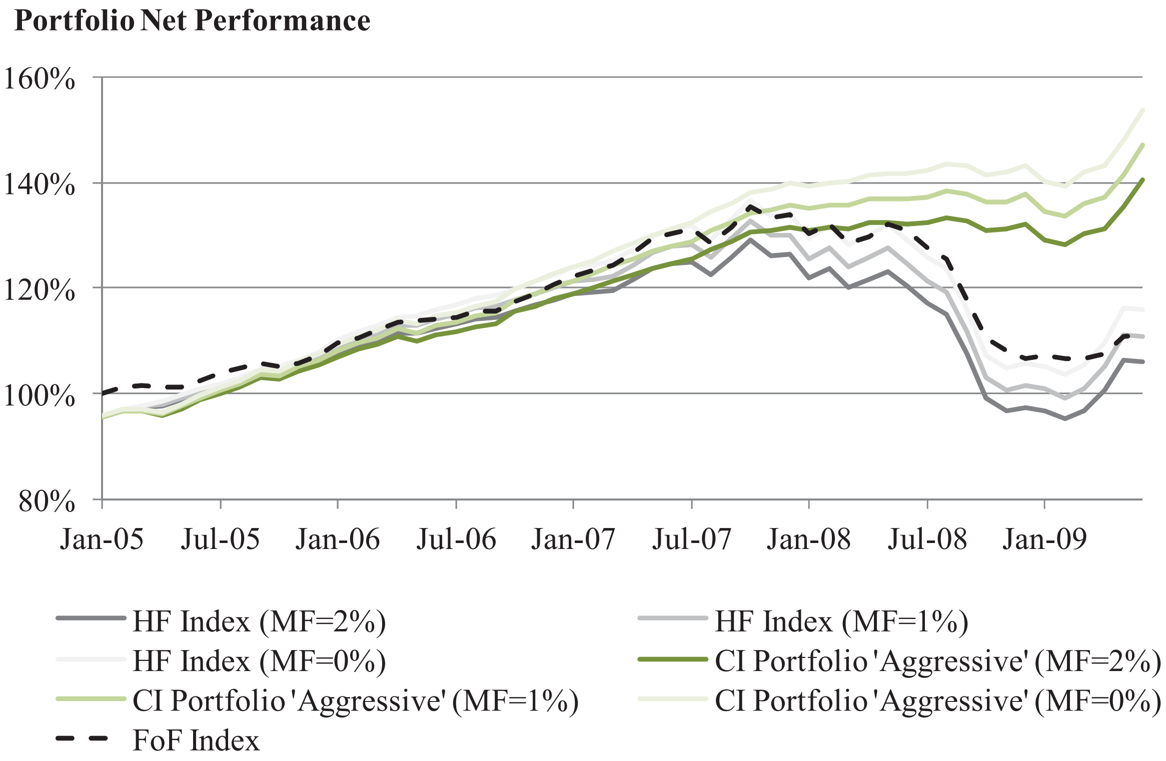
Family offices typically charge their clients with management fees (MF) that range from 0.25% to 1.50% of AuM annually (FOX, 2011; Silverman, 2008). While the author assumes management fees to stand at 1% on AuM annually in the base case, two further levels, specifically MF= 0% and MF = 2% are tested here.

mark requires that previous losses have to be off-set by new profits in order to apply the incentive fee; this mechanism shields investors from paying incentive fees although they are still recovering from previous losses (Lhabitant, 2006)

154 Post application of hypothetical management fees and transaction costs.

Figure 29 highlights the role of management fees. In general, the 'Combined Indicator - Aggressive' portfolio seems to be moderately sensitive to management fees. Interestingly, the portfolio seems to be more affected by changes in management fees than by the presence of reasonable performance fees. Regardless of the management fees, however, the 'Combined Indicator' shows a higher net performance than the HF index and the FoF index.

Figure 29: Sensitivity Analysis — Management Fees[155]



Source: Author's own illustration based on Eurekahedge (2009b, 2009c)

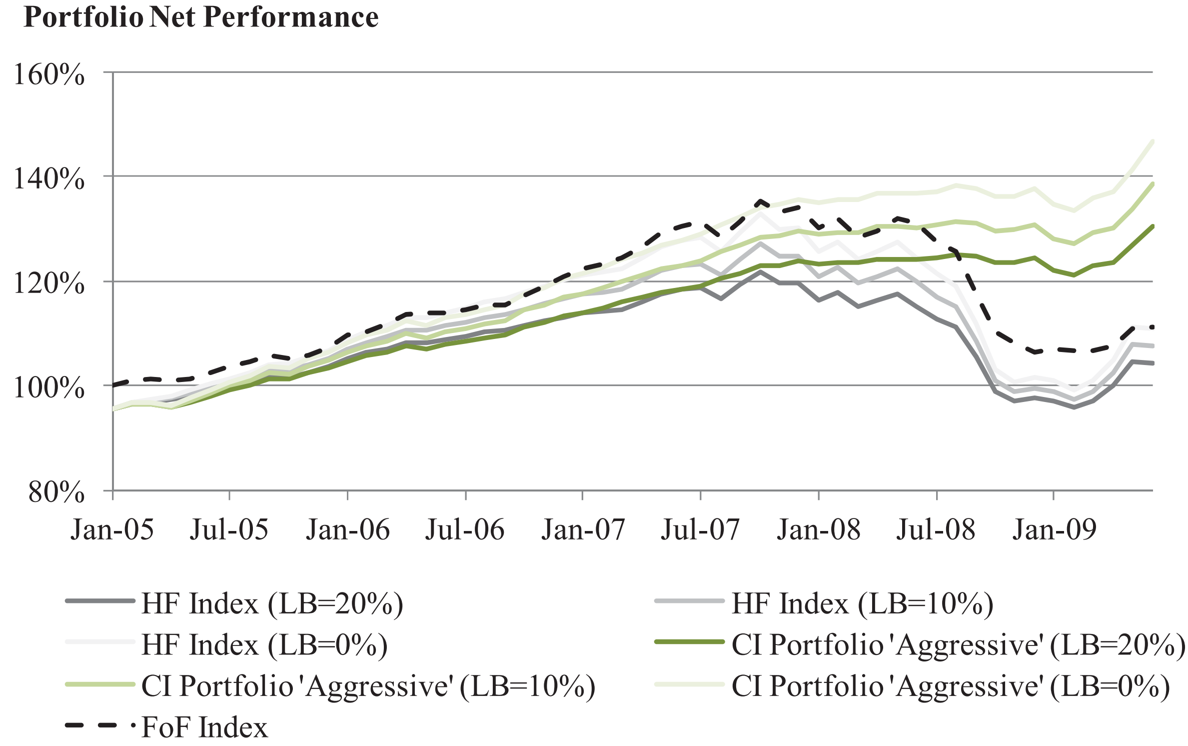
[155] Post application of hypothetical management fees and transaction costs.

4.2.4.4 Liquidity Buffers

FoFs usually have flexible redemption policies. In order to provide such liquidity, all FoFs have liquidity buffers (LB), which are characterized, naturally, by very low returns. Family offices strive to preserve and grow their clients' assets in the long run. They usually have a long-term investment horizon and do not need to provide the same liquidity as FoFs on their HF investments. The base case, therefore, does not take liquidity buffers into consideration. Still, for the reason of completeness, the author includes these fees in the sensitivity analysis. The scenarios tested here feature liquidity buffers of LB = 0%, LB = 10%, and LB = 20%. For the reason of simplicity and in order to provide a conservative estimate, the author assumes that no interest is paid on these buffers.

Figure 30 illustrates that the proposed investment approach is relatively sensitive to the presence of liquidity buffers. At the end of the observation period, the 'Combined Indicator' portfolio exhibits AuM that are 16% higher in the most favourable (LB=0%) than in the most unfavourable (LB=20%) scenario. Still, even in the worst case, the 'Combined Indicator' portfolio is able to generate positive net returns and outperform its benchmarks over the observation period.

Figure 30: Sensitivity Analysis ─ Liquidity Buffers[156]



Source: Author's own illustration based on Eurekahedge (2009b, 2009c)

4.2.4.5 Asset Recovery Rates

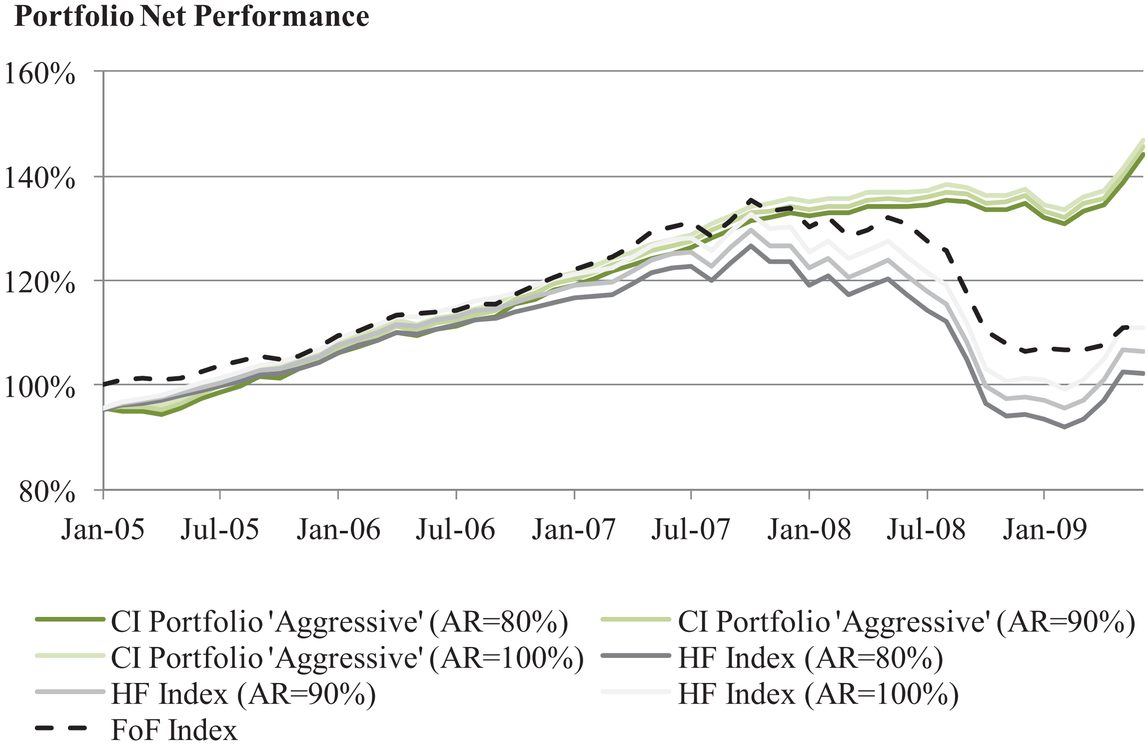
Although research asset recovery rates (AR) are neglected in previous academic research, they play a critical role. Academics usually assume that HFs going out of business are able to recover 100% of their AuM at the point of liquidation. This, however, may not always be the case as many HFs are active in illiquid markets. If these HFs are liquidated, investors may lose a considerable share of their AuM. While an asset recovery of 100% represents the base case, the impact of less favourable assumptions, specifically AR = 90% and AR = 80%, is tested in the sensitivity analysis.

As can be seen in Figure 31, different asset recovery rates have only a marginal impact on the performance of the 'Combined Indicator' portfolio. Their impact on the HF index, on the other hand, seems to be comparatively higher. These results

[156] Post application of hypothetical management fees and transaction costs.

may imply that the ‘Combined Indicator’ in itself tends to favour HFs with a lower risk of liquidation over their peers. As a consequence, the ‘Combined Indicator’ shows a higher net performance than the HF index and the FoF index regardless of the applied asset recovery rate.

Figure 31: Sensitivity Analysis ─ Asset Recovery Rates[157]



Source: Author’s own illustration based on Eurekahedge (2009b, 2009c)

4.2.4.6 Hedge Fund Size

HF returns are supposedly affected by a number of individual HF characteristics. The relationship between HF size and performance has been intensively discussed in previous literature. Getmansky (2004) finds a positive and concave relationship between HF size and HF performance. His findings indicate that HFs have an optimal size, which, if exceeded, adversely affects HF return levels. Ammann and Moerth (2005) also find evidence of a negative relationship between HF sizes and

[157] Post application of hypothetical management fees and transaction costs.

returns. In their study, HFs of less than US$100 million in AuM show a better performance than their larger peers. However, they also discover that extremely small HFs with AuM of below US$1 million underperform on average.[158]

The investment approach presented in this dissertation tries to build on Getmansky's and Ammann and Moerth's works. It concentrates on comparatively small HFs of between US$1 million and US$100 million in AuM because these have been identified as particularly attractive for investment. In order to evaluate whether such a focus is prudent, the author divides the 'attractive HF universe' into several subgroups.[159] HFs are allocated to these subsets according to their AuM. On the whole, nine different subsets are created. In a next step, the average HF net return is calculated for each of these subsets and the net returns of these subgroups are compared.

Figure 32 highlights the net performance comparison of the different subsets. At most HF sizes, an average monthly net return of 0.3%-0.4% appears to be typical. Still, there seems to be a negative correlation between HF size and HF net returns. This is in particular due to the smallest and the largest HFs in the sample. In fact, HFs with AuM of US$1-19 million show a considerable outperformance and HFs with AuM in excess of US$750 million show a considerable underperformance relative to their peers.

This finding implies that a focus on comparatively small HFs, as suggested by Ammann and Moerth (2005) seems to be sensible. Furthermore, it could potentially prove advantageous for future HF investment approaches to narrow down the investment universe even further and only focus on the smallest HFs in the sample, specifically those with AuM below US$20 million.[160]

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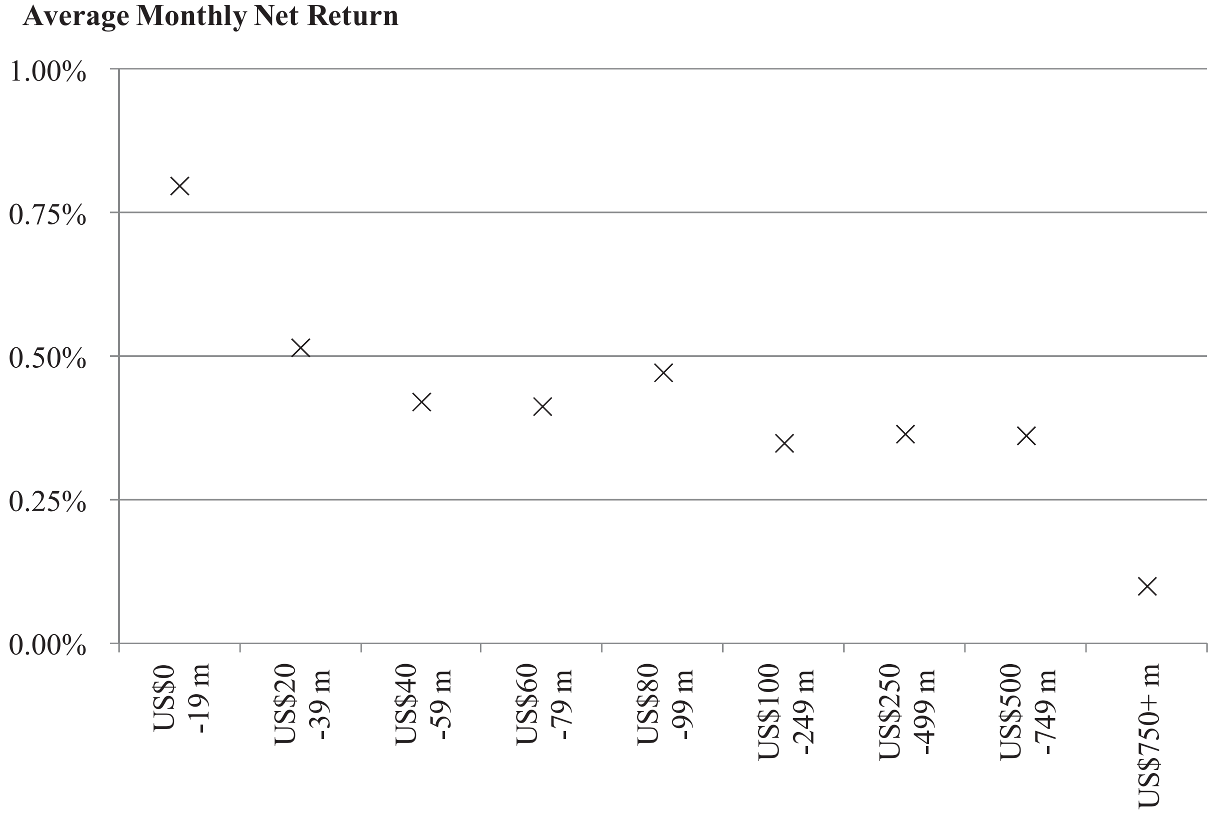
158 They attribute this underperformance to the higher total expense ratios of small funds.

159 A detailed description of the 'attractive HF universe' is provided in chapter 4.1.1.

160 The author abandons this option in this dissertation because it would be an example of a backward readjustment.

Figure 32: Sensitivity Analysis ─ Hedge Fund Size (Jan 2005 – Jun 2009)[161]



Source: Author's own illustration based on Eurekahedge (2009c)

4.2.4.7 Length of Hedge Fund Track Record

The question of whether there is a relationship between HF performance and HF age, measured as the length of track record, has been examined extensively in academic literature. The most relevant studies indicate a clear negative relationship between the length of HFs' track records and their performance. Howell (2001) compares portfolios consisting of HFs of different ages. He shows that on average younger HFs, with track records below three years, outperform older ones with longer track records.[162] Herzberg and Mozes (2003) further quantify the difference in returns between younger and older HFs. They show that HFs with less than three years of history display annual returns that are 3-4% higher than those of older HFs.

[161] Post application of hypothetical management fees and transaction costs.
[162] However, he also shows that younger HFs are more likely to be liquidated (Howell, 2001).

The investment approach presented in this dissertation tries to capitalize on these findings and considers only those HFs with comparatively short track records of up to 36 months for investment.[163] In order to assess whether such a focus is sensible, the 'attractive HF universe' is again divided into several subsets.[164] This time, HFs are allocated to these subsets based on the lengths of their track records. Several different subsets are created. Then, the author calculates the average HF net return for each of these subsets and compares the net returns of these subsets. The results of this procedure are shown in Figure 33. Most subgroups show average monthly net returns around 0.4%. Still, the very young HFs with track records below two years show a considerable outperformance relative to their peers.

This finding seems to imply that a focus on the very young HFs in the sample may be prudent. This point, however, has to be analyzed carefully: As a matter of fact, these returns could be significantly overstated because the average returns shown here do not account for HF survivorship. This is crucial because previous academic literature on the topic shows that the very young HFs have a much higher chance of being liquidated than their older peers.[165] Moreover, it should be noted that it may prove practically difficult to exploit the outperformance of the very youngest HFs if one considers the long lock-ups periods that most HFs require and a reasonable level of transaction costs. Finally, it must be stressed that the average performance of very young HFs erodes rapidly. While these HFs appear to generate net returns of almost 1% per month in their first year of existence, the average net returns shrink around 0.7% in their second year and below 0.4% thereafter. If one considers that the investment approach presented in this thesis requires 24-months of in-sample return data before making an investment decision, it becomes clear that by the time the investment decision is made, the opportunity may already have eroded. Thus, the author concludes that even though very young HFs show high return levels, it is not possible to take advantage of this with a RAPM-based investment approach as the one presented here.

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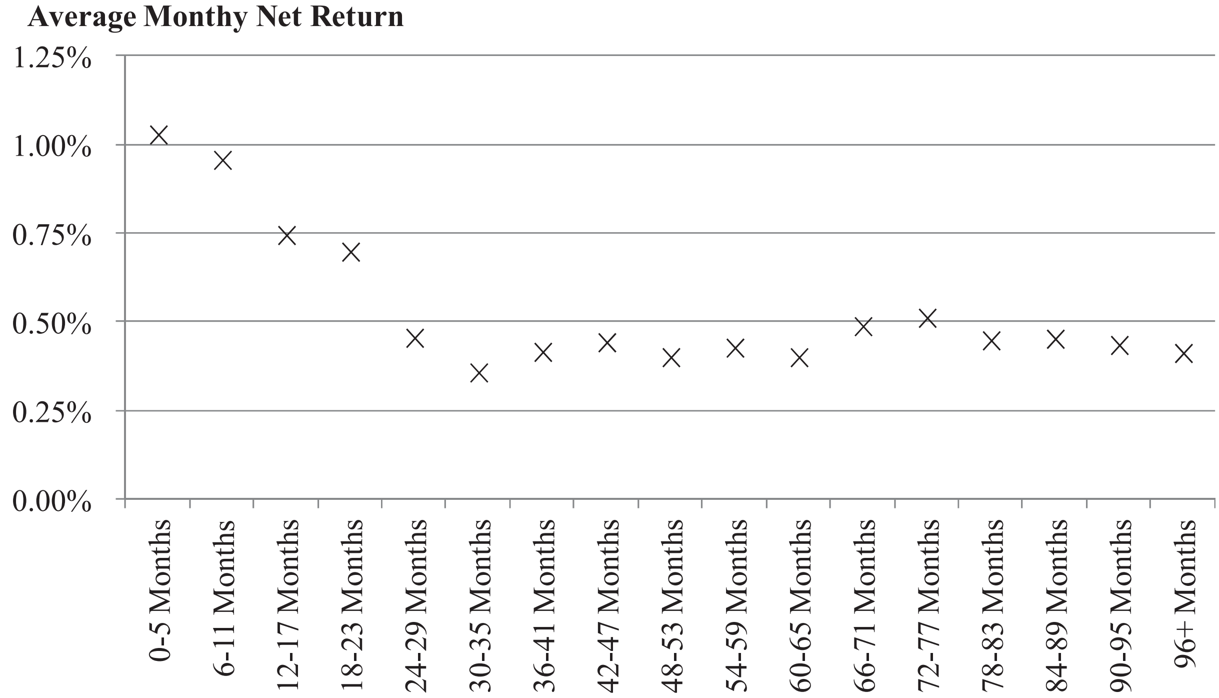
[163] The minimum length of the required track record is 24 months; this is necessary to be able to calculate reliable RAPM values.
[164] A detailed description of the 'attractive HF universe' is provided in chapter 4.1.1.
[165] See for instance Howell (2001).

Figure 33: Sensitivity Analysis ─ Hedge Fund Age (Jan 2005 – Jun 2009)[166]



Source: Author's own illustration based on Eurekahedge (2009c)

4.2.5 Summary of the Empirical Study

In this dissertation the author develops a purely quantitative HF investment approach. In order to test the approach, several portfolios are constructed and benchmarked against the HF and FoF indices. Most portfolios that are constructed clearly outperform these benchmarks:

- The vast majority of HF portfolios outperform the HF index between January 2005 and June 2009 on a net return basis. While the established portfolios typically show a high correlation with the HF index in the 'bull market' from 2005 - 2007, they appear to be considerably less affected by the 'bear market' from 2007 - 2009. Moreover, most of these portfolios are characterized by lower standard deviations than this benchmark. The high net returns and low standard deviations displayed by most of these portfolios, however, are partly outweighed by a negative skewness and a high kurtosis.

[166] Post application of hypothetical management fees and transaction costs.

- 16 out of 23 test portfolios with a 24-months holding period clearly outperform the FoF index after the deduction of hypothetical detriments, specifically transaction costs and management fees. These 16 portfolios show higher net returns along with lower standard deviations and more attractive 3rd and 4th moments. Thus, they clearly dominate their benchmark on a risk / return basis.[167] This implies that the applied methodology is indeed capable of constructing portfolios superior to real-life FoFs under close-to-reality assumptions.[168]

In this context, it is interesting to note that the Sharpe Ratio and ERoVaR, which operate under the assumption of standard normally-distributed returns, are absolutely capable of producing HF portfolios that outperform their respective benchmarks. This is remarkable as most HFs' returns do not follow a normal distribution.

By merging the different HF rankings into one single equally-weighted ranking, a 'Combined Indicator' portfolio can be created. The comparison of the 'Combined Indicator' portfolio against the HF index and the FoF index shows that this portfolio is able to outperform both of these benchmarks on a risk-return basis: The 'Combined Indicator' portfolio is characterized by higher monthly returns than the two indices. At the same time it displays a lower standard deviation along with a higher skewness and a lower kurtosis than these benchmarks imply. Thus, it clearly dominates these benchmarks on a risk / return basis. These results imply that the proposed methodology represents a viable and promising approach to the construction of a HF portfolio.

In the context of a sensitivity analysis, several different levels of transaction costs, performance fees, management fees, liquidity buffers, and asset recovery rates are simulated in order to assess the sensitivity of the proposed 'Combined Indicator' approach to the parameter changes. The 'Combined Indicator' portfolio is shown to

[167] These results, however, do not hold true for shorter holding periods; this can be ascribed to a high level of transaction costs.

[168] Still, it must be stressed that the portfolio management approach developed here offers none of the aforementioned benefits that FoFs provide, specifically accessibility, liquidity, and professional management. Therefore, benchmarking against the FoF index cannot be considered as a like-with-like comparison and is included for reference only.

outperform its respective benchmarks on a net return basis for all tested parameter values.

Moreover, the link between HF size and performance is examined. It can be shown that there is a negative correlation between HF size and HF returns. This is in particular due to the smallest and the largest HFs in the sample. As a matter of fact, HFs with AuM of US$1-19 million considerably outperform their peers whereas HFs with AuM in excess of US$750 million considerably underperform their peers. This finding implies that an investment focus on comparatively small HFs may indeed be sensible.

Correspondingly, the association between HF age and performance is examined. It can be shown that young HFs with track records below two years considerably outperform their older peers. From a practitioners' point of view, however, it may prove difficult to exploit this outperformance because of the presence of lock-up periods, transaction costs, and these HFs' lack of a financial track record.

Following the summary of the main findings of this thesis, the author reviews the proposed investment approach and puts the findings in the context of current academic literature in the next part of this dissertation (5).

5 Conclusion

This chapter consists of several parts. The first part (5.1) highlights the opacity of the HF industry and sums up the academic approaches to active portfolio management that have been made. This is followed by a short recapitulation of the proposed investment heuristic (5.2) which is further exemplified in the next section (5.3). Then, the findings are critically reviewed (5.4) and the contribution of this dissertation to the current academic literature and the value for practitioners is outlined (5.5). Subsequently, the author makes some concluding remarks (5.6).

5.1 A Tailor-made Investment Approach

The HF universe is "notorious for its opacity and its subsequently highly asymmetric and incomplete information flow" (Laube et al., 2011, p. 77). In fact, "information access and control presents one of the key skills for successful asset management in the HF industry" (Laube et al., 2011, p. 77).

Bearing these peculiarities of the HF market in mind, it becomes clear that there is significant private information that is not available to all investors and not reflected in market prices. As a consequence, the HF market must be considered as semi-strongly efficient rather than strongly efficient. In such a market, skilled active management is expected to deliver superior results compared to a buy-and-hold strategy.

In recent years, several active approaches to portfolio management within a large universe of HFs have been discussed in academia. Unfortunately, previous academic designs are not easily applicable to the reality of family offices seeking HF exposure as they fail to consider significant practical restrictions that industry professionals face. In addition, many previous studies are based on data sets of questionable relevance for practitioners.

Against this background, it has become a necessity to develop an effective HF investment approach that is of straightforward practical relevance for family offices.

In the dissertation at hand, the author developed such an active investment approach to help close this research gap. The precise approach is revisited in the next section.

5.2 Recapitulation of the Investment Approach

The investment approach developed in this thesis involves three major steps: data preparation, investment selection, and fund allocation; each of which is explained below.

The first step, data preparation, starts off from a comprehensive and up-to-date HF database, such as the Eurekahedge Global HF database. The investor narrows down the number of active HFs by discarding all HFs that

- are closed to new investment or non-flagship funds
- have AuM below US$1 million or exceeding US$100 million
- have track records beyond three years
- have higher minimum investment requirements than 10% of the investor's capital
- have not reported returns for more than two consecutive months in the past two years

If the investor wishes to follow a 'conservative' strategy and to invest in market-neutral HFs only, directional HFs may be removed from the sample as well. The HFs remaining after this procedure represent the most promising funds for investment.

In the second step, investment selection, the author calculates a 'Combined Indicator', a measure comprised of 23 different RAPMs, for all remaining funds using 24-months in-sample data.[169] All HFs are ranked from best to worst according to their 'Combined Indicator' values.

[169] The 'Combined Indicator' is comprised of Lower partial moment (LPM)-based RAPMs, Drawdown-based RAPMs, Value at Risk (VaR)-based RAPMs.

- Lower partial moment (LPM)-based RAPMs include Omega, the Sortino Ratio, Kappa 3, the Upside Potential Ratio, and Excess Return on Probability of Shortfall (ERoPS).
- Drawdown-based RAPMs comprise of the Calmar, Sterling, and Burke Ratios.
- Value at Risk (VaR)-based RAPMs include Excess Return on Value at Risk (ERoVaR), the Conditional Sharpe Ratio, and the Modified Sharpe Ratio.
- Other RAPMs consist of the D-Ratio, the Hurst Ratio, and the Manipulation-proof Performance Measure (MPPM).

The third step, fund allocation, is straightforward. The investor allocates 10% of the disposable capital to each of the top ten HFs with the highest 'Combined Indicator' values.[170] With the investor refraining from any action during the following two years, the portfolio weights of the individual HFs will fluctuate over the course of this period and give more weight to the successful HFs. At the end of the two years, all HFs in the portfolio are sold irrespective of their performance. This investment process is repeated every two years.

5.3 The New Investment Approach in Operation

This approach is exemplified below with the help of two exemplary family offices: 'Family Office A' strives to invest US$10 million into HFs and has a 4-year investment horizon. 'Family Office B', on the other hand, seeks to allocate US$20 million to HFs. 'Family Office B' has an investment horizon of just two years; it expects imminent market upheavals.

According to the strategy outlined above, both family offices narrow down the universe of investment choices by focusing on investable HFs that are small, young, and have shown good reporting discipline in the past. Moreover, 'Family Office B' decides to concentrate on 'market-neutral' HFs only because it has a relatively short investment horizon and expects markets to plummet in the near future.

After that, both family offices calculate a 'Combined Indicator' for their remaining HFs and rank them according to their 'Combined Indicator' values. Then, 'Family Office A' allocates US$1 million, 10% of its disposable capital, to each of the top ten HFs with the highest 'Combined Indicator' values. 'Family Office B', on the other hand, invests US$2 million, 10% of its disposable capital, in the ten highest-ranking 'market-neutral' HFs.

After two years, all HFs in the portfolios are sold. At that point in time, 'Family Office A', which has a 4-year investment horizon, repeats the investment process from the start.

[170] Any transaction costs such as pre-sales charges are included in this amount.

This exemplification shows that, although both investors appear to be very different, they take a strikingly similar investment approach.

Despite the different sizes of their investments, both family offices buy in merely ten different HFs at a time. They do so in order to avoid 'overdiversification'. Previous research clearly shows that most diversification benefits in are captured by an equally-weighted portfolio of just 10 HFs.[171] A further diversified portfolio is more likely to include poor performers and to be associated with higher fees at the same time.[172]

Although both family offices have different investment horizons, they both hold their portfolios for two years. This is for the following reasons: Firstly, the performance of superior HFs has clearly been shown to persist over a two-year horizon, which is a prerequisite for the investment approach.[173] Secondly, the transaction costs incurred are kept at the lowest possible level by forgoing more frequent portfolio reallocations.[174]

While both family offices buy in the same number of HFs and hold them over the same 24-months period, they follow slightly different strategies. 'Family Office A' follows a 'Combined Indicator - Aggressive' approach and 'Family Office B' a 'Combined Indicator - Conservative' approach by focusing exclusively on market-neutral HFs for investment.

As previously illustrated (4.2.3), both 'Combined Indicator' portfolio variants were able to clearly outperform an equally-weighted HF index and an equally-weighted FoF index with regard to their risk and return characteristics. Both portfolios

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171 See for instance Park and Staum (1998), Henker (1998), Amin and Kat (2003), Lhabitant and Learned (2004), and Lhabitant and Laporte (2006). Interestingly, this academic finding seems to be in line with the practice of many family offices; a recent survey of North American family offices found that they were typically invested in 10 different HFs or FoFs (Preqin, 2009).

172 This is why a portfolio consisting of a winning HF and a losing one will end up paying performance fees to one of the managers, although the overall performance is zero (Lhabitant, 2006).

173 See for instance Caglayan and Edwards (2001), Kouwenberg (2003), Harri and Brorsen (2004), Moerth (2007), and Jagannathan et al. (2010). Some of these studies discover performance persistence over even longer horizons.

174 This is illustrated in chapter 4.2.2 of this thesis.

displayed higher average monthly returns than these indices. At the same time, they exhibited lower standard deviations, a higher skewness, and a lower kurtosis than their benchmarks. While the ‘Combined Indicator - Aggressive’ portfolio dominated the ‘Combined Indicator - Conservative’ portfolio on a return basis, the latter displayed a superior risk profile.

After the proposed investment approach has been recapitulated and exemplified, the author critically reviews his findings in the next part of this dissertation.

5.4 Critical Discussion

The simple heuristic disclosed above has proven superior to a HF index and a FoF index in a series of extensive out-of-sample tests. Thus, there seems to be overwhelming evidence that the proposed investment approach represents a valuable tool for industry professionals. Still, in the light of this success, it seems worthwhile to discuss its limitations plainly.

First of all, the proposed investment approach has only been tested during a relatively short observation period from January 2003 to June 2009. Although this has been a deliberate choice – in order to safeguard data quality – one has to be aware of this shortcoming. At the same time it must be pointed out that this period covers the larger part of a full economic cycle and one of the most severe financial crises in recent history. Still, it would be advantageous to observe the performance over a longer period.

Moreover, the proposed investment approach is not scalable. It relies essentially on the availability of investment opportunity in small HFs. A significant inflow of capital into this approach would erode performance levels due to diminishing returns to scale. Therefore, the strategy is only apt for few and small investors.

Furthermore, it must be mentioned that the proposed investment approach is a heuristic and does, as such, not produce optimal allocations. Still, it represents a fully transparent, easy-to-implement, and inexpensive-to-operate decision-making guideline for investors seeking exposure to a diversified HF portfolio. While the heuristic is tailored to the needs of family offices, it may also be appropriate for other investor groups such as endowments and foundations.

Finally, it has to be pointed out that the proposed methodology is a niche solution that is only apt for special types of investors such as family offices. Family offices usually have significant AuM combined with a long-term planning horizon and a qualified body of investment professionals. Thus, they are less dependent on the benefits that FoFs provide, namely accessibility, liquidity, and professional portfolio oversight. In other words, a direct investment in HFs as discussed in this study is not per se advisable for all investor groups in all situations. Still, certain kinds of investors, such as family offices might use this new approach to generate equal or even higher returns than FoFs.

Considering all these factors, the limitations of the proposed heuristic become evident: It represents a valuable decision-making guideline for investors; however, it cannot be considered as a silver bullet to HF investment.

5.5 Contribution to Academic Literature and Value for Practitioners

Contribution to Academic Literature

In this dissertation, the author strives to make a distinctive contribution to the academic literature in the field of HF selection and portfolio management within a broad universe of HFs. While there are several academic studies in the field, they do not take the major practical limitations and restrictions into account that family offices are faced with. Against this background and considering the importance of HFs for family offices, it has become a necessity to develop an effective HF investment approach that is of straightforward practical relevance for family office practitioners. Some studies, such as Jöhri and Leippold's (2006), have tried to bridge this gap. The study at hand follows their research line further by incorporating a larger number of practically relevant restrictions: Unlike Jöhri and Leippold's work (2006) this dissertation considers lock-up periods and minimum investment requirements on an individual fund level as well as transaction costs.

Furthermore, the 'Combined Indicator' put forward in this study comprises of a different and larger selection of RAPMs. Therefore, this study can be regarded as one of the most inclusive works to prove that an entirely quantitative RAPM-based investment approach represents – in all probability – a capable and viable option in a real-life HF investment setting.

This dissertation is also closely related to Eling and Schuhmacher's work (2007). Eling and Schuhmacher test the Sharpe Ratio as well as different LPM-, drawdown, and VaR-based RAPMs and find that the HF rankings established by these RAPMs are highly correlated. They conclude that the choice of RAPM is not critical to the evaluation of HFs and that the Sharpe Ratio is generally adequate. This finding is confirmed by a follow-up study (Eling et al., 2011).

The dissertation at hand considers all RAPMs analyzed in Eling and Schuhmacher's work (2007). In addition, several other RAPMs are analyzed; specifically, ERoPS, the MPPM, the D-Ratio, and the Hurst Ratio. While the author agrees with Eling and Schuhmacher that the Sharpe Ratio is well apt for the construction of a HF portfolio, their conclusion is not affirmed by this thesis. Instead, the author shows that portfolios constructed under different RAPMs can follow very different return distributions. This finding is in line with two of the latest academic publications in the field of RAPMs by Nguyen-Thi-Thanh (2010) and Ornelas et al. (2009).[175]

This dissertation also strives to add to the academic literature on HF characteristics and their impact on performance. The thesis clearly shows that very small HFs with AuM below US$20 million and very young HFs with track records below two years considerably outperform their peers. This finding is in line with previous works in the field such as Boyson's (2008, 2010), who confirms that young and small HFs generate significantly higher returns than older and bigger ones.

[175] Nguyen-Thi-Thanh (2010) tests different RAPMs against a sample of HFs. Despite strong positive correlations between HF rankings established by different RAPMs, she observes significant modifications in the rankings in absolute terms. She concludes that the choice of RAPM is crucial for the evaluation and the selection of HFs. Ornelas et al. (2009) apply several RAPMs to US mutual funds. While they discover high ranking correlations for the majority of tested RAPMs, they show that other RAPMs, such as the MPPM, have significantly lower correlations with the other measures. This dissertation can affirm this assessment of the MPPM with regard to global HFs.

Value for Practitioners

The value of this dissertation for industry practitioners is straightforward: The heuristic at hand represents a fully transparent, easy-to-implement, and inexpensive-to-operate decision-making guideline for investors seeking exposure to a sufficiently diversified HF portfolio. While the heuristic is tailored to the needs of family offices, it may also be appropriate for other investor groups such as endowments and foundations.

5.6 Concluding Remarks

This dissertation is aimed at the development of a viable investment heuristic for family offices seeking HF exposure. It demonstrates clearly that it is possible to construct an effective approach to HF investment that relies entirely on historical data. A portfolio of HFs constructed under the proposed heuristic proved able to outperform a HF index and a FoF index in an out-of-sample analysis. While the heuristic presented here is doubtlessly subject to several limitations, there seems to be evidence that it represents – in all probability – a valuable decision-making guideline for investors in a real-life HF investment setting.

Appendix A: The Family Office Industry

Table A1: Family Wealth in Single Family Offices (2007)[176]

	Americas	Europe	RoW
US$100 m - US$ 500 m	52%	30%	34%
US$500 m - US$1,000 m	17%	11%	33%
> US$1,000 m	26%	53%	33%
No answer	5%	6%	0%

Source: Amit et al. (2008)

Table A2: Number of Employees in Single Family Offices (2007)[177]

	Americas	Europe	RoW
Head of the family office	0.9	1.2	1
Investment professionals	1.8	3	1.9
Accountants	1.6	2.1	2.3
Lawyers/legal advisors	0.4	1	0.2
Investment advisors	0.3	0.4	0.2
Other professionals	1.1	1.7	0.2
Staff	2.7	3.9	5.9
Total number of employees	**8.7**	**13.2**	**11.8**

Source: Amit et al. (2008)

[176] Information based on over 40 interviews and on 138 completed surveys.
[177] Information based on over 40 interviews and on 138 completed surveys.

Table A3: Single Family Office Objective with Respect to Wealth (2007)[178]

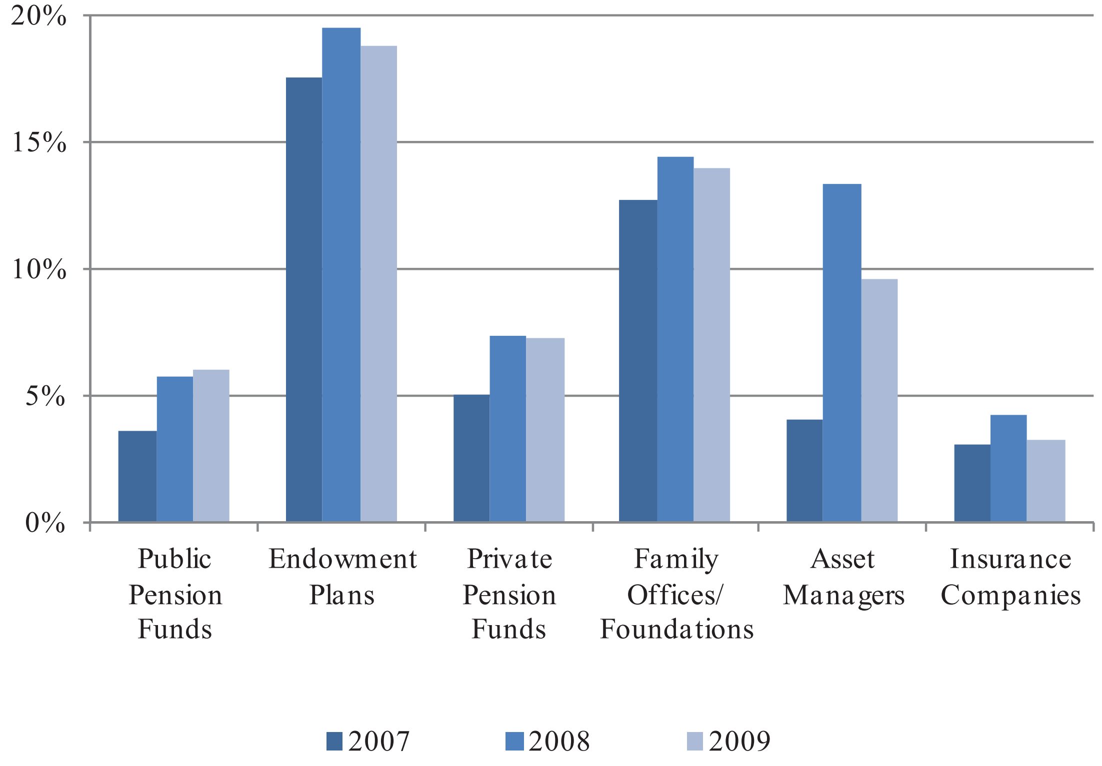
	Americas	Europe	RoW
Preserve very conservatively	5%	1%	11%
Preserve	10%	10%	33%
Balanced Approach	35%	53%	11%
Grow	34%	30%	34%
Aggressively Grow	14%	3%	11%
No Answer	2%	3%	0%

Source: Amit et al. (2008)

[178] Information based on over 40 interviews and on 138 completed surveys.

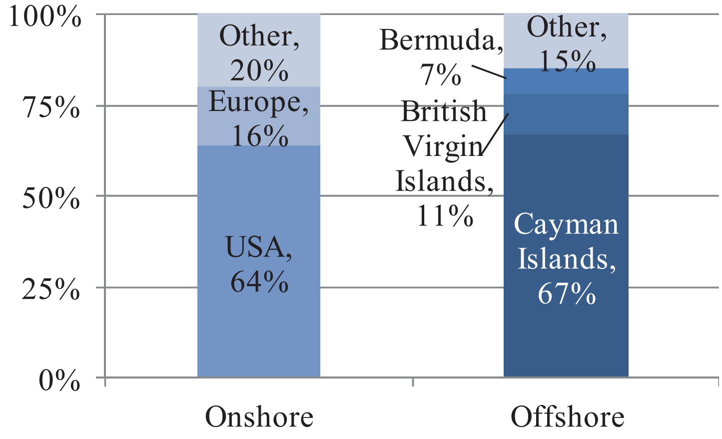
Appendix B: The Hedge Fund Industry

Figure B1: Global Mean Percentage Allocation to HFs by Investor Type



Source: Preqin (2009)

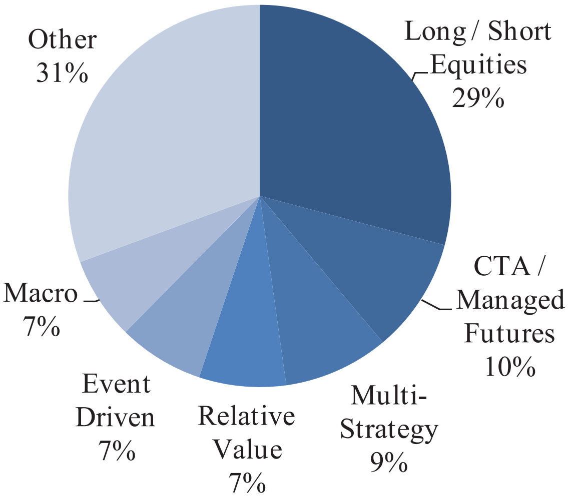
Figure B2: Global HFs by Domicile (2008)[179]



Source: Maslakovic (2010)

179 Percentage share by number

Figure B3: Breakdown of HF AuM by Investment Strategy (June 2009)[180]

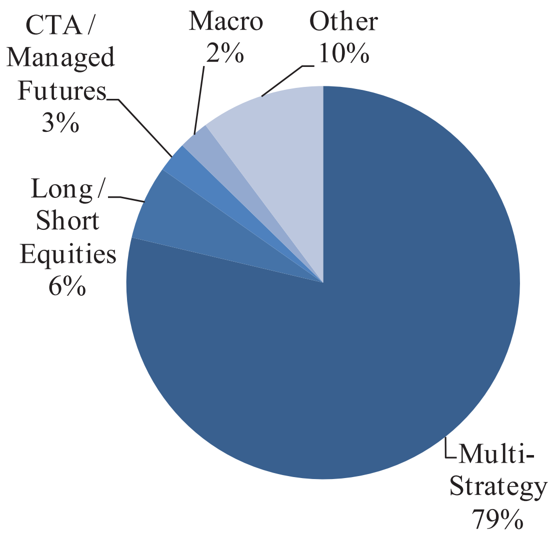


Source: Author's own illustration based on Eurekahedge (2009c)

[180] Unweighted breakdown of 3,609 HFs reporting AuM. This includes closed and non-flagship funds.

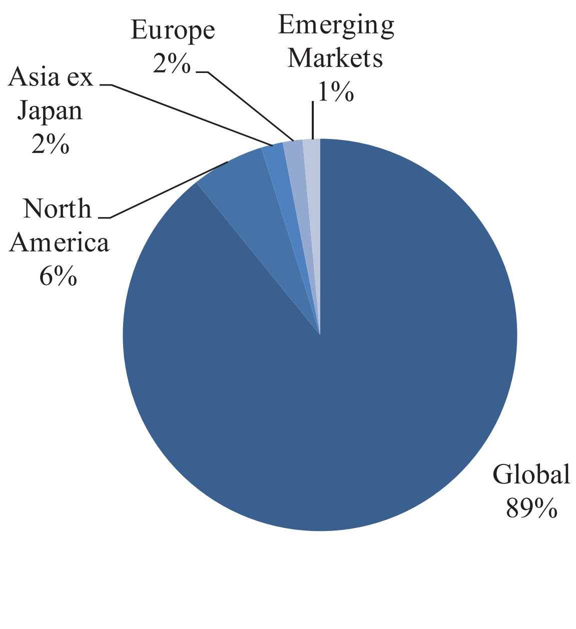
Appendix C: The Fund of Hedge Funds Industry

Figure C1: Breakdown of FoF AuM by Investment Strategy (June 2009)



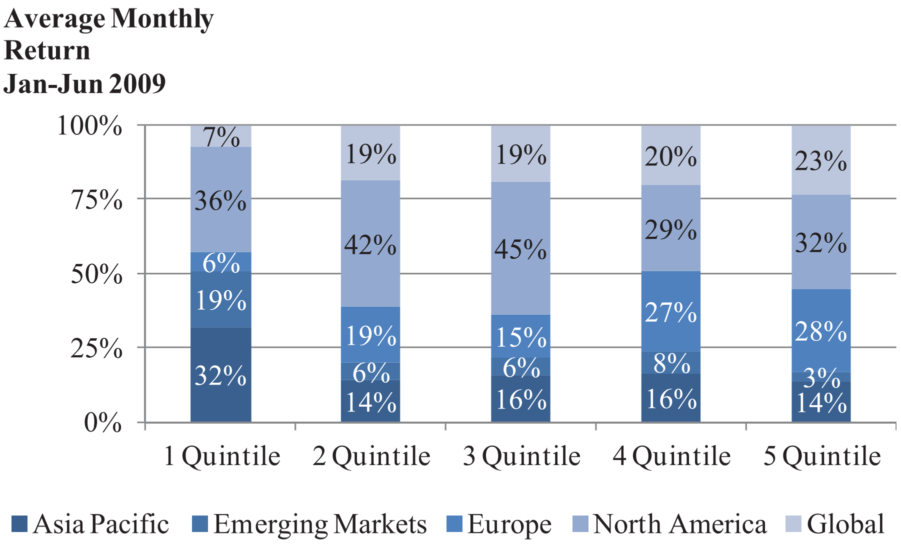
Source: Author's own illustration based on Eurekahedge (2009b)

Figure C2: Breakdown of FoF AuM by Investment Focus (June 2009)



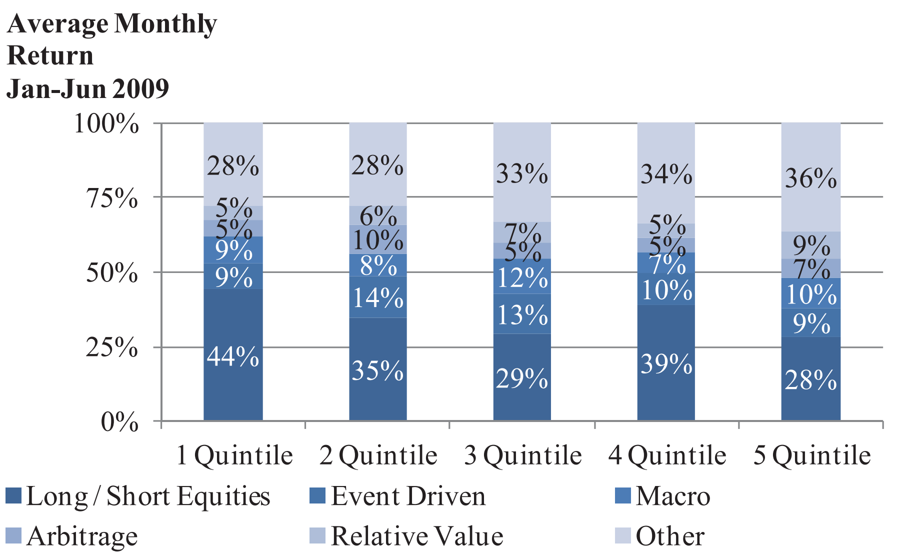
Source: Author's own illustration based on Eurekahedge (2009b)

Figure C3: FoF Portfolios by Investment Geography (Jan – Jun 2009)



Source: Author's own illustration based on Eurekahedge (2009b)

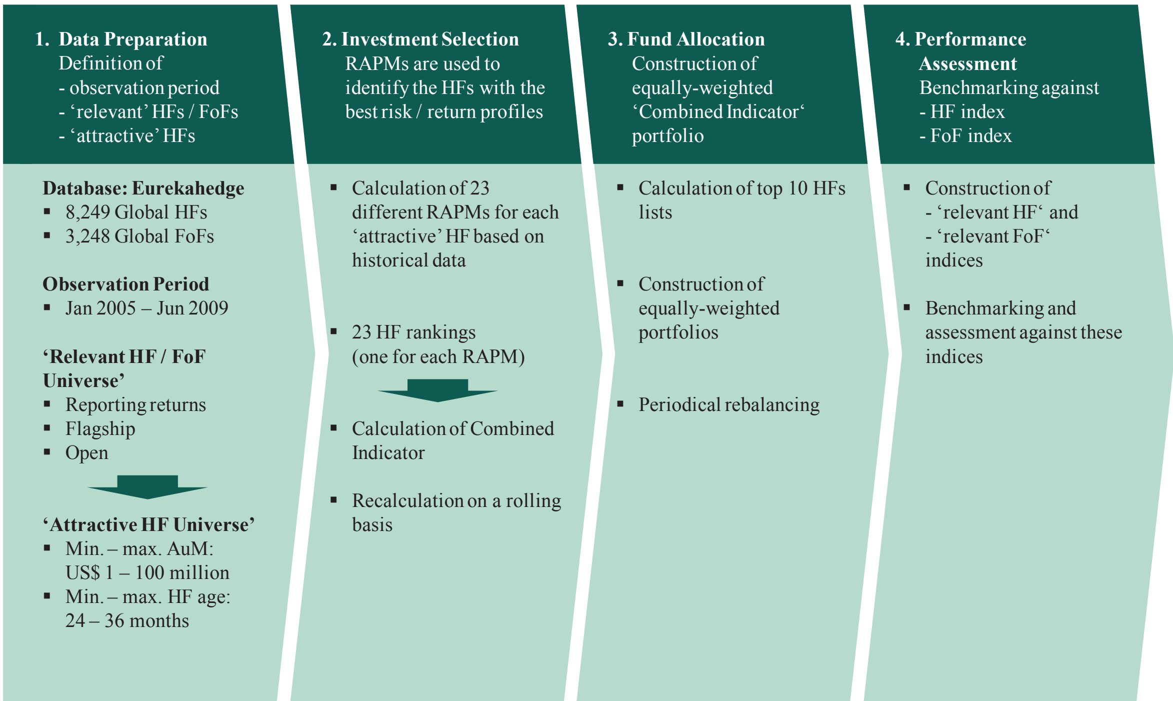
Figure C4: FoF Portfolios by Strategy of Invested HFs (Jan – Jun 2009)



Source: Author's own illustration based on Eurekahedge (2009b)

Appendix D: Research Design

Figure D1: Simplified Overview of Research Design



Source: Author's own illustration

Table D1: Prominent RAPMs Not Discussed in This Dissertation

RAPM (Source)	Reason for Exclusion
▪ Jensen's Alpha (Jensen, 1968) ▪ Treynor Index (Treynor, 1965) ▪ Q-Ratio (Gulko, 2003)	These RAPMs are explicitly targeted at adding HFs to a portfolio of traditional assets. As this is not the case in this dissertation, these RAPMs are not considered.
▪ Generalized Sharpe Ratio (Kazemi, Mahdavi, & Schneeweis, 2003) ▪ Appraisal Ratio (Treynor & Black, 1973) ▪ X-Ratio (Jöhri & Leippold, 2006)	These are relative RAPMs as they measure risk / return against a certain benchmark. These RAPMs are not considered in this dissertation as this thesis is focused on stand-alone risk / return measurement on the basis of individual HF returns.
▪ Sharpe Omega (Kazemi, Schneeweis, & Gupta, 2003)	This RAPM is essentially proportional to 1-Omega; thus, it delivers the same HF rankings as Omega (Géhin, 2004).

Source: Author's own illustration

Appendix E: Portfolio Return Statistics

Table E1: Average Monthly Portfolio Returns (January 2005 - June 2009)
Pre Hypothetical Transaction Costs and Management Fees

	Holding Period			
	6 Months	12 Months	18 Months	24 Months
HF Index	**0.51%**	**0.52%**	**0.57%**	**0.60%**
Lower Partial Momements (LPM)-Based RAPMs				
ERoPS	1.07%	0.77%	0.81%	0.46%
Omega	0.79%	0.56%	0.76%	0.89%
Sortino Ratio	0.83%	0.51%	0.76%	0.78%
Kappa 3	0.77%	0.39%	0.61%	0.53%
Upside Potential Ratio	0.78%	0.47%	0.59%	0.91%
Drawdown (DD)-Based RAPMs				
Calmar Ratio	0.68%	0.44%	0.55%	0.72%
Sterling Ratio	0.71%	0.40%	0.51%	0.80%
Burke Ratio	0.72%	0.39%	0.61%	0.71%
Value at Risk (VAR)-Based RAPMs				
Excess Return on VAR (α=1%)	0.68%	0.46%	0.65%	0.81%
Excess Return on VAR (α=5%)	0.69%	0.46%	0.65%	0.85%
Excess Return on VAR (α=10%)	0.68%	0.36%	0.68%	0.85%
Conditional Sharpe Ratio (α=1%)	0.70%	0.46%	0.65%	0.81%
Conditional Sharpe Ratio (α=5%)	0.68%	0.46%	0.65%	0.81%
Conditional Sharpe Ratio (α=10%)	0.69%	0.46%	0.65%	0.81%
Modified Sharpe Ratio (α=1%)	0.54%	0.45%	0.74%	0.53%
Modified Sharpe Ratio (α=5%)	0.76%	0.47%	0.79%	0.83%
Modified Sharpe Ratio (α=10%)	0.80%	0.44%	0.78%	0.82%
Other RAPMs				
Sharpe Ratio	0.66%	0.64%	0.84%	0.81%
D-Ratio	0.73%	0.61%	0.76%	0.78%
Hurst Ratio	1.08%	0.95%	0.51%	0.89%
MPPM (ρ=2)	1.10%	1.05%	1.00%	0.43%
MPPM (ρ=3)	1.16%	1.02%	0.98%	0.60%
MPPM (ρ=4)	1.05%	0.93%	0.78%	0.67%

Source: Author's own illustration based on Eurekahedge (2009c)

Table E2: Standard Deviation of Portfolio Returns (January 2005 - June 2009) Pre Hypothetical Transaction Costs and Management Fees

	Holding Period			
	6 Months	12 Months	18 Months	24 Months
HF Index	**2.33%**	**2.31%**	**2.28%**	**2.20%**
Lower Partial Momements (LPM)-Based RAPMs				
ERoPS	3.89%	2.76%	3.05%	2.82%
Omega	1.85%	1.94%	2.34%	0.92%
Sortino Ratio	1.86%	2.11%	2.49%	1.41%
Kappa 3	1.91%	2.28%	2.50%	1.84%
Upside Potential Ratio	1.83%	2.37%	2.50%	1.13%
Drawdown (DD)-Based RAPMs				
Calmar Ratio	1.73%	1.88%	2.17%	1.18%
Sterling Ratio	1.78%	1.98%	2.29%	0.97%
Burke Ratio	1.80%	2.22%	2.53%	1.23%
Value at Risk (VAR)-Based RAPMs				
Excess Return on VAR (α=1%)	2.22%	2.13%	2.48%	0.68%
Excess Return on VAR (α=5%)	2.23%	2.13%	2.48%	0.86%
Excess Return on VAR (α=10%)	2.24%	2.58%	3.09%	0.86%
Conditional Sharpe Ratio (α=1%)	2.19%	2.13%	2.48%	0.68%
Conditional Sharpe Ratio (α=5%)	2.22%	2.13%	2.48%	0.68%
Conditional Sharpe Ratio (α=10%)	2.23%	2.13%	2.48%	0.68%
Modified Sharpe Ratio (α=1%)	2.31%	2.71%	3.44%	1.74%
Modified Sharpe Ratio (α=5%)	1.92%	2.61%	3.17%	0.74%
Modified Sharpe Ratio (α=10%)	2.13%	2.82%	3.36%	0.68%
Other RAPMs				
Sharpe Ratio	1.94%	1.82%	2.27%	0.68%
D-Ratio	1.56%	1.61%	2.08%	0.82%
Hurst Ratio	2.98%	3.26%	2.22%	4.26%
MPPM (ρ=2)	4.70%	5.07%	6.35%	4.61%
MPPM (ρ=3)	4.67%	5.03%	6.27%	4.78%
MPPM (ρ=4)	4.78%	5.04%	6.25%	4.86%

Source: Author's own illustration based on Eurekahedge (2009c)

Table E3: Skewness of Portfolio Returns (January 2005 - June 2009)
Pre Hypothetical Transaction Costs and Management Fees

	Holding Period			
	6 Months	12 Months	18 Months	24 Months
HF Index	**(1.01)**	**(1.13)**	**(1.22)**	**(1.30)**
Lower Partial Momements (LPM)-Based RAPMs				
ERoPS	(0.64)	(2.22)	(1.18)	(1.70)
Omega	(1.89)	(1.44)	(0.33)	0.13
Sortino Ratio	(1.63)	(1.62)	(0.60)	(1.13)
Kappa 3	(1.26)	(1.20)	(0.71)	(1.16)
Upside Potential Ratio	(1.67)	(1.61)	(1.20)	0.40
Drawdown (DD)-Based RAPMs				
Calmar Ratio	(1.62)	(1.57)	(0.72)	(0.74)
Sterling Ratio	(1.71)	(1.84)	(0.75)	(0.19)
Burke Ratio	(1.54)	(1.86)	(0.90)	(0.59)
Value at Risk (VAR)-Based RAPMs				
Excess Return on VAR (α=1%)	(1.77)	(1.68)	(0.53)	(0.11)
Excess Return on VAR (α=5%)	(1.75)	(1.68)	(0.53)	0.06
Excess Return on VAR (α=10%)	(1.71)	(1.92)	(0.60)	0.06
Conditional Sharpe Ratio (α=1%)	(1.76)	(1.68)	(0.53)	(0.11)
Conditional Sharpe Ratio (α=5%)	(1.77)	(1.68)	(0.53)	(0.11)
Conditional Sharpe Ratio (α=10%)	(1.75)	(1.68)	(0.53)	(0.11)
Modified Sharpe Ratio (α=1%)	(1.63)	(2.98)	(0.67)	(1.42)
Modified Sharpe Ratio (α=5%)	(1.75)	(3.78)	(1.64)	(0.19)
Modified Sharpe Ratio (α=10%)	(2.05)	(3.51)	(1.60)	(0.13)
Other RAPMs				
Sharpe Ratio	(1.54)	(2.59)	(0.71)	(0.11)
D-Ratio	(1.49)	(2.42)	(0.53)	(1.17)
Hurst Ratio	2.73	2.31	(0.25)	1.35
MPPM (ρ=2)	(0.66)	(1.29)	(0.71)	(1.78)
MPPM (ρ=3)	(0.67)	(1.25)	(0.72)	(1.45)
MPPM (ρ=4)	(0.47)	(1.13)	(0.34)	(1.34)

Source: Author's own illustration based on Eurekahedge (2009c)

Table E4: Kurtosis of Portfolio Returns (January 2005 - June 2009)
Pre Hypothetical Transaction Costs and Management Fees

	Holding Period			
	6 Months	12 Months	18 Months	24 Months
HF Index	**2.49**	**3.00**	**3.51**	**3.79**
Lower Partial Momements (LPM)-Based RAPMs				
ERoPS	2.01	8.10	5.91	4.16
Omega	4.39	2.11	1.57	1.73
Sortino Ratio	3.36	2.45	1.73	2.34
Kappa 3	2.08	1.24	1.18	2.60
Upside Potential Ratio	3.48	2.72	2.74	0.89
Drawdown (DD)-Based RAPMs				
Calmar Ratio	3.21	3.10	2.79	2.06
Sterling Ratio	3.96	4.06	3.39	1.81
Burke Ratio	3.13	4.06	3.12	1.54
Value at Risk (VAR)-Based RAPMs				
Excess Return on VAR (α=1%)	3.71	2.63	2.83	0.36
Excess Return on VAR (α=5%)	3.63	2.63	2.83	1.32
Excess Return on VAR (α=10%)	3.44	3.96	3.05	1.32
Conditional Sharpe Ratio (α=1%)	3.71	2.63	2.83	0.36
Conditional Sharpe Ratio (α=5%)	3.71	2.63	2.83	0.36
Conditional Sharpe Ratio (α=10%)	3.63	2.63	2.83	0.36
Modified Sharpe Ratio (α=1%)	3.50	12.76	6.55	3.93
Modified Sharpe Ratio (α=5%)	5.52	19.33	10.04	(0.26)
Modified Sharpe Ratio (α=10%)	5.87	16.60	9.85	0.39
Other RAPMs				
Sharpe Ratio	2.51	9.67	5.36	0.36
D-Ratio	4.53	10.00	4.52	2.32
Hurst Ratio	12.83	10.06	0.43	4.58
MPPM (ρ=2)	0.29	2.65	2.89	6.06
MPPM (ρ=3)	0.50	2.99	3.14	5.86
MPPM (ρ=4)	0.58	3.07	3.49	5.62

Source: Author's own illustration based on Eurekahedge (2009c)

Table E5: Portfolio Return Statistics (January 2005 - June 2009)
Pre Hypothetical Transaction Costs and Management Fees
Portfolios Reallocated Every 6 Months

	CMGR of Net Returns	Standard Deviation	Skewness	Kurtosis
HF Index	**0.48%**	**2.33%**	**(1.01)**	**2.49**
Lower Partial Momements (LPM)-Based RAPMs				
ERoPS	1.00%	3.89%	(0.64)	2.01
Omega	0.77%	1.85%	(1.89)	4.39
Sortino Ratio	0.81%	1.86%	(1.63)	3.36
Kappa 3	0.75%	1.91%	(1.26)	2.08
Upside Potential Ratio	0.76%	1.83%	(1.67)	3.48
Drawdown (DD)-Based RAPMs				
Calmar Ratio	0.67%	1.73%	(1.62)	3.21
Sterling Ratio	0.70%	1.78%	(1.71)	3.96
Burke Ratio	0.70%	1.80%	(1.54)	3.13
Value at Risk (VAR)-Based RAPMs				
Excess Return on VAR (α=1%)	0.66%	2.22%	(1.77)	3.71
Excess Return on VAR (α=5%)	0.66%	2.23%	(1.75)	3.63
Excess Return on VAR (α=10%)	0.66%	2.24%	(1.71)	3.44
Conditional Sharpe Ratio (α=1%)	0.68%	2.19%	(1.76)	3.71
Conditional Sharpe Ratio (α=5%)	0.66%	2.22%	(1.77)	3.71
Conditional Sharpe Ratio (α=10%)	0.66%	2.23%	(1.75)	3.63
Modified Sharpe Ratio (α=1%)	0.51%	2.31%	(1.63)	3.50
Modified Sharpe Ratio (α=5%)	0.74%	1.92%	(1.75)	5.52
Modified Sharpe Ratio (α=10%)	0.77%	2.13%	(2.05)	5.87
Other RAPMs				
Sharpe Ratio	0.64%	1.94%	(1.54)	2.51
D-Ratio	0.72%	1.56%	(1.49)	4.53
Hurst Ratio	1.04%	2.98%	2.73	12.83
MPPM (ρ=2)	0.99%	4.70%	(0.66)	0.29
MPPM (ρ=3)	1.05%	4.67%	(0.67)	0.50
MPPM (ρ=4)	0.94%	4.78%	(0.47)	0.58

Source: Author's own illustration based on Eurekahedge (2009c)

Table E6: Portfolio Return Statistics (January 2005 - June 2009)
Pre Hypothetical Transaction Costs and Management Fees
Portfolios Reallocated Every 12 Months

	CMGR of Net Returns	Standard Deviation	Skewness	Kurtosis
HF Index	**0.49%**	**2.31%**	**(1.13)**	**3.00**
Lower Partial Momements (LPM)-Based RAPMs				
ERoPS	0.73%	2.76%	(2.22)	8.10
Omega	0.54%	1.94%	(1.44)	2.11
Sortino Ratio	0.49%	2.11%	(1.62)	2.45
Kappa 3	0.37%	2.28%	(1.20)	1.24
Upside Potential Ratio	0.45%	2.37%	(1.61)	2.72
Drawdown (DD)-Based RAPMs				
Calmar Ratio	0.42%	1.88%	(1.57)	3.10
Sterling Ratio	0.38%	1.98%	(1.84)	4.06
Burke Ratio	0.37%	2.22%	(1.86)	4.06
Value at Risk (VAR)-Based RAPMs				
Excess Return on VAR (α=1%)	0.43%	2.13%	(1.68)	2.63
Excess Return on VAR (α=5%)	0.43%	2.13%	(1.68)	2.63
Excess Return on VAR (α=10%)	0.33%	2.58%	(1.92)	3.96
Conditional Sharpe Ratio (α=1%)	0.43%	2.13%	(1.68)	2.63
Conditional Sharpe Ratio (α=5%)	0.43%	2.13%	(1.68)	2.63
Conditional Sharpe Ratio (α=10%)	0.43%	2.13%	(1.68)	2.63
Modified Sharpe Ratio (α=1%)	0.41%	2.71%	(2.98)	12.76
Modified Sharpe Ratio (α=5%)	0.44%	2.61%	(3.78)	19.33
Modified Sharpe Ratio (α=10%)	0.40%	2.82%	(3.51)	16.60
Other RAPMs				
Sharpe Ratio	0.62%	1.82%	(2.59)	9.67
D-Ratio	0.60%	1.61%	(2.42)	10.00
Hurst Ratio	0.90%	3.26%	2.31	10.06
MPPM (ρ=2)	0.92%	5.07%	(1.29)	2.65
MPPM (ρ=3)	0.89%	5.03%	(1.25)	2.99
MPPM (ρ=4)	0.80%	5.04%	(1.13)	3.07

Source: Author's own illustration based on Eurekahedge (2009c)

Table E7: Portfolio Return Statistics (January 2005 - June 2009)
Pre Hypothetical Transaction Costs and Management Fees
Portfolios Reallocated Every 18 Months

	CMGR of Net Returns	Standard Deviation	Skewness	Kurtosis
HF Index	**0.55%**	**2.28%**	**(1.22)**	**3.51**
Lower Partial Momements (LPM)-Based RAPMs				
ERoPS	0.76%	3.05%	(1.18)	5.91
Omega	0.73%	2.34%	(0.33)	1.57
Sortino Ratio	0.73%	2.49%	(0.60)	1.73
Kappa 3	0.58%	2.50%	(0.71)	1.18
Upside Potential Ratio	0.56%	2.50%	(1.20)	2.74
Drawdown (DD)-Based RAPMs				
Calmar Ratio	0.53%	2.17%	(0.72)	2.79
Sterling Ratio	0.49%	2.29%	(0.75)	3.39
Burke Ratio	0.58%	2.53%	(0.90)	3.12
Value at Risk (VAR)-Based RAPMs				
Excess Return on VAR (α=1%)	0.62%	2.48%	(0.53)	2.83
Excess Return on VAR (α=5%)	0.62%	2.48%	(0.53)	2.83
Excess Return on VAR (α=10%)	0.63%	3.09%	(0.60)	3.05
Conditional Sharpe Ratio (α=1%)	0.62%	2.48%	(0.53)	2.83
Conditional Sharpe Ratio (α=5%)	0.62%	2.48%	(0.53)	2.83
Conditional Sharpe Ratio (α=10%)	0.62%	2.48%	(0.53)	2.83
Modified Sharpe Ratio (α=1%)	0.68%	3.44%	(0.67)	6.55
Modified Sharpe Ratio (α=5%)	0.74%	3.17%	(1.64)	10.04
Modified Sharpe Ratio (α=10%)	0.73%	3.36%	(1.60)	9.85
Other RAPMs				
Sharpe Ratio	0.81%	2.27%	(0.71)	5.36
D-Ratio	0.73%	2.08%	(0.53)	4.52
Hurst Ratio	0.49%	2.22%	(0.25)	0.43
MPPM (ρ=2)	0.80%	6.35%	(0.71)	2.89
MPPM (ρ=3)	0.78%	6.27%	(0.72)	3.14
MPPM (ρ=4)	0.58%	6.25%	(0.34)	3.49

Source: Author's own illustration based on Eurekahedge (2009c)

Table E8: Portfolio Return Statistics (January 2005 - June 2009)
Pre Hypothetical Transaction Costs and Management Fees
Portfolios Reallocated Every 24 Months

	CMGR of Net Returns	Standard Deviation	Skewness	Kurtosis
HF Index	**0.58%**	**2.20%**	**(1.30)**	**3.79**
Lower Partial Momements (LPM)-Based RAPMs				
ERoPS	0.42%	2.82%	(1.70)	4.16
Omega	0.88%	0.92%	0.13	1.73
Sortino Ratio	0.77%	1.41%	(1.13)	2.34
Kappa 3	0.51%	1.84%	(1.16)	2.60
Upside Potential Ratio	0.91%	1.13%	0.40	0.89
Drawdown (DD)-Based RAPMs				
Calmar Ratio	0.71%	1.18%	(0.74)	2.06
Sterling Ratio	0.80%	0.97%	(0.19)	1.81
Burke Ratio	0.70%	1.23%	(0.59)	1.54
Value at Risk (VAR)-Based RAPMs				
Excess Return on VAR (α=1%)	0.81%	0.68%	(0.11)	0.36
Excess Return on VAR (α=5%)	0.84%	0.86%	0.06	1.32
Excess Return on VAR (α=10%)	0.84%	0.86%	0.06	1.32
Conditional Sharpe Ratio (α=1%)	0.81%	0.68%	(0.11)	0.36
Conditional Sharpe Ratio (α=5%)	0.81%	0.68%	(0.11)	0.36
Conditional Sharpe Ratio (α=10%)	0.81%	0.68%	(0.11)	0.36
Modified Sharpe Ratio (α=1%)	0.51%	1.74%	(1.42)	3.93
Modified Sharpe Ratio (α=5%)	0.82%	0.74%	(0.19)	(0.26)
Modified Sharpe Ratio (α=10%)	0.81%	0.68%	(0.13)	0.39
Other RAPMs				
Sharpe Ratio	0.81%	0.68%	(0.11)	0.36
D-Ratio	0.78%	0.82%	(1.17)	2.32
Hurst Ratio	0.81%	4.26%	1.35	4.58
MPPM (ρ=2)	0.32%	4.61%	(1.78)	6.06
MPPM (ρ=3)	0.48%	4.78%	(1.45)	5.86
MPPM (ρ=4)	0.55%	4.86%	(1.34)	5.62

Source: Author's own illustration based on Eurekahedge (2009c)

Table E9: Portfolio Return Statistics (January 2005 - June 2009)
Post Hypothetical Transaction Costs and Management Fees
Portfolios Reallocated Every 6 Months

	CMGR of Net Returns	Standard Deviation	Skewness	Kurtosis
FoF Index	**0.21%**	**1.98%**	**(1.35)**	**2.39**
HF Index (Post Costs & Fees)	**(0.53%)**	**2.31%**	**(1.01)**	**2.49**
Lower Partial Momements (LPM)-Based RAPMs				
ERoPS	(0.02%)	3.86%	(0.64)	2.01
Omega	(0.25%)	1.83%	(1.89)	4.39
Sortino Ratio	(0.21%)	1.84%	(1.63)	3.36
Kappa 3	(0.27%)	1.89%	(1.26)	2.08
Upside Potential Ratio	(0.26%)	1.81%	(1.67)	3.48
Drawdown (DD)-Based RAPMs				
Calmar Ratio	(0.35%)	1.71%	(1.62)	3.21
Sterling Ratio	(0.32%)	1.77%	(1.71)	3.96
Burke Ratio	(0.32%)	1.79%	(1.54)	3.13
Value at Risk (VAR)-Based RAPMs				
Excess Return on VAR (α=1%)	(0.36%)	2.20%	(1.77)	3.71
Excess Return on VAR (α=5%)	(0.35%)	2.21%	(1.75)	3.63
Excess Return on VAR (α=10%)	(0.36%)	2.22%	(1.71)	3.44
Conditional Sharpe Ratio (α=1%)	(0.34%)	2.17%	(1.76)	3.71
Conditional Sharpe Ratio (α=5%)	(0.36%)	2.20%	(1.77)	3.71
Conditional Sharpe Ratio (α=10%)	(0.35%)	2.21%	(1.75)	3.63
Modified Sharpe Ratio (α=1%)	(0.50%)	2.29%	(1.63)	3.50
Modified Sharpe Ratio (α=5%)	(0.28%)	1.91%	(1.75)	5.52
Modified Sharpe Ratio (α=10%)	(0.25%)	2.12%	(2.05)	5.87
Other RAPMs				
Sharpe Ratio	(0.38%)	1.92%	(1.54)	2.51
D-Ratio	(0.30%)	1.55%	(1.49)	4.53
Hurst Ratio	0.02%	2.95%	2.73	12.83
MPPM (ρ=2)	(0.03%)	4.66%	(0.66)	0.29
MPPM (ρ=3)	0.03%	4.63%	(0.67)	0.50
MPPM (ρ=4)	(0.08%)	4.73%	(0.47)	0.58

Source: Author's own illustration based on Eurekahedge (2009b, 2009c)

Table E10: Portfolio Return Statistics (January 2005 - June 2009)
Post Hypothetical Transaction Costs and Management Fees
Portfolios Reallocated Every 12 Months

	CMGR of Net Returns	Standard Deviation	Skewness	Kurtosis
FoF Index	**0.16%**	**1.94%**	**(1.46)**	**2.99**
HF Index (Post Costs & Fees)	**(0.11%)**	**2.30%**	**(1.13)**	**3.00**
Lower Partial Momements (LPM)-Based RAPMs				
ERoPS	0.13%	2.74%	(2.22)	8.10
Omega	(0.06%)	1.93%	(1.44)	2.11
Sortino Ratio	(0.10%)	2.10%	(1.62)	2.45
Kappa 3	(0.23%)	2.27%	(1.20)	1.24
Upside Potential Ratio	(0.15%)	2.36%	(1.61)	2.72
Drawdown (DD)-Based RAPMs				
Calmar Ratio	(0.17%)	1.87%	(1.57)	3.10
Sterling Ratio	(0.21%)	1.97%	(1.84)	4.06
Burke Ratio	(0.23%)	2.21%	(1.86)	4.06
Value at Risk (VAR)-Based RAPMs				
Excess Return on VAR (α=1%)	(0.16%)	2.12%	(1.68)	2.63
Excess Return on VAR (α=5%)	(0.16%)	2.12%	(1.68)	2.63
Excess Return on VAR (α=10%)	(0.27%)	2.56%	(1.92)	3.96
Conditional Sharpe Ratio (α=1%)	(0.16%)	2.12%	(1.68)	2.63
Conditional Sharpe Ratio (α=5%)	(0.16%)	2.12%	(1.68)	2.63
Conditional Sharpe Ratio (α=10%)	(0.16%)	2.12%	(1.68)	2.63
Modified Sharpe Ratio (α=1%)	(0.18%)	2.70%	(2.98)	12.76
Modified Sharpe Ratio (α=5%)	(0.16%)	2.60%	(3.78)	19.33
Modified Sharpe Ratio (α=10%)	(0.20%)	2.81%	(3.51)	16.60
Other RAPMs				
Sharpe Ratio	0.02%	1.81%	(2.59)	9.67
D-Ratio	(0.00%)	1.60%	(2.42)	10.00
Hurst Ratio	0.30%	3.25%	2.31	10.06
MPPM (ρ=2)	0.32%	5.04%	(1.29)	2.65
MPPM (ρ=3)	0.29%	5.01%	(1.25)	2.99
MPPM (ρ=4)	0.20%	5.02%	(1.13)	3.07

Source: Author's own illustration based on Eurekahedge (2009b, 2009c)

**Table E11: Portfolio Return Statistics (January 2005 - June 2009)
Post Hypothetical Transaction Costs and Management Fees
Portfolios Reallocated Every 18 Months**

	CMGR of Net Returns	Standard Deviation	Skewness	Kurtosis
FoF Index	**0.19%**	**1.88%**	**(1.68)**	**3.79**
HF Index (Post Costs & Fees)	**0.09%**	**2.28%**	**(1.22)**	**3.51**
Lower Partial Momements (LPM)-Based RAPMs				
ERoPS	0.30%	3.04%	(1.18)	5.91
Omega	0.27%	2.33%	(0.33)	1.57
Sortino Ratio	0.27%	2.48%	(0.60)	1.73
Kappa 3	0.12%	2.49%	(0.71)	1.18
Upside Potential Ratio	0.11%	2.49%	(1.20)	2.74
Drawdown (DD)-Based RAPMs				
Calmar Ratio	0.07%	2.16%	(0.72)	2.79
Sterling Ratio	0.03%	2.29%	(0.75)	3.39
Burke Ratio	0.12%	2.52%	(0.90)	3.12
Value at Risk (VAR)-Based RAPMs				
Excess Return on VAR (α=1%)	0.16%	2.47%	(0.53)	2.83
Excess Return on VAR (α=5%)	0.16%	2.47%	(0.53)	2.83
Excess Return on VAR (α=10%)	0.17%	3.08%	(0.60)	3.05
Conditional Sharpe Ratio (α=1%)	0.16%	2.47%	(0.53)	2.83
Conditional Sharpe Ratio (α=5%)	0.16%	2.47%	(0.53)	2.83
Conditional Sharpe Ratio (α=10%)	0.16%	2.47%	(0.53)	2.83
Modified Sharpe Ratio (α=1%)	0.22%	3.42%	(0.67)	6.55
Modified Sharpe Ratio (α=5%)	0.28%	3.16%	(1.64)	10.04
Modified Sharpe Ratio (α=10%)	0.27%	3.34%	(1.60)	9.85
Other RAPMs				
Sharpe Ratio	0.35%	2.26%	(0.71)	5.36
D-Ratio	0.27%	2.07%	(0.53)	4.52
Hurst Ratio	0.03%	2.21%	(0.25)	0.43
MPPM (ρ=2)	0.34%	6.32%	(0.71)	2.89
MPPM (ρ=3)	0.32%	6.25%	(0.72)	3.14
MPPM (ρ=4)	0.12%	6.23%	(0.34)	3.49

Source: Author's own illustration based on Eurekahedge (2009b, 2009c)

Table E12: Portfolio Return Statistics (January 2005 - June 2009)
Post Hypothetical Transaction Costs and Management Fees
Portfolios Reallocated Every 24 Months

	CMGR of Net Returns	Standard Deviation	Skewness	Kurtosis
FoF Index	**0.20%**	**1.86%**	**(1.72)**	**3.94**
HF Index (Post Costs & Fees)	**0.19%**	**2.20%**	**(1.30)**	**3.79**
Lower Partial Momements (LPM)-Based RAPMs				
ERoPS	0.03%	2.81%	(1.70)	4.16
Omega	0.49%	0.92%	0.13	1.73
Sortino Ratio	0.38%	1.41%	(1.13)	2.34
Kappa 3	0.12%	1.83%	(1.16)	2.60
Upside Potential Ratio	0.52%	1.13%	0.40	0.89
Drawdown (DD)-Based RAPMs				
Calmar Ratio	0.33%	1.17%	(0.74)	2.06
Sterling Ratio	0.41%	0.97%	(0.19)	1.81
Burke Ratio	0.31%	1.22%	(0.59)	1.54
Value at Risk (VAR)-Based RAPMs				
Excess Return on VAR (α=1%)	0.42%	0.68%	(0.11)	0.36
Excess Return on VAR (α=5%)	0.45%	0.86%	0.06	1.32
Excess Return on VAR (α=10%)	0.45%	0.86%	0.06	1.32
Conditional Sharpe Ratio (α=1%)	0.42%	0.68%	(0.11)	0.36
Conditional Sharpe Ratio (α=5%)	0.42%	0.68%	(0.11)	0.36
Conditional Sharpe Ratio (α=10%)	0.42%	0.68%	(0.11)	0.36
Modified Sharpe Ratio (α=1%)	0.13%	1.73%	(1.42)	3.93
Modified Sharpe Ratio (α=5%)	0.44%	0.74%	(0.19)	(0.26)
Modified Sharpe Ratio (α=10%)	0.42%	0.68%	(0.13)	0.39
Other RAPMs				
Sharpe Ratio	0.42%	0.68%	(0.11)	0.36
D-Ratio	0.39%	0.81%	(1.17)	2.32
Hurst Ratio	0.42%	4.24%	1.35	4.58
MPPM (ρ=2)	(0.07%)	4.60%	(1.78)	6.06
MPPM (ρ=3)	0.09%	4.77%	(1.45)	5.86
MPPM (ρ=4)	0.16%	4.85%	(1.34)	5.62

Source: Author's own illustration based on Eurekahedge (2009b, 2009c)

Appendix F: Systematic Overview of Selected Research

Table F1: Systematic Analysis and Summary of Selected Research Papers ─ Data Biases[181]

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Ackermann, McEnally, & Ravenscraft *Journal of Finance* (1999)	The Performance of Hedge Funds: Risk, Return and Incentives	MAR, HFR	908	1988-1995	▪ In this paper, the authors benchmark the performance of HF performance against that of mutual funds and market indices. Furthermore, they discuss several data biases.	▪ HFs are more volatile than mutual funds and standard market indices. Still, they appear to generate higher risk-adjusted returns. However, HFs are not able to consistently outperform the standard market indices on the basis of raw or risk-adjusted returns. ▪ HFs are frequently characterized by low Beta values and can be an interesting source of diversification for investors. ▪ The termination and the self-selection biases are powerful, whereas the liquidation, backfilling, and multi-year sampling biases are rather small. Positive and negative survival- related biases seem to offset one another.

[181] This table is comprised of abridged and edited versions of the relevant key literature. It is entirely based on and includes excerpts and quotations of the original research.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Amin & Kat *Journal of Financial & Quantitative Analysis* (2003)	Do the "Money Machines" Really Add Value?	MAR	77 HFs and 13 HF indices	1990-2000	▪ The authors evaluate the performance of HFs and FoFs on a standalone basis and in a portfolio context using a payoff distribution pricing model.	▪ HF returns are non-normal, skewed and non-linearly related to equity returns. Thus, traditional performance measures are not suitable for their evaluation. ▪ HF returns show a weak correlation with the returns of other investment classes. ▪ The majority of inefficiency costs of an investment in a single HF can be diversified away by investing in a HF portfolio. ▪ The average FoF does not compensate its investors for the fees paid.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Bollen & Pool *Journal of Finance* (2009)	Do Hedge Fund Managers Misreport Returns? Evidence from the Pooled Distribution	CISDM	4,286	1994-2005	▪ This paper discusses the question of whether HFs misreport their returns with private data vendors. To this end, the authors examine the histogram of HF returns in order to determine whether certain return categories are systematically underrepresented.	▪ There is a significant discontinuity in the pooled distribution HF returns: The number of small positive returns exceeds the number of small negative returns by far. ▪ HF managers seem to distort returns when they are not closely monitored, e.g. they intentionally avoid reporting losses. ▪ As a consequence, investors that rely on the reported information may underestimate the loss potential.

Author(s) *Journal* (Year)	Title	Database	Number of Funds	Investigation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
W. Fung & Hsieh *Journal of Financial & Quantitative Analysis* (2000)	Performance Characteristics of Hedge Funds and Commodity Funds: Natural vs. Spurious Biases	TASS	1,722	1994-1998	▪ This articles studies the data biases that are the most relevant for research with HFs.	▪ HFs are characterized by return profiles that are noticeably different from those of mutual funds. Thus, they represent a viable diversification opportunity for investors. ▪ As any quantitative information on HF returns has to be sourced from private data vendors, HF data are necessarily subject to a number of biases, specifically the survivorship, instant history, selection, and multi-period sampling bias. These biases may lead to an overestimation of HF returns and an underestimation of HF risks.

Author(s) *Journal* (Year)	**Title**	**Data-base**	**Num-ber of Funds**	**Investi-gation Period**	**Relevant Research Objective**	**Relevant Key Findings and Conclusions**
Grecu, Malkiel, & Saha *Journal of Portfolio Manage-ment* (2007)	Why Do Hedge Funds Stop Reporting Perfor-mance?	TASS	1,392	1994-2003	▪ This study explores the question of whether HFs stop reporting their returns due to particularly high or due to particularly low performance. To this end, the authors examine the funds' time to liquidation with the help of survival time analysis techniques.	▪ HF liquidation rates are extremely high. ▪ HFs cease to report their returns not because they are successful but because they are unsuccessful. ▪ HF returns deteriorate considerably at the end of their reporting lives. Better performing and larger HFs have lower liquidation probabilities than their peers. ▪ The likelihood of liquidation peaks at a HF age of around five and a half years; HFs that are bound to fail will likely to do so in their formative period.
Ibbotson, Chen, & Zhu *Financial Analysts Journal* (2011)	The A,B,Cs of Hedge Funds: Alphas, Betas, and Costs	TASS	8,421	1995-2009	▪ The authors examine the survivorship bias and the backfill bias in the reported returns of HFs. Furthermore they analyse HF performance by decomposing HF returns into three components: systematic market exposure (Beta), excess return (Alpha), and fees.	▪ The survivorship and the backfill biases can pose serious problems when working with HF data. After the removal of both biases, the larger HFs outperform their smaller peers, however, they are also characterized by higher risks. ▪ HFs produce a positive Alpha throughout the observation period, in other words, the average HF manager is successful in bear as well as in bull markets.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Kouwen-berg *Journal of Asset Manage-ment* (2003)	Do Hedge Funds Add Value to a Passive Portfolio? Correcting for Non-normal Returns and Disap-pearing Funds	Zurich (MAR)	2,614	1995-2000	▪ This paper investigates HF performance from a passive investor's point of view.	▪ On average, HFs generate positive Alphas, even after correcting for the non-normality of HF return distributions. ▪ HFs that pursue event-driven, market neutral, and emerging markets strategies tend to be characterised by distinct non-normally distributed returns. ▪ There is clear evidence of performance persistence. However, the chance of selecting a surviving winning HF is reduced considerably by the large number of disappearing funds. These funds usually leave the database after poor performance. Investors can partly avoid investing in the disappearing funds by requiring a good track record.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Liang *Journal of Financial and Quantitative Analysis* (2000)	Hedge Funds: The Living and the Dead	TASS, HFR	2,789	1993-1998	▪ This study analyzes the survivorship bias in HF returns. In this context, the author compares HFs' filings with two different HF databases.	▪ The survivorship bias is different across investment strategies; it may exceed 2% per year. ▪ The main reason for the disappearance of HFs is low performance. ▪ The filings of HFs that report to both different databases (TASS and HFR) are significantly different with respect to fund returns, AuM, inception dates, fees, and investment styles.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Malkiel *Financial Analysts Journal* (1995)	Hedge Funds: Risk and Return	TASS	800+	1994-2003	▪ This paper discusses several biases in the HF space, namely, the self-reporting, backfill, and survivorship biases.	▪ Reporting returns on a voluntary basis and backfilling of past results can lead to an upward bias. ▪ Moreover, the substantial attrition of HFs can leads to a substantial survivorship bias if indices are only composed of alive funds. ▪ HFs exhibit low correlations with equity indices and are excellent means of portfolio diversification. However, direct investors in HFs run the substantial risk of selecting a poorly performing or failing fund.

Source: Author's own illustration

Table F2: Systematic Analysis and Summary of Selected Research Papers ─ Hedge Fund Characteristics[182]

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Amenc & Martellini *Working Paper EDHEC* (2003)	The Alpha and the Omega of Hedge Fund Performance Measure-ment	CISDM	581	1996-2001	▪ This paper investigates HF managers' ability to generate abnormal returns. Thereby, the paper compares several models of performance measurement.	▪ Different models strongly disagree whether HFs deliver absolute risk-adjusted performance. Still, these different models largely agree on HFs relative performance in the sense that they tend to rank order HFs in the same way. ▪ Large HFs have excess returns exceeding those of smaller HFs.

[182] This table is comprised of abridged and edited versions of the relevant key literature. It is entirely based on and includes excerpts and quotations of the original research.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Ammann & Moerth *Journal of Asset Manage-ment* (2005)	Impact of Fund Size on Hedge Fund Performance	TASS	4,014	1994-2005	▪ This study examines whether the increased capital in-flows in the HF industry diminish returns and whether larger HFs underperform smaller ones. ▪ The impact of HF size on performance is analysed with respect to returns, standard deviations, Sharpe Ratios, and Alphas.	▪ There is a negative relationship between HF size and return implying that smaller HFs outperform larger ones. However, there is also a negative relationship between and HF size and standard deviation implying that smaller HFs have a higher return volatility than larger ones. ▪ Very small HFs with AuM below US$1 million underperform on average. This may be due to their higher Total Expense Ratios.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Boyson *Journal of Empirical Finance* (2010)	Implicit Incentives and Reputational Herding by Hedge Fund Managers	TASS	2,345	1994-2004	▪ This paper investigates how incentives affect HF managers' actions. To this end HF managers' herding behaviour over their careers is analyzed.	▪ Experienced HF managers herd more than less-experienced ones. This is because experienced managers that deviate from the herd have a significantly higher probability of failure and do not achieve higher capital inflows than their less-experienced counterparts. ▪ More experienced HF managers tend to underperform less-experienced ones. This relative underperformance, however, is not directly related to herding and thus likely to be caused by other factors.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Brown, Goetzmann, & Park *Journal of Finance* (2001)	Careers and Survival: Competition and Risk in the Hedge Fund and CTA Industry	TASS	715	1989-1995	▪ This paper investigates HF risk in the light of managerial career concerns.	▪ HF managers typically have incentive contracts that asymmetrically compensate them based on annual performance. Still, there is little evidence that HFs increase risk to take advantage of incentive contract terms. Their risk-taking is rather driven by peer performance. ▪ HF survival depends on absolute and relative performance. The younger a HF, the more likely it is to be closed / terminated.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Getmansky *Working Paper MIT Sloan* (2004)	The Life Cycle of Hedge Funds: Fund Flows, Size and Performance	TASS	3,928	1977-2003	▪ This paper studies the impact of various drivers such as age, size, return, capital inflow, and positioning on the life cycle of HFs.	▪ HFs have a high probability of closure / liquidation. The annual attrition due to liquidation averages at 7.1% between 1994 and 2002. ▪ Performance, size, capital in-flows, and favourable positioning positively affect HF survival probability. Based on these factors, an optimal HF size can be calculated for the major HF strategies. If this optimal size is exceeded, HF return levels cannot be sustained. ▪ HFs that are active in illiquid markets are subject to high market impact, have limited investment opportunities, and are more likely to exhibit an optimal size behaviour compared to HFs that are active in more liquid markets.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Gregoriou & Rouah *Journal of Alternative Investments* (2003)	Large versus Small Hedge Funds: Does Size Affect Perfor-mance?	Zurich, LaPorte	276	1994-1999	▪ This study explores the relationship between HF size and HF performance.	▪ There is no evidence of a relationship between HF size and HF performance. As HFs grow in size, however, their ability to buy and sell large positions could diminish and thereby impede their strategies. Moreover, increasing HF size is likely to decrease the speed of HF operations which may decrease returns.
Hedges *Journal of Financial Transfor-mation* (2003)	Size vs. Performance in the Hedge Fund Industry	LJH Global Invest-ments	268	1995-2002	▪ This study investigates the impact of HF size on HF performance. To this end the performance of portfolios consisting of differently sized HFs is compared.	▪ Smaller HFs outperform medium-sized and larger ones. HFs pursuing global macro and convertible arbitrage strategies are an exception to this rule since they sustain their performance levels regardless of their size. ▪ Larger HFs may be hampered by the constraints of internal asset allocation guidelines impeding their performance.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Howell The Journal of Alternative Investments (2001)	*Fund Age and Perfor-mance*	Tremont, TASS	2,183	1994 - 2000	▪ This article investigates HF age as a driver of performance. To this end the performance of portfolios consisting of HFs of different ages is compared.	▪ There is a clear negative relationship between HF age and return implying that younger HFs are more profitable than older ones.[183] However, younger HFs have a higher closure / liquidation probability than older ones.
H. Fung, Xu, & Yau *Financial Analysts Journal* *(2002)*	Global Hedge Funds: Risk, Return, and Market Timing	Various indices	115	1994- 2000	▪ This study examines the performance of equity-based HFs with reference to their target geographical markets.	▪ Global HF managers do not demonstrate positive market-timing ability but superior security-selection ability. ▪ Incentive fees and leverage both have a significant positive impact on risk-adjusted HF return. Moreover leverage does not significantly affect the systematic risk of HFs. ▪ Incentive fees can lower the systematic risk of HFs in bull and bear markets. ▪ Large HFs have excess returns exceeding those of smaller HFs.

[183] Younger HFs are those with a track record of less than 3 years.

Author(s) *Journal* (Year)	**Title**	**Data-base**	**Num-ber of Funds**	**Investi-gation Period**	**Relevant Research Objective**	**Relevant Key Findings and Conclusions**
Kazemi & Schneeweis *Working Paper Isenberg School of Manage-ment* (2003)	Conditional Performance of Hedge Funds	HFR, CISDM, Altvest, Hedge-fund.net, TASS	13 indices	1990-2001	▪ This study measures HF performance using a stochastic discount factor approach.	▪ Historically, HFs have generated positive risk-adjusted excess returns. However, there is no evidence that HF returns are correlated with HF size. ▪ The results obtained by the application of a stochastic discount factor approach are not significantly different from those obtained with more traditional approaches.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Mozes & Orchard *Journal of Derivatives & Hedge Funds* (2012)	The Relation Between Hedge Fund Size and Risk	Hedge-fund.net	10,680	1995-2010	▪ This study investigates the risks and returns associated with HF size.	▪ Large HFs are riskier than their smaller peers since they are more likely to close or restrict investor liquidity. ▪ Small HFs tend to have are less costly to unwind and have more economical infrastructure and staffing expenses. Thus, they are able to cope more easily with revenue declines. ▪ Larger funds tend to generate less Alpha since managers who generate high Alphas are likely to receive large capital inflows that erode excess performance in the medium-term.

Source: Author's own illustration

Table F3: Systematic Analysis and Summary of Selected Research Papers ─ Risk-adjusted Performance Measures[184]

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Agarwal & Naik *Review of Financial Studies* (2004)	Risks and Portfolio Decisions Involving Hedge Funds	CSFB/ Tremont, HFR	12 indices	1990-2000	▪ This paper discusses the risk exposure of equity-oriented HF strategies with the means of buy-and-hold and option-based strategies.	▪ Equity-oriented HF strategy returns are frequently characterized by returns that resemble those of a put option on the equity index. Thus, they bear significant left-tail risks which is not considered by the mean-variance framework.
Bacmann & Scholz *AIMA Journal* (2003)	Alternative Performance Measures for Hedge Funds	CSFB/ Tremont, HFR, Stark	44[185] indices	1994-2003	▪ This study evaluates the usefulness of the Sharpe Ratio against other RAPMs in the HF space. To that end the authors compare different HF rankings established by the Sharpe and Sortino Ratios, Omega, and the Stutzer Index.	▪ Higher moments play an important role for the performance evaluation of HFs. The Sharpe Ratio does not take higher moments into account and is thus a poor choice for the evaluation of HFs. RAPMs such as Omega appear more apt for performance measurement in the HF space.

[184] This table is comprised of abridged and edited versions of the relevant key literature. It is entirely based on and includes excerpts and quotations of the original research.

[185] Thereof four traditional indices (MSCI World, Russell 2000, S&P500 and Salomon World Government Bond)

Author(s) *Journal* (Year)	Title	Database	Number of Funds	Investigation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Brooks & Kat *Journal of Alternative Investments* (2002)	The Statistical Properties of Hedge Fund Index Returns and Their Implications for Investors	HFR, Zurich, CSFB/ Tremont, Hennessee, Van, Altvest, Tuna	48 indices	1995-2001	▪ This paper discusses the statistical properties of several different HF indices.	▪ Many HF index returns do not follow a normal distribution but exhibit negative a skewness and positive excess kurtosis. This renders the Sharpe Ratio inadequate for the evaluation of HF performance. ▪ A large number of HF indices show significant positive first-order autocorrelation. This is particularly true for convertible arbitrage, distressed securities, and emerging markets indices. ▪ HF index returns frequently show a high correlation with the stock market; still, the correlation of most indices with the bond market is low. ▪ HF index returns appear to be correlated. This suggests that they are subject to shared risk factors.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Burke *Futures* (1994)	A Sharper Sharpe Ratio	n.a.	n.a.	n.a.	▪ This paper introduces a new RAPM to the HF space.	▪ The Sharpe Ratio penalizes desirable upside variability just as undesirable downside variability. This problem is eliminated by replacing the Sharpe Ratio‘s denominator with a drawdown term.
Dowd *Internat-ional Review of Economics and Finance* (2000)	An Improved Sharpe Ratio	n.a.	n.a.	n.a.	▪ The author proposes a new RAPM that represents a generalization of the Sharpe Ratio.	▪ The new RAPM, ERoVaR, is shown deliver results substantially different from and superior to the Sharpe Ratio. However, it is derived in a mean-variance setting and is not apt to cope with departures from normality.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Eling & Schuh-macher *Journal of Banking & Finance* (2007)	Does the Choice of Performance Measure Influence the Evaluation of Hedge Funds?	Ehedge	2,763	1985-2004	▪ This study compares the Sharpe Ratio with several alternative RAPMs for the evaluation of HFs.	▪ Although HF returns do not follow normal distributions, the comparison of the Sharpe Ratio with other RAPMs results in virtually identical rank ordering across the analyzed HFs. ▪ The choice of RAPM does not have a crucial influence on the relative evaluation of HFs. Since the Sharpe Ratio is the best known and understood RAPM, it might be considered superior to other RAPMs from a practitioner's point of view.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Gueyie & Gregoriou *Journal of Alternative Investments* (2003)	Risk-Adjusted Performance of Funds of Hedge Funds Using a Modified Sharpe Ratio	Zurich	90	1997-2001	▪ In this study the authors assess the performance of the Modified Sharpe Ratio against the traditional Sharpe Ratio in a FoF setting by comparing the rankings established by both of these RAPMs.	▪ The Sharpe Ratio is a poor choice for the evaluation of FoF returns it as tends to underestimate the tail risk that is inherent in most FoF investments. ▪ Investors should make use of the Modified Sharpe Ratio in order to correctly determine risk-adjusted returns. In contrast to the traditional VAR, the MVAR considers the first four moments of the return distribution making it the tool of choice under non-normality.
Ingersoll, Spiegel, Goetzmann, & Welch *Review of Financial Studies* (2007)	Portfolio Performance Manipu-lation and Manipu-lation-proof Performance Measures	n.a.	n.a.	n.a.	▪ This article investigates whether popular RAPMs can be gamed by HF managers. Furthermore, the authors introduce an innovative RAPM that is less likely be dodged.	▪ Popular RAPMs can theoretically be gamed. This observation holds even true in a high transactions costs environment. ▪ It is possible to create a manipulation-proof performance measure (MPPM) on the basis of a power utility function. The use of the MPPM is particularly compelling for HFs that make unconstraint use of derivatives.

Author(s) ***Journal*** **(Year)**	**Title**	**Data-base**	**Num-ber of Funds**	**Investi-gation Period**	**Relevant Research Objective**	**Relevant Key Findings and Conclusions**
Kaplan & Knowles *Morning-star Associates and York Hedge Fund Strategies* (2004)	Kappa: A Generalized Downside Risk-Adjusted Performance Measure	HFR	11 indices	1990-2003	▪ In this study the authors portray Kappa, a generalized RAPM that operates on the basis of drawdown.	▪ Omega and the Sortino Ratio are two special cases of the generalized RAPM Kappa. ▪ The estimation of Kappa is usually possible with the help of the first four moments of a return distribution. Therefore, Kappa can be used to measure risk-adjusted performance if detailed return data are not available.
Kestner *Futures* (1996)	Getting a Handle on True Performance	n.a.	n.a.	n.a.	▪ This study discusses the Sterling and the Calmar Ratios as alternatives to the Sharpe Ratio.	▪ The Sharpe Ratio appears inappropriate to reflect performance when the returns exhibit positive or negative autocorrelation. ▪ RAPMs based solely on maximum drawdown can over- or underestimate risk. Thus, secondary drawdowns should be considered.

Author(s) *Journal* (Year)	**Title**	**Data-base**	**Num-ber of Funds**	**Investi-gation Period**	**Relevant Research Objective**	**Relevant Key Findings and Conclusions**
Koh, Lee, & Fai *Singapore Economic Review* (2002)	Markets and Industry - An Evaluation of Hedge Funds: Risk, Return and Pitfalls	HFR, MAR, CSFB/ Tremont, Hennes-see, Van, Altvest, Tuna, AsiaHedge	18 indices	1995-2001	▪ The authors present the reader with an overview of HFs, their development, and their risk and return characteristics. Moreover, they discuss the pitfalls that investors face when sourcing HF data from private data vendors.	▪ Common statistics such as the mean and standard deviation must be used with extreme caution when dealing with HFs because HF returns are not normally-distributed. ▪ The Sortino, Hurst, and D-Ratios are more useful measures of risk and return for the analysis of HFs. ▪ Sources of HF risk include HF strategy purity and consistency, size, the usage of leverage, liquidity, and asset concentration.
Lo *Financial Analysts Journal* (2002)	The Statistics of Sharpe Ratios	Altvest	12 HFs and 10 mutual funds	various start dates -2000	▪ This study examines the statistical properties of the Sharpe Ratio when applied to HF return series.	▪ HFs have different return characteristics from mutual funds. HF returns do not follow the normal distribution and show serial correlation. Ignoring these circumstances can lead to an overstatement of the annual Sharpe Ratio by over 65%.

Author(s) *Journal* (Year)	**Title**	**Data-base**	**Num-ber of Funds**	**Investi-gation Period**	**Relevant Research Objective**	**Relevant Key Findings and Conclusions**
Nguyen-Thi-Thanh *Journal of Perfor-mance Measure-ment* (2009)	On the Consistency of Performance Measures for Hedge Funds	CISDM	149	2000-2005	▪ In this paper a comparative study of RAPMs in the HF space is conducted. To this end the author compares HF rankings under the different RAPMs.	▪ The choice of RAPM is crucial to the evaluation and the selection of HFs. ▪ Some RAPMs seem to lead to stable HF rankings. In other words, they display a certain predictive power of HFs' future performance.
Shadwick & Keating *Journal of Perfor-mance Measure-ment* (2002)	A Universal Performance Measure	HFR, MAR	18 HF indices	1993-2001	▪ The authors propose a new RAPM named Omega as a tool to analyze return distributions.	▪ In contrast to the Sharpe Ratio, Omega captures the third and fourth moments of return distributions making it an ideal tool for the analysis of HF returns. ▪ The application of Omega to a set of HF index returns results in a ranking that is considerably different from those established by the Sharpe Ratio or the tracking error.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Sharma *Journal of Investment Manage-ment* (2004)	AIRAP - Alternative RAPMs for Alternative Investments	HFR	787	1997-2001	▪ The author discusses Omega, a RAPM that captures the third and forth moment information of a return distribution.	▪ Omega captures more information from the return distribution than other traditional performance measures. It establishes HF rankings that are noticeably different from those established under the Sharpe Ratio.
Sortino & van der Meer *Journal of Portfolio Manage-ment* (1991)	Downside Risk	n.a.	n.a.	n.a.	▪ The authors analyze the problem of measuring risk and discuss three downside-based RAPMs.	▪ In many investment settings downside variance represents a superior measure of risk. This is particularly true in situations which require a certain minimum return to be achieved such as benefit plans.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Young *Futures* (1991)	Calmar Ratio: A Smoother Tool	n.a.	n.a.	n.a.	▪ This study introduces a new RAPM, the Calmar Ratio.	▪ The HF rankings established by the Sharpe, Sterling, and Calmar Ratios differ materially. The Calmar Ratio shows a truer picture of investment performance than the other RAPMs and thus represents a valuable tool for investors.

Source: Author's own illustration

Table F4: Systematic Analysis and Summary of Selected Research Papers ─ Fund Allocation[186]

Author(s) ***Journal*** **(Year)**	**Title**	**Data-base**	**Num-ber of Funds**	**Investi-gation Period**	**Relevant Research Objective**	**Relevant Key Findings and Conclusions**
Alexander & Dimitriu *Journal of Alternative Investments* (2005)	Rank Alpha Funds of Hedge Funds	HFR	282	1990-2003	▪ This paper develops an investment approach designed for FoFs. Promising HFs are selected according to their Alpha values. In a second step, the portfolio weights are determined based on a constrained minimum variance optimizer.	▪ FoFs composed of HFs, that are selected based on their Alphas and allocated using constrained minimum variance optimization, are shown to perform much better than equally-weighted portfolios of all funds or minimum variance portfolios of randomly selected funds.

[186] This table is comprised of abridged and edited versions of the relevant key literature. It is entirely based on and includes excerpts and quotations of the original research.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Bergh & van Rensburg *Journal of Derivatives & Hedge Funds* (2008)	Hedge Funds and Higher Moment Portfolio Selection	CSFB/ Tremont	14 (indi-ces)	1994-2004	▪ This study empirically compares the results of the Markowitz mean–variance optimisation approach with a higher moment methodology. This comparison is conducted both when constructing FoF portfolios and when adding HFs to a portfolio of traditional assets.	▪ Most HF strategies have non-normal return distributions and have a substantially higher probability of extreme losses than suggested by the normal distribution. ▪ Portfolio optimization approaches that take higher moments of HF index returns into account prove superior to Markowitz' mean–variance approach. ▪ When constructing multi-asset class portfolios that include HFs, mean–variance optimisation significantly over-allocates to HFs in comparison to portfolio optimization approaches that take skewness and kurtosis into account.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Davies, Kat, & Lu *Journal of Derivatives & Hedge Funds* (2009)	Fund of Hedge Funds Portfolio Selection: A Multiple-objective Approach	Tremont, TASS	2,183	1994-2001	▪ This paper explores a new optimization approach. It incorporates investor preferences for return distributions' higher moments into a Polynomial Goal Programming (PGP) optimisation model.	▪ Introducing investor preferences for skewness and kurtosis in the portfolio construction process may yield portfolios that are very different from the mean-variance optimal portfolio. ▪ Irrespective of investor preferences, the PGP optimal portfolios contain hardly any allocation to long/short equity, distressed securities, and emerging markets HFs. Equity market neutral and global macro HFs on the other hand tend to receive very high allocations. ▪ In PGP optimal portfolios of traditional assets and HFs, HFs and stocks do not combine very well. This suggests that investors may be better off using HFs to replace stocks instead of bonds.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
De Souza & Gokcan *The Journal of Alternative Investments* (2004)	Allocation Methodologies and Customizing Hedge Fund Multi-Manager Multi-Strategy Products	HFR	8 (indices)	1990-2002	▪ This paper develops a HF strategy investment approach which is based on conditional value at risk (CVaR). The constructed portfolios are compared to reference portfolios that are established by a mean-variance optimization.	▪ Mean-variance optimization underspecifies the risk of HF strategies and is therefore inferior to CVaR-based optimization. ▪ The return distributions of most HF strategy indices display significant negative skewness, as well as serial correlation and unstable correlation structures. Although these HF strategy indices are highly attractive when only mean and standard deviation are considered, this is much less the case when the statistical effects of serial correlation are considered.

Author(s) *Journal* (Year)	Title	Database	Number of Funds	Investigation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Fang, Phoon, & Xiang *Journal of Wealth Management* (2008)	A Heuristic Approach to Asian Hedge Fund Allocation	Eureka-hedge (Asian funds)	70	2000-2004	▪ This study develops a heuristic approach to HF investment. This approach is based on semivariance as a measure for downside risk.	▪ Unlike traditional investment vehicles, HFs seem to produce return distributions with significant non-normal skewness and kurtosis. Therefore, mean-variance optimization is not appropriate in the HF space. ▪ Utilizing a portfolio optimizer in the HF space causes a 'butterfly effect': Small changes in inputs, especially mean returns, can cause large changes in the optimal asset weights. This phenomenon, coupled with the illiquidity of HFs, renders optimizers in the HF space useless. ▪ The developed heuristic approach is able to construct portfolios with higher returns, lower risk, and more diversification compared to portfolios constructed on the basis of mean-variance and mean-semivariance optimizers.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Glaffig *Funds of Hedge Funds – Perfor-mance, Assessment, Diversifica-tion, and Statistical Properties* (2006)	Investor's Choice: An Investor-Driven, Forward-looking Optimi-zation Approach to Fund of Hedge Fund Construc-tion	CSFB/ Tremont	11 (indi-ces)	1994-2004	▪ This article proposes a new approach to HF investment that is based on an optimizer which takes investor preferences into account.	▪ The developed approach allows investors to express preferences about markets and trading strategies to be included in the optimization instead of having them imposed ex ante. As a result, investor preferences are directly translated into portfolio weights in the optimization.

Author(s) ***Journal*** **(Year)**	**Title**	**Data-base**	**Num-ber of Funds**	**Investi-gation Period**	**Relevant Research Objective**	**Relevant Key Findings and Conclusions**
Gregoriou, Hübner, Papageor-giou, & Rouah *Journal of Derivatives & Hedge Funds* (2007)	Funds of Funds versus Simple Portfolios of Hedge Funds: A Compara-tive Study of Persis-tence in Performance	HFR	2,300	1995-2003	▪ This study investigates a new HF investment approach. Equal-weights HF portfolios are constructed by selecting the HFs with the highest Alphas, Information Ratios, and / or Sharpe Ratios. The performance of the constructed portfolios is compared to that of real-life FoFs.	▪ There is sufficient persistence in returns, especially for non-directional strategies to create simple portfolios of HFs. These portfolios greatly outperform the best FoFs on the basis of Alpha, the Sharpe Ratio, and the Information Ratio. This difference is mainly due to the second layer of fees imposed by FoFs on their investors. ▪ The extra layer of fees paid to FoF managers is largely unmerited. As it is possible to create portfolios of HFs, using simple portfolio construction rules and readily available market information, institutional investors can construct their own FoFs rather than buying in pre-packaged FoFs. That way they can avoid a second layer of management and performance fees, which dig into performance.

Author(s) ***Journal*** **(Year)**	**Title**	**Data-base**	**Num-ber of Funds**	**Investi-gation Period**	**Relevant Research Objective**	**Relevant Key Findings and Conclusions**
Gregoriou & Rouah *Derivatives Use, Trading & Regulation* (2001)	Last Year's Winning HF as this Year's Selection: A Simple Trading Strategy	Zurich, LaPorte	n/a	1988-1999	▪ This study examines a simple trading strategy. This trading strategy involves investing the HF with the highest returns in the previous year. The procedure is carried out yearly throughout the observation period.	▪ It is not possible to outperform the market by simply investing in the HF with the highest raw returns in the previous year. ▪ HFs deliver more volatile returns than stock market indices; still, certain HF strategies are less volatile than mutual funds and stock market indices.
Hakamada, Takahashi, & Yamamoto *Journal of Alternative Investments* (2007)	Selection and Performance Analysis of Asia-Pacific Hedge Funds	Eureka-hedge (Asian funds)	108	2002-2005	▪ This study investigates the returns of HFs whose locations or investment targets are within the Asia-Pacific region. Moreover, different portfolio optimizers are tested against this HF sample.	▪ HFs whose locations or investment targets are within the Asia-Pacific region have significant tail risks. ▪ Conditional value-at-risk (CVaR) and conditional drawdown (CDD) optimizers are powerful tools in forming a portfolio of Asian HFs when sufficient in-sample data is available.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Henker *Journal of Alternative Investments* (1998)	Naive Diversification for Hedge Funds	LaPorte	47	1992-1997	▪ In this study the author discusses portfolio diversification in a HF context with the help of a Monte Carlo simulation.	▪ HF portfolios consist of several HFs with different return characteristics. While diversification increases with the number of HFS in the portfolio, this relationship is nor linear. In fact 5-10 HFs is a sufficient amount to be able to seize most diversification benefits.
Jöhri & Leippold *Funds of Hedge Funds – Perfor-mance, Assessment, Diversifica-tion, and Statistical Properties* (2006)	Quantitative Hedge Fund Selection for Funds of Funds	TASS	3,130	1994-2005	▪ This study proposes a strictly quantitative approach to HF investing. ▪ Several RAPMs are calculated based on historical return data and capital is invested in the top ranked HFs.	▪ Basing fund allocation on RAPMs, instead of purely return based measures, leads to more favourable results in terms of portfolio statistics and decreases portfolio turnover. ▪ Some RAPMs are appropriate to construct portfolios of HFs with low volatility, others can be used to construct portfolios with high returns. From the RAPMs tested, the Information Ratio and Average Drawdown provide the most favourable results. However, portfolios based on these RAPMs have difficulties coping with bear markets.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Kaiser, Schweizer, & Wu *Working Paper Frankfurt School of Finance & Manage-ment* (2008)	Strategic Hedge Fund Portfolio Construc-tion that Incorporates Higher Moments	HFI, Absolute Return, Eureka-hedge	9 (indi-ces)	1996-2006	▪ This paper develops an innovative portfolio optimization approach. The empirical return distributions of different HF strategies are replaced with two normal distributions to approximate a best-fit distribution.[187] The estimated return distributions are used for portfolio optimization.	▪ Markowitz's mean-variance approach fails to include further risk factors like skewness and kurtosis. This can lead to non-optimal portfolio weight suggestions. ▪ The new approach is superior to classic mean-variance optimization since it incorporates the heterogeneity of different HF strategies and investor preferences.

[187] This procedure is known as the 'mixture of normal method'.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
L'habitant & Learned *The Journal of Financial Transfor-mation* (2004)	Finding the Sweet Spot of Hedge Fund Diversifi-cation	MAR, HFR, TASS, Altvest, and others[188]	6,985	1990-2002	▪ In this study the authors strive to find the optimal number of HFs in a FoF portfolio.	▪ 10 HFs in a FoF portfolio are sufficient to capture most diversification benefits. Too much diversification is likely to negatively influence overall portfolio performance. ▪ The deliberate inclusion HFs following different strategies into the portfolio proves more effective than randomly choosing regardless of their investment strategies.

[188] 'Others' includes data received from 'Evaluation Associates Capital Management' and data directly from HF administrators.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective	Relevant Key Findings and Conclusions
Lamm *Journal of Alternative Investments* (2003)	Asymmetric Returns and Optimal Hedge Fund Portfolios	HFR, CSFB/ Tremont	10 (indi-ces)	1990-2002	▪ This paper compares various optimization techniques applied to HF portfolio construction. Thereby, a specific focus is set on HF strategy allocation. ▪ The author constructs portfolios of HF strategy indices with optimizers that operate on the basis of mean variance, mean semivariance, mean downside risk, mean absolute deviation, and the Cornish-Fisher expansion.	▪ The choice of optimization technique has an effect on HF portfolio construction. The most efficient portfolios are constructed under an approach based on the Cornish-Fisher expansion. Other optimization techniques based on mean semivariance and mean downside risk also generate decent portfolio allocations. ▪ Significant allocations to market neutral equity, convertible arbitrage, and merger arbitrage strategies are appropriate for the construction of low-risk HF portfolios.
Nawrocki Journal of Financial Planning (2000)	Portfolio Optimiza-tion, Heuristics and the ‘Butterfly Effect’.	Morning-star Principia Plus	35 mutual funds	1994-1998	▪ This paper investigates the ‘Butterfly Effect’, a concept in chaos theory, in a portfolio context.	▪ The usage of historic data with an optimizer cannot be considered an effective forecasting technique and thus not an effective portfolio management approach. ▪ In a fund allocation context, a small change to an input may result in a large change in asset allocations with a potentially negative effect on the portfolio returns.

Author(s) ***Journal*** **(Year)**	**Title**	**Data-base**	**Num-ber of Funds**	**Investi-gation Period**	**Relevant Research Objective**	**Relevant Key Findings and Conclusions**
Park & Staum *Journal of Alternative Investments* (1998)	How Much is Enough?	TASS	n.a.	1989-1996	▪ In this paper analyses portfolio diversification in an equities and a HF context.	▪ There are diminishing marginal risk benefits in adding HFs to a FoF portfolio. ▪ In general, 10 assets can be enough for an effective diversification.

Source: Author's own illustration

Table F5: Systematic Analysis and Summary of Selected Research Papers ─ Performance Persistence[189]

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective & Methodology	Relevant Key Findings and Conclusions
Agarwal, Daniel, & Naik *Journal of Finance* (2009)	Role of Managerial Incentives and Discretion in Hedge Fund Performance	CISDM, HFR, MSCI, TASS	7,535	1994-2002	▪ This study examines the role of managerial incentives and discretion in HF performance. ▪ Analyzed time horizon: 12 months. ▪ Performance measure applied: return. ▪ Statistical methodologies used: chi-square test, regression analysis.	▪ Unlike mutual funds, HFs charge performance-based incentive fees, require co-investment by manager, and often long term capital commitment. ▪ HFs with greater managerial incentives, proxied by the delta of the option-like incentive fee contracts, higher levels of managerial ownership, and the inclusion of high-water mark provisions in the incentive contracts, are associated with superior performance. ▪ Overall, the findings strongly suggest that several of the features of HF contracts are effective in motivating managerial effort and in alleviating agency problems.

[189] This table is comprised of abridged and edited versions of the relevant key literature. It is entirely based on and includes excerpts and quotations of the original research.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective & Methodology	Relevant Key Findings and Conclusions
Agarwal & Naik *Journal of Financial & Quantitative Analysis* (2000)	Multi-Period Performance Persistence Analysis of Hedge Funds	HFR	746	1982-1998	▪ This paper investigates the pre- and post-fee return persistence of HFs using a two-period and a multi-period framework. ▪ Analyzed time horizons: 3, 6, 12 months. ▪ Performance measures applied: Alpha, Appraisal Ratio. ▪ Statistical methodologies used: cross-product ratio test, chi-square test, regression analysis, Kolmogorov-Smirnov test.	▪ Maximum HF performance persistence is observed at a quarterly horizon. This indicates that HF performance persistence is of short term nature. As HFs employ long lock-up periods, it may be difficult for investors to take advantage of the observed short-term performance persistence. ▪ Both directional and non-directional HFs exhibit similar degrees of performance persistence. Overall, performance persistence does not seem to be related to the strategy that a HF follows.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective & Methodology	Relevant Key Findings and Conclusions
Agarwal & Naik *Journal of Alternative Investments* (2000)	On Taking the Alternative Route: Risks, Rewards, and Performance Persistence of Hedge Funds	HFR	167	1995-1998	▪ This paper provides an analysis of the risk-return characteristics, risk exposures, and performance persistence of various HF strategies. ▪ Analyzed time horizon: 3 months. ▪ Performance measures applied: Alpha, Appraisal Ratio. ▪ Statistical methodologies used: cross-product ratio test, regression analysis.	▪ In a mean variance setting, a combination of traditional assets with HFs can considerably improve overall portfolio performance. ▪ HFs show high abnormal returns. These are associated with high risk taking. Non-directional strategies in particular exhibit higher Sharpe Ratios and lower downside risk as compared to the directional strategies. ▪ There is reasonable performance persistence in the HF space. This seems to be attributable to losers continuing to be losers rather than winners continuing to be winners.

Author(s) *Journal* (Year)	**Title**	**Data-base**	**Num-ber of Funds**	**Investi-gation Period**	**Relevant Research Objective & Methodology**	**Relevant Key Findings and Conclusions**
Amenc, El Bied, & Martellini *Financial Analysts Journal* (2003)	Predictabi-lity in Hedge Fund Returns	CSFB/ Tremont	9 (indi-ces)	1994-2000	▪ This paper explores the predictability of HF returns by using multifactor models on nine HF indices. ▪ Analyzed time horizon: 1 month. ▪ Performance measure applied: return. ▪ Statistical methodology used: regression analysis.	▪ There is strong evidence that HF returns are predictable. Thus, there are potentially large benefits in terms of tactical capital allocation to different HF strategies. This is the case for FoFs as well as portfolios of traditional assets and HFs. These results do not seem to be significantly affected by the presence of transaction costs.
Baquero, Horst, & Verbeek *Journal of Financial & Quantitative Analysis* (2005)	Survival, Look-Ahead Bias, and Persistence in Hedge Fund Performance	TASS	1,797	1994-2000	▪ This paper analyzes the performance persistence of US HFs. To this end, the attrition of HFs is analyzed in the context of historical performance. ▪ Analyzed time horizons: 3, 12, 24 months. ▪ Performance measures applied: return, Alpha. ▪ Statistical methodology used: descriptive comparison of rankings.	▪ HF attrition is driven by historical returns with attrition rates being higher for funds that perform poorly. ▪ There is clear evidence of short term performance persistence in HF returns. This may be due to special HF features such as regulatory restrictions, lock-up periods, and management incentives.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective & Methodology	Relevant Key Findings and Conclusions
Barès, Gibson, & Gyger *Journal of Alternative Investments* (2003)	Performance in the Hedge Funds Industry: An Analysis of Short and Long-Term Persistence	HFR	314	1997-2002	▪ This paper investigates performance persistence of HFs. ▪ Analyzed time horizons: 1, 3, 6, 12, 36 months. ▪ Performance measures applied: return, Alpha. ▪ Statistical methodologies used: descriptive comparison of rankings, regression analysis.	▪ HFs show significant short term performance persistence. This effect vanishes rapidly for longer holding periods.
Boyson *Financial Analysts Journal* (2008)	Hedge Fund Performance Persistence: A New Approach	TASS	1,659	1994-2000	▪ This study investigates whether HF performance persistence varies with fund characteristics, such as size and age. ▪ Analyzed time horizon: 3 months. ▪ Performance measure applied: Alpha. ▪ Statistical methodology used: regression analysis.	▪ Performance persistence is strongest among small, young HFs. A portfolio of such funds with prior good performance outperforms a portfolio of large, mature HFs with prior poor performance by almost 10% per year. ▪ By selecting HFs on the basis of age and size in addition to past performance, investors can substantially improve the likelihood of superior performance compared to a selection process based on past performance alone.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective & Methodology	Relevant Key Findings and Conclusions
Brown & Goetzmann *Journal of Portfolio Manage-ment* (2003)	Hedge Funds with Style	TASS	1,295	1992-1998	▪ This paper studies HF strategies and their return persistence. ▪ Analyzed time horizon: 12 months. ▪ Performance measure applied: return. ▪ Statistical methodology used: regression analysis.	▪ The risk exposure of a particular HF depends very much on the strategy it follows. ▪ Self-reported strategy characterizations issued by HFs must be treated with considerable care. Since HFs are rather unregulated and since there are no generally accepted standards for HF strategy classification, there are vast opportunities for individual HFs to engage in strategic self-misclassification.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective & Methodology	Relevant Key Findings and Conclusions
Brown, Goetzmann, & Ibbotson *Journal of Business* (1999)	Offshore Hedge Funds: Survival and Performance	US Offshore Funds Directory	399	1989-1995	▪ This study examines the performance of the US off-shore HF industry between 1989 and 1995. ▪ Analyzed time horizon: 12 months. ▪ Performance measures applied: return, Alpha, Appraisal Ratio. ▪ Statistical methodology used: regression analysis.	▪ The US off-shore HF industry is characterized by high attrition rates and a low covariance with the US stock market. ▪ US off-shore HFs have, on average, a positive risk-adjusted performance: 10 out of 11 analyzed HF strategies provide positive risk-adjusted returns. ▪ There is little evidence of differential manager skill. While some star managers such as George Soros have a strong track record, they do not outperform their peers every year.
Capocci, Corhay, & Hübner *European Journal of Finance* (2005)	Hedge Fund Performance and Persistence in Bull and Bear Markets	CISDM, HFR, TASS	2,894	1994-2002	▪ This paper tests the performance persistence of HFs in bull and bear markets. ▪ Analyzed time horizon: 12 months. ▪ Performance measure applied: Alpha. ▪ Statistical methodology used: regression analysis.	▪ Most HFs outperform equities significantly during bull markets. In contrast, no significant underperformance is observed in bear markets. ▪ Market neutral strategies show an abnormal performance in both market states. ▪ Performance persistence among HFs is strongest for middle performers.

Author(s) ***Journal*** **(Year)**	**Title**	**Data-base**	**Num-ber of Funds**	**Investi-gation Period**	**Relevant Research Objective & Methodology**	**Relevant Key Findings and Conclusions**
Capocci & Hübner *Journal of Empirical Finance* (2004)	Analysis of Hedge Fund Performance	HFR, MAR	2,796	1988-1995	▪ This paper investigates HF performance persistence using a combination of various models. ▪ Analyzed time horizon: 12 months. ▪ Performance measure applied: Alpha. ▪ Statistical methodology used: regression analysis.	▪ The best and worst performing HFs do not show performance persistence, but there is limited evidence of performance persistence for HFs that have average returns. ▪ About one fourth of individual HFs delivers significant positive excess returns. Most of these HFs seem to prefer smaller stocks. ▪ The best performing HFs follow momentum strategies whereas worst performing ones tend to be momentum contrarians. ▪ Average return HFs prefer high book-to-market stocks, whereas best and worst performing funds rather prefer low book-to-market stocks. ▪ Bad performance is a major factor for HF closure / liquidation. Good performance, however, is not a protection against closure / liquidation.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective & Methodology	Relevant Key Findings and Conclusions
De Souza & Gokcan *Journal of Wealth Manage-ment* (2004)	Hedge Fund Investing: A Quantitative Approach to Hedge fund Manager Selection and De-Selection	HFR	314	1997-2002	▪ This study analyzes HF performance persistence and makes suggestions for managing a FoF portfolio. Furthermore, it suggests a portfolio construction approach called 'risk budgeting'. This is a fund allocation approach which allocates capital to HFs considering their risks but not their returns. ▪ Analyzed time horizons: 24, 36 months. ▪ Performance measures applied: return, standard deviation, Sharpe Ratio. ▪ Statistical methodologies used: cross-product ratio test, regression analysis.	▪ The selection of individual managers is the most important factor in HF investment. Therefore, strategy selection alone is not sufficient to construct a HF portfolio. ▪ HF portfolios based on the risk budgeting approach show better statistical characteristics as compared to equal-weights portfolios. ▪ Moribound HFs are characterized by lower AuM, and lower average returns than their surviving peers.

Author(s) *Journal* (Year)	**Title**	**Data-base**	**Num-ber of Funds**	**Investi-gation Period**	**Relevant Research Objective & Methodology**	**Relevant Key Findings and Conclusions**
Edwards & Caglayan *Journal of Futures Markets* (2001)	Hedge Fund Performance and Manager Skill	MAR	1,665	1990-1998	▪ This study investigates return persistence with the help of a factor model. ▪ Analyzed time horizons: 12, 24 months. ▪ Performance measure applied: Alpha. ▪ Statistical methodologies used: cross-product ratio test, regression analysis.	▪ There is performance persistence both among winning and losing HFs. The degree of performance persistence varies by investment strategy. ▪ Most HFs earn significant positive excess returns. These returns differ markedly by investment strategy. ▪ Incentive fees are positively related to performance: HFs that pay incentive fees of 20% or more show yearly excess returns that are 3-6 percentage points higher than those of HFs with lower incentive fees.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective & Methodology	Relevant Key Findings and Conclusions
Eling *Does Hedge Fund Perfor-mance Persist? Overview and New Empirical Evidence* (2009)	European Financial Manage-ment	CISDM	4,314	1996-2005	▪ This paper analyzes HF performance persistence and gives an overview of the relevant academic literature. ▪ Analyzed time horizons: 1, 2, 3, 6, 12, 24 months. ▪ Performance measures applied: return, Sharpe Ratio, Alpha, Appraisal Ratio. ▪ Statistical methodologies used: cross-product ratio test, chi-square test, rank information coefficient, Spearman rank correlation test, cross-sectional regression, and Kolmogorov-Smirnov test.	▪ Different levels of performance persistence can be observed depending on HF strategy. HFs that pursue convertible arbitrage and emerging market strategies are characterized by high levels of performance persistence. Equity long only funds, on the other hand, have low levels of performance persistence. ▪ There is short term performance persistence for horizons of up to six months. Still, it might be problematic for investors to exploit this short-term performance persistence due to lockup periods and transaction costs.

Author(s) *Journal* (Year)	**Title**	**Data-base**	**Num-ber of Funds**	**Investi-gation Period**	**Relevant Research Objective & Methodology**	**Relevant Key Findings and Conclusions**
Harri & Brorsen *Applied Financial Economics* (2004)	Performance Persistence and the Source of Returns for Hedge Funds	LaPorte	1,209	1977-1998	▪ This paper investigates HF performance persistence. ▪ Analyzed time horizons: 1, 2, 3,..., 24 months. ▪ Performance measures applied: return, Information Ratio, Sharpe Ratio, Alpha. ▪ Statistical methodologies used: Spearman rank correlation test, regression analysis.	▪ Some HF strategies exhibit higher performance persistence than others. Market neural HFs show the most return persistence. ▪ There is a strong negative relation between HF capitalization and returns. This is consistent with the hypothesis that HF managers exploit market inefficiencies.
Herzberg & Mozes *Journal of Alternative Investments* (2003)	The Persistence of Hedge Fund Risk: Evidence and Implications for Investors	Hedge-Fund.net, Altvest, Spring Mountain Capital	3,300	1995-2001	▪ This study investigates HF performance persistence and develops an investment approach based on RAPMs. ▪ Analyzed time horizon: 12 months. ▪ Performance measures applied: return, Sharpe Ratio, maximum drawdown, standard deviation, correlation. ▪ Statistical methodology used: rank information coefficient.	▪ HF risk is highly persistent. Less risky funds tend to outperform riskier ones on a risk-adjusted basis. It may be sensible for an investor to externally leverage an investment in less risky HFs than making an unlevered investment in riskier HFs. ▪ Portfolios constructed under the suggested approach generate significantly higher risk-adjusted returns than portfolios containing all HFs, portfolios of HFs selected solely on the basis of past returns, and portfolios constructed on the basis of past Sharpe Ratios.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective & Methodology	Relevant Key Findings and Conclusions
Jagan-nathan, Malakhov, & Novikov *Journal of Finance* (2010)	Do Hot Hands Exist among Hedge Fund Managers?	HFR	2,141	1996-2003	▪ In this paper a statistical model is developed for the evaluation HF performance. ▪ Analyzed time horizon: 36 months. ▪ Performance measure applied: Alpha. ▪ Statistical methodology used: regression analysis.	▪ There is significant performance persistence among winning HFs, but little evidence of performance persistence among losing HFs. This provides support to the interpretation of performance persistence as evidence of superior managerial talent. ▪ HF returns exhibit option-like features that must be taken into account when evaluating performance. Furthermore, since HFs invest in illiquid assets, care has to be taken in measuring their systematic risk.
Kat & Menexe *Journal of Alternative Investments* (2003)	Persistence in Hedge Fund Perfor-mance: The True Value of a Track Record	TASS	324	1994-2001	▪ This paper studies the persistence and predictability of HF returns. ▪ Analyzed time horizon: 36 months. ▪ Performance measures applied: return, standard deviation, skewness, kurtosis, correlation. ▪ Statistical methodologies used: cross-product ratio test, regression analysis.	▪ There is little evidence of persistence in HF mean returns, but strong persistence in HF standard deviations and correlations with the stock market. Therefore, the main value of a HF's track record lies in the insight that it provides into the HF's risk profile.

Author(s) *Journal* (Year)	**Title**	**Data-base**	**Num-ber of Funds**	**Investi-gation Period**	**Relevant Research Objective & Methodology**	**Relevant Key Findings and Conclusions**
Koh, Koh, & Teo *Working Papaer Singapore Manage-ment University* (2003)	Asian Hedge Funds: Return Persistence, Style, and Fund Characteris-tics	Eureka-hedge, Asia-Hedge	3,810 (Asian funds)	1999-2003	▪ This paper explores the return persistence of HFs that mainly invest in Asia. ▪ Analyzed time horizons: 1, 2, 3, 6, 12 months. ▪ Performance measures applied: return, Alpha. ▪ Statistical methodologies used: cross-product ratio test, chi-square test, Kolmogorov-Smirnov test.	▪ Asian HFs show the strongest performance persistence at monthly to quarterly horizons. Their performance persistence weakens considerably for longer periods. ▪ There is a positive relationship between holding firm size and HF returns. This is consistent with an 'economies of scale' explanation. ▪ On average HFs with longer lock-up periods generate higher returns due to their ability to extricate from their positions in a timely fashion in the face of redemptions. ▪ There is no evidence that HFs with higher management and performance fees generate higher returns.

Author(s) *Journal* (Year)	Title	Database	Number of Funds	Investigation Period	Relevant Research Objective & Methodology	Relevant Key Findings and Conclusions
Kosowski, Naik, & Teo *Journal of Financial Economics* (2007)	Do Hedge Funds Deliver Alpha? A Bayesian and Bootstrap Analysis	TASS, HFR, CISDM, MSCI	9,338	1990-2002	▪ This study examines performance persistence in the HF space. ▪ Analyzed time horizon: 12 months. ▪ Performance measure applied: Alpha. ▪ Statistical methodologies used: regression analysis, bootstrap approach, Bayesian approach.	▪ The performance of star HF managers cannot be explained by pure luck. ▪ The evidence of performance persistence is weaker for HFs with high capital inflows. On the other hand, performance persistence is stronger for HFs that pursue certain strategies such as ‘long / short equity’ and ‘relative value’.

Author(s) *Journal* (Year)	Title	Data-base	Num-ber of Funds	Investi-gation Period	Relevant Research Objective & Methodology	Relevant Key Findings and Conclusions
Kouwen-berg *Journal of Asset Manage-ment* (2003)	Do Hedge Funds Add Value to a Passive Portfolio? Correcting for Non-normal Returns and Disap-pearing Funds	Zurich (MAR)	2,614	1995-2000	▪ This paper investigates HF performance from a passive investor's point of view. ▪ Analyzed time horizon: 36 months. ▪ Performance measures applied: return, Alpha, Sharpe Ratio. ▪ Statistical methodology used: chi-square test.	▪ On average, HFs generate positive Alphas, even after correcting for the non-normality of HF return distributions. ▪ HFs that pursue event-driven, market neutral, and emerging markets strategies tend to be characterised by distinct non-normally distributed returns. ▪ There is clear evidence of performance persistence. However, the chance of selecting a surviving winning HF is reduced considerably by the large number of disappearing funds. These funds usually leave the database after poor performance. Investors can partly avoid investing in the disappearing funds by requiring a good track record.

Author(s) *Journal* (Year)	**Title**	**Data-base**	**Num-ber of Funds**	**Investi-gation Period**	**Relevant Research Objective & Methodology**	**Relevant Key Findings and Conclusions**
Malkiel & Saha *Financial Analysts Journal* (2005)	Hedge Funds: Risk and Return	TASS	2,065	1996-2003	▪ This study analyzes the determinants of HF survival and explores HF return persistence. ▪ Analyzed time horizon: 12 months. ▪ Performance measure applied: return. ▪ Statistical methodology used: chi-square test.	▪ Reported HF performance is substantially upward biased. This is primarily due to the practice of voluntary reporting. Moreover, there is a substantial survivorship bias in the returns of HF indices composed of all currently existing funds. ▪ The reported low correlations of HF returns with standard equity indexes is at least in part due to asset pricing within HFs that may sometimes rely on stale or managed prices. ▪ The substantial flow of capital into the HF industry may reduce returns significantly in the future. Thus, the very success of the HF industry in attracting capital may make HF investing less profitable in the future.

Source: Author's own illustration, Eling (2009)

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Curriculum Vitae Martin Raasch

Research

2008 - 2012	**University of St. Gallen**	**Switzerland**
	• Ph.D. candidate	
	• Exchange terms at Tsinghua University,	China
	Indian Institute of Management Bangalore (IIMB),	India
	and Singapore Management University (SMU)	Singapore

Professional Experience

2006 - 2008	**Greenhill & Co.**	**Germany**
	• Mergers & acquisitions analyst	
	• International corporate finance advisory	

Internships

2005	Roland Berger Strategy Consultants	Switzerland
2004	Mercedes-Benz Finance	Japan

Education

2004 - 2006	**University of St. Gallen**	**Switzerland**
	• M.A. HSG in Banking and Finance	
	• Exchange term at Rotman School of Management	Canada
2001 - 2004	**University of St. Gallen**	**Switzerland**
	• B.A. HSG in Economics	
	• Exchange term at Singapore Management University (SMU)	Singapore