Aalto University
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Hedge fund styles in the financial crisis

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Abstract of master's thesis

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Abstract

This study aims to examine the difference in performance between hedge fund styles during the 2007 financial crisis. While it is perceived that hedge funds aim to follow a market-neutral investment style, hedge funds today are a very heterogeneous group when it comes to their strategies. Additionally, performance studies in hedge funds are known for hefty self-selection biases, namely survivorship and look-ahead bias, both of which are expected to be more vigorous in a bad economy. By removing database biases and correcting reported returns for survival and look-ahead bias, this paper aims to study whether certain investment styles outperformed others during the financial crisis in 2007-2010.

The objective of this study is threefold. Firstly, this paper aims to study the extent to which the raw database reports were upwards biased during the crisis period due to self-selection biases. Secondly, this paper studies hedge fund's performance persistence and tests whether reported returns exaggerate their true ability to perform. Finally, these results will be interpreted style specifically to see whether there are significant differences in performance patterns between styles.

I find the reported returns to be exceedingly skewed during the financial crisis together with record-high attrition level. After correcting for self-selection, the left tail returns were much lower than reported returns. While positive returns on average were only mildly over reported, poor returns were statistically significantly more than 17% lower after excluding biases from the database.

Short-term performance persistence was found even during financial crisis, however, this effect diminished over time. On average, the best performing funds had the same likelihood to continue to perform extremely good as well as extremely bad. After adjusting for database biases, performance persistence weakened furthermore. However, performance persistence varied wildly between investment styles.

During the financial crisis period 2007-2010, Multi-strategy funds outperformed all other styles measured in absolute returns and came in second on risk-adjusted basis. Moreover, Multi-strategy funds' showed lower attrition, more performance persistence than other funds, and frequently appeared as a top performing fund. Global Macro also performed relatively well during the financial crisis and reported highest risk-adjusted returns after correcting for database biases. Fund of funds, on the other hand, clearly underperformed all other style during the financial crisis, as they failed to generate returns and exhibited no persistency in performance.

Despite of self-selection biases, a thorough analysis can help an investor to choose the appropriate fund to invest in, while styles remain a crucial part in determining the success of the fund.

Keywords hedge funds, investment style, financial crisis, performance persistence, survivorship bias, look-ahead bias, back-filling bias

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Tiivistelmä

Tässä tutkielmassa tarkastellaan hedgerahastojen eri sijoitustyyliluokkien tuottoja finanssikriisin 2007-2010 aikana. Hedgerahastot ovat absoluuttisten tuottotavoitteiden rahastoja ja poikkeavat tavanomaisista sijoitusrahastoista sijoitusstrategioiden ja säätelyn osalta. Hedgerahastoilla ei ole lakisääteistä raportointivelvollisuutta ja raportointi tapahtuukin vapaaehtoisesti erilaisiin kaupallisiin tietokantoihin. Vapaaehtoisuuden takia saatavilla oleva informaatio on kyseenalaista, joten tuottohavaintoja analysoitaessa tulisi ottaa huomioon muun muassa selviytymis- ja look-ahead-harhojen mahdolliset vaikutukset tuloksiin. Tässä tutkielmassa pyrin korjaamaan näistä edellä mainituista tietokantaharhoista tuottohavainnot selvittääkseni erilaisten sijoitusstrategioiden todelliset tuotot sekä näiden strategioiden suorituskyvyn pysyvyyttä finanssikriisin keskellä.

Tutkielman tavoitteet voidaan jakaa kolmeen osaan. Ensimmäisessä osassa pyrin selvittämään hedgerahastojen raportoitujen historiallisten tuottojen vääristymän laajuutta sekä niiden vaikutusta raportoinnin lopettamispäätökseen. Seuraavassa osassa tutkin korjattujen tuottojen vaikutusta hedgerahastojen suorityskyvyn pysyvyyteen. Vertaamalla raakadataa tietokantaharhoista korjattuihin tuottoihin pyrin selvittämään vääristävätkö selviytysmisharha ja look-ahead harha myös tuottojen pysyvyyttä. Jälkimmäisessä osassa perehdyn syvemmin hedgerahastojen eri sijoitustyyliluokkiin, näiden keskinäisiin tuottoeroihin sekä suorituskyvyn pysyvyyden eroihin finanssikriisin aikana.

Tulokset osoittivat, että finanssikriisin aikana ennätysmäärä hedgerahastoja lopetti raportoinnin. Heikoiten pärjänneiden hedgerahastojen tulosten raportointi oli myös vääristynyttä tietokantaharhojen vuoksi ja näiden todelliset tuotot olivat jopa 17 % alhaisempia kuin raportoidut tuotot antoivat ymmärtää. Suorituskyvyn pysyvyyttä oli havaittavissa selvästi kuukausitasolla, mutta pidemmälle aikajänteelle mentäessä tuottojen pysyvyys heikkeni selvästi. Keskimäärin vuositasolla hedgerahastojen positiivinen suorituskyvyn pysyvyys ei eronnut huomattavasti negatiivisesta pysyvyydestä. Huomioitavaa oli kuitenkin se, että erot suorituskyvyn pysyvyydessä olivat merkittäviä eri sijoitustyyliluokkien välillä.

Parhaiten pärjäsivät vertailuissa yhdistelmästrategiarahastot sekä makrostrategiaa soveltavat hedgerahastot. Yhdistelmästrategiarahastot tuottivat korkeimmat absoluuttiset tuotot ja toiseksi parhaat riskikorjatut tuotot. Lisäksi yhdistelmästrategiarahastojen tuottojen pysyvyys oli huomattava finanssikriisin aikana. Makrostrategiarahastot pärjäsivät riskikorjatuilla tuotoilla mitattuina suhteellisesti paremmin kuin muut strategiat ja jonkin verran menestyksen pysyvyyttä oli myös havaittavissa. Rahastojen rahastot taas strategiana tuottivat suosiostaan huolimatta keskimäärin tappiota ilman minkäänlaista näyttöä suorituskyvyn pysyvyydestä.

Haasteellisista tietokantaharhoista huolimatta hedgerahastojen arviointi on mahdollista ja kokonaisvaltainen analyysi voi auttaa sijoittajaa valitsemaan menestyksekkään rahaston. Erot sijoitusstrategioissa on otettava huomioon sijoituspäätöksiä tehdessä.

Avainsanat hedgerahastot, sijoitustyyliluokka, finanssikriisi selviytymisharha, look-ahead harha, suorituskyvyn pysyvyys

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I. INTRODUCTION

The legal definition of the term “hedge fund” is used to characterize a broad class of skill-based asset management companies that do not qualify as mutual funds and are, therefore, not regulated as such. Generally, hedge funds are similar to mutual funds in that they are actively managed investment portfolios holding positions in tradable securities.[1] Traditionally, hedge funds are arranged private partnerships in order to provide maximum flexibility in constructing a portfolio. While hedge funds are also managed by a fund manager, similarly to mutual funds, hedge funds follow strategies that are dramatically different from mutual funds, and these strategies are substantially more dynamic than those of mutual funds (Fung and Hsieh, 1997).

Due to their unregulated nature, hedge funds have broad flexibility in the types of securities they hold and the types of positions they take; hedge funds may invest in a diverse range of assets, including private and highly illiquid. Most hedge fund investment strategies aim to maximize return on investment regardless of whether markets are rising or falling, by using a wider range of investment strategies such as leverage, derivatives and short selling. Nonetheless, hedge funds are often subject to lock-up periods, which allow them to also invest in highly illiquid assets. As of yet, there is no generally accepted exhaustive definition of hedge funds (Jylhä, 2012).

When the financial crisis of 2007 struck, it also had a powerful impact in the hedge fund industry. Ultimately, hedge funds as a group lost about 18% of total value, in 2008[2] which was double the loss of 1998, their prior worst year on record. During the financial crisis when stocks and commodities lost between 35%–40% on average, many hedge funds failed to generate their promised absolute returns. In addition to the magnitude of losses, the consecutive number of negative monthly performances was unparalleled in hedge fund performance datasets. In this environment, risk aversion suddenly spiked among hedge fund investors, and they reacted fairly uniformly by redeeming their shares in (funds of) hedge funds. Many funds did manage to make payouts according to their standard redemption terms.[3] Nonetheless, performance fee rates have fallen since the start of the credit crunch. [4]

[1] This broad definition would also include private equity funds and real estate partnerships that are not generally considered hedge funds.
[2] Bloomberg: *“Hedge Funds Lost Record 18.3% on Misjudged Markets”* by Saijel Kishan
[3] In fact, many managers now feel they were used as “ATM machines” during that period.
[4] According to Hedge Fund Research Inc.

Due to hedge funds' ability to change their positions accordingly to the market, their performance cannot be measured by their ability to track a passive benchmark (see e.g. Fung and Hsieh (2002), Fung and Hsieh (2004)). In addition, they are expected to produce superior performance, since hedge fund strategies may differ highly from those of open-end equity mutual fund managers. While hedge funds have the freedom to invest in whichever strategy they please, more often than not they follow one investment strategy more closely than another. Whether there is one strategy with the ability to outperform other strategies is up to debate.

A notable downside to managing and tracking hedge funds is that they frequently disappear. Commercial databases in the hedge fund industry may ask current hedge funds to report their returns – both current and historical – which understandably causes certain biases in the fund databases. For example, it is expected that back-filling returns if often due to self-selection and fund managers' efforts to make an aesthetic procedure on their funds' performance. As a result, many hedge funds choose not to report at all, and even the results that are reported are affected by a myriad of biases due to self-selection.

The motivation of this study is driven by the unique setting offered by the financial crisis to test the durability and persistence of hedge fund strategies. By taking advantage of the extreme conditions of the 2007 financial crisis, this paper aims to scrutinize survivorship and look-ahead bias in performance studies of hedge funds in order to further examine differences in returns and performance persistence between investment styles in hedge funds.

1.1 Objective of this research

The objective of this study is to evaluate the performance of hedge fund investment styles in a crisis period. Most performance studies treat hedge funds as a single investment category (see e.g. Agarwal and Naik (2000)), when in fact, hedge funds practicing different investment styles maybe be polar opposites of each other. Moreover, the focus of performance studies often lies in the reporting biases caused by hedge fund's unregulated policy.

Understanding the dynamics of hedge fund survival is complex due to industry specific characteristics. The ability to track the existence of hedge funds is more or less dependent the hedge fund manager's willingness to report. Nonetheless, and for the same reason, hedge funds remains an interesting and crucial mechanism in shaping and influencing the financial markets.

The research questions of this study are as follows:

1. Are hedge fund database biases more evident during a financial crisis period?
2. Given that hedge funds are supposed to generate returns regardless of the market condition, can we expect certain investment strategies to outperform others during the 2007 financial crisis?

The first part of this thesis will discuss fund attrition in the context of the financial crisis. Failure to eliminate survivorship bias can lead to spurious conclusions about the effect of fund characteristics on return (Brown, Goetzmann and Ibbotson, 1997). Hence, in order to measure persistence, I will need to correct for survivorship bias using appropriate determinants for attrition.

The second part studies the true performance persistence of hedge funds, corrected for survivorship bias and look-ahead bias caused by back-filling into these databases. Since hedge fund returns exhibit non-linear exposures, traditional linear factor are often too limited to help in evaluating true performance of hedge funds. I will use predicted values obtained from the attrition model and implement a weighting procedure in order to correct for survivorship and look-ahead bias. The goal of this section is to find a proper model to explain the attrition process and use this method to further examine and explore hedge funds persistence and performance, a priori.

The last part of this paper will take use of the results obtained from the previous sections and apply them to in practice. The financial crisis in 2007 offers a unique setting to test whether hedge funds are, in fact, able to diversify themselves away from unsystematic and even systemic risk. While unsystematic risk should be able to be mitigated through diversification, systemic risk can only be managed through appropriate hedging or by using the right asset allocation strategy; both tools that hedge funds are permitted to use. The ultimate goal of this section is to answer the following question: Based on the performance of hedge funds in the financial crisis, was there an investment style that truly beat the market better than others?

1.2 Contribution to existing research

Hedge funds are widely studied vehicles in the literature. The main themes on existing academic literature on hedge funds can be broadly organized into four groups (Jylhä, 2012). The first and largest branch deals with the returns and risks of hedge funds (see e.g. Brown, Goetzmann and

Ibbotson, (1997), Ackermann, McEnally et al. (1999), Liang (1999), Brown, Goetzmann et al. (1997)). The second branch discusses the impact of hedge funds in the financial markets and individuals companies (see e.g. Ben-David andFranzoni et al. (2012), Ivashina and Scharfstein (2010)). The third group of hedge fund research focuses on behavior of hedge fund investors and the last group investigate the misbehavior and skills of hedge fund managers (see e.g. Edwards and Caglayan 2001). Nonetheless, there are also increasing amount of literature focusing on specific investment styles and or differences between investment strategies (see e.g. Fung and Hsieh (2002).

The contribution of this paper to existing research lies in the fact that the first and last branch of studies are often disconnected from each other. The challenges of performance studies are often linked to either difficultness of finding a proper benchmark or focus on database problems. The investment styles studies, on the other hand, often overlook the fact that fund databases are unreliable and solely focus on other external factors that may or may not drive a certain investment style to outperform. This paper aims to connect these angles of approach and examine *true* performance persistence and differences between styles. Compared to traditional performance persistence studies, where hedge funds are treated as a single investment vehicle and style factors treated as a control (Baquero, Ter Horst et al. 2005), this paper aims to explore persistence studies from a style specific point of view.

Additionally, the data set used for this study includes all global hedge funds spanning over a major financial bubble and another financial crisis. The extensiveness of using global data dismisses the effect of local risk factors and thus emphasizes more on style specific strategies. Furthermore, this has a better ability to show the different levels of impact of the different investment styles during the financial crisis. Furthermore, the comparison between different investment styles is taken into account, which contributes to existing literature of finding a superior investment strategy in a bear market. In addition, less performance studies have been conducted using global data, suggesting that hedge fund returns and attrition results – if statistically significant – are not specific to geographic regions. However, by initially including global hedge fund data, I will exclude the effects determining fund attrition that are associated to region specific macroeconomic factors.

In addition, much of the previous research on risks and return of hedge funds was conducted well before the financial crisis, hence the studies used smaller samples due to the fact that hedge funds available in the market before 21st century was significantly lower than today. Given the enormous growth and volatility of the hedge fund industry in the last decade, the majority of the most noteworthy studies conducted in the early 2000s consisted of a significantly smaller pool of hedge funds. Consequently, its impact on the financial markets and vice versa could not be as substantial as it has been today.

1.3 Structure of the thesis

The remainder of this paper is organized as follows. Section II provides an academic overview and further introduces the dynamics of hedge funds and discusses more in depth the motivation of this study. Followed by this, in Section III I will present my hypotheses. In section IV, I will describe the data sample of hedge funds used in this study and introduce the models used to examine my hypotheses. The sample shows that the number of funds that leaves the sample is substantial and their average returns are below those of surviving funds. This indicates the potential for biases, thus I will introduce the model to correct for these biases. Section V examines survival and performance persistence for a sample of hedge funds over the period 2007-2010, taking into account their investment strategies, and discusses the robustness of these results. Section VI discusses the impact of the results obtained and Section VII concludes.

II. LITERATURE REVIEW

This section provides a literature review on previous relevant studies conducted on hedge fund industry and their performance persistence, survivorship and look-ahead bias. In addition, academic papers on mutual funds are also worthwhile to discuss, as they provide further insight into measuring fund performance and survivorship.

2.1 Development of hedge fund industry

The very first hedge fund managers, Alfred Winslow Jones, set up his hedged fund in 1949. Whilst he did not possess a business or quantitative finance degree[5], he figured out that he could "hedge" his long stock positions against market risk by selling short other stocks, he could enhance the potential return. Seventeen years later *Fortune Magazine* published that Jones' hedge fund had "outperformed the best mutual fund by 44% that year and the best five-year performing mutual fund by 85% net of all fees" (Sudak et al. 2003). With this simple novel investment approach he had invented the platform for the complex investment structures to come.

In 1968, the Securities and Exchange Commission counted 140 investment partnerships that it considered hedge funds. However, inexperienced hedge fund managers soon grew tired of hedging their bets and began wagering more heavily on long investments and less on short ones, thus exposing themselves to the stock market. When markets started to slide, so did many hedge funds. By 1970, assets managed by the 28 largest hedge funds had declined by 70 percent. Many were liquidated, and the total value of the remaining hedge funds at the time was $300 million (Eichengreen and Mathieson, 1999).

The prevailing academia before 1980s considered markets to be efficient, prices follow a random walk and hence hedge funds could not be successful for other reason than luck (Malkiel, 2003). However, since an article published in 1986 in *Institutional Investor* reported the double-digit performance of Julian Robertson's Tiger Fund, the general consensus changed. Investors now flocked to an industry that offered thousands of funds and an ever-increasing array of exotic strategies.

[5] Sebastian Mallaby – More money than God (2010)

However, a decade after the sensational success of Tiger Fund, another hedge fund led by Nobel Prize-winning economists – Long-Term Capital Management (LTCM) — nearly collapsed the global financial system as a result of high-risk arbitrage trading strategies (Lowenstein, 2000). Furthermore, this was followed by the meltdown of the Tiger Funds in March of 2000.[6] In addition, the once multibillion dollar Quantum Fund led by Soros – which had historically boasted compounded annual returns exceeding 30% for more than two decades – needed a reorganization a month later in April of 2000 (Ineichen and Warburg, 2001).

The growth of the hedge fund industry over the past decades has brought an unusual attention to the industry. In the beginning 21st century hedge fund industry began once again to grow, now an even more rapid pace due to technical advances in the financial markets. Funds of funds as an investment vehicle attracted a larger customer base for the hedge fund industry, as they minimum initial investment was substantially lower than for other hedge funds, making hedge funds more and more attainable to the ordinary investor (Sender, 2012).

2.2 Hedge fund characteristics

Hedge funds are largely unregulated because they are typically limited partnerships with fewer investors. In addition, since hedge funds are not sold to the general public or retail investors, the funds and their managers have historically been exempt from some of the regulation that governs other funds and investment managers with regards to how the fund may be structured and how strategies and techniques are employed. Hedge funds are by comparison much less restricted and consequently, their responsibilities are less strictly monitored. For example in the US, depending on the amount of assets in the hedge funds advised by a manager, hedge fund managers may not be required to register or to file public reports with the SEC.[7]

Although mutual funds may "hedge" securities by investing in other instruments with uncorrelated returns, in general mutual funds are limited to stock, money market accounts and bonds. Compared to mutual funds, hedge funds prefer smaller, opaque value securities, and have higher turnover and more active share bets. Due to the simplicity and restrictions imposed to mutual funds, anyone can

[6] CNN *" Tiger Management closes"* by Jennifer Karchmer March 30, 2000
[7] Source: http://www.sec.gov

invest in them; however, hedge funds are only open to individuals or institutions that are considered to have the knowledge and resources to understand the nature of the funds.

Hedge fund managers typically invest their own money in the fund they manage, which serves to align their interests with investors in the fund. Management fees for hedge funds are designed to cover the operating costs of the manager, whereas the performance fee for incentive purposes provides the manager's profits. The compensation structure of managers within the industry is also based largely on performance; often a high watermark is applied to ensure that manager does not receive compensation for poor performance.[8] Clearly, hedge fund operators are paid to take risks, and the further implication is that investors believe that the manager has the skill to offset the high costs.

The exact number of hedge funds and the value of hedge fund capital remain unknown. This is due to the fact that commercial services reporting hedge funds rely on fund managers for information. This may bias both upward average returns as worst reporting managers are also least likely to provide any information. In addition, newer smaller funds may be reported with a lag, as they will be willing to report pursuant of some initial success (Aiken, Clifford et al. 2012). Double counting for returns may also occur as many hedge funds' invest in other hedge funds (fund of funds).

Ackermann, McEnally et al. (1999) found using hedge fund data from 1988-1995 that hedge funds did consistently outperform mutual funds, but not standard market indices. Another additional interesting finding was that hedge funds more volatile than both mutual funds and market indices. This latter finding contradicts with the basic idea of hedge funds, as the aim of hedge funds is to generate returns despite of market conditions using dynamic trading strategies.

High incentive structures may lead to excessive risk taking. That is, while these performance fees are intended to provide motivation for a manager to generate profits, they have also been highly criticized; given that often hedge funds share only the profits and not the losses this can result in excessive risk taking from the manager's side. This may be balanced by significant managerial investments within the fund, which often partake the unnecessary overbearing of risk. Nonetheless, due to the high costs, investing with a hedge fund manager would only appear to be rational if the fund provided a large, positive risk-adjusted return in compensation (Goetzmann et al., 2003).

[8] Typical management fee for a hedge fund is to 1-2% of assets under management and performance fee is 20-50% of the increase in funds' value.

2.3 Hedge fund strategies

Due to the unregulated nature of hedge funds they may take different types of positions at all times. The dynamics of investment strategies and positions enable hedge fund to maximize their return at all times by diversifying away from the market risk. More often than not, hedge funds will follow one strategic approach more closely than another.

Today, the term "hedge fund" encompasses investment philosophies that range far from the original "market neutral" strategy. Hedge funds will use a various different strategies, with different managers arguing their strategy being unique and giving better returns than their competitors. Brown and Goetzmann (2001) studied the monthly return history of hedge funds over the period 1989 through to January 2000 and found that there are in fact a number of distinct styles of management and that these differences in investment style contribute about 20 per cent of the cross sectional variability in hedge fund performance. Nonetheless, it can be assumed that the management style becomes an even more critical factor during a financial crisis period and henceforth remains a relevant indicator on fund performance.

Bali, Brown et al. (2012) studied hedge funds exposure to systemic risk and found that hedge funds following directional dynamic trading strategies, such as global macro, emerging markets, and managed futures funds, had the ability to correctly adjust their exposure to changes in the market and, hence, a positive and stronger link exists between their systematic risk and future returns. However, the cross-sectional relation between systematic risk and future returns is insignificant for the funds following non-directional strategies, such as equity market neutral, fixed income arbitrage, and convertible arbitrage funds.

Edwards and Caglayan (2001) used monthly returns of hedge funds during the period January 1990 to August 1998, and estimated six-factor Jensen alphas for individual hedge funds, employing eight different investment styles. They found that about 25% of the hedge funds earn positive excess returns and that the frequency and magnitude of funds' excess returns differ markedly with investment style.

However, many of these strategies can be categorized into certain groups helping the investor to understand the manager's skills and evaluate how a particular strategy might perform under certain macroeconomic conditions.

This section gives a quick glance on the strategies that are most commonly used to categorize hedge funds. The classification of styles follows the classification LipperTASS uses in its database.[9] The primary hedge fund investment categories are:

- *Convertible Arbitrage*
- *Dedicated Short Bias*
- *Event Driven*
- *Emerging Market*
- *Equity Market Neutral*
- *Global Macro*
- *Fund of Funds*
- *Fixed Income Arbitrage*
- *Long /Short Equity*
- *Managed Futures*
- *Multi-Strategy (Other)*

2.3.1 Convertible arbitrage

Convertible arbitrage is a non-directional type of equity long-short strategy, which takes a long position on a specific company's convertible securities while simultaneously taking a short position in the same company's common stock. Positions are designed to generate profits from the fixed income security as well as the short sale of stock, while protecting principal from market moves.

The idea behind convertible arbitrage is that a company's convertible bonds are sometimes priced inefficiently relative to the company's stock. A hedge fund using convertible arbitrage will buy a company's convertible bonds simultaneously as it shorts the company's stock. Convertible arbitrage funds may by this establish a market-neutral profile with very little correlation to the equity (Calamos, 2011).

Hutchinson and Gallagher (2004) tested the convertible arbitrageur's strategy by replicating the core underlying strategy of a convertible bond arbitrageur to produce daily convertible bond arbitrage returns. The results indicate that convertible arbitrageurs generate abnormal positive

[9] Additionally, categories may be further divided based on Investment Focus, Geographic Focus or Sector Focus, which are not included in this study. Fund manager selects the appropriate classification for the fund using LipperTASS questionnaire. The answers are ensured to be consistent with the offering memorandum, investment focus indicated and marketing materials submitted.

returns of 3% per annum. However, the returns are positively correlated with equity markets in severe downturns and consequently negatively correlated with equity markets in severe upturns due to their high implied volatility in these market conditions.

Convertible arbitrageurs risk lie at timing. Given that convertibles must be held as bonds for a specified amount of time before they can be converted into stock, the ability to time and evaluate the market carefully is essential for the strategy to work. Unpredictable events are the biggest risk for convertible arbitrageurs. [10] For example, during the market crash of 1987, many convertible bonds declined more than the stocks into which they were convertible, causing convertible arbitrageurs facing lose-lose situation.

Since the 2008 financial crisis, the universe of convertible bond investors has shifted significantly to a long-only majority investor base. Right before the financial crisis, many traditional convertible arbitrage portfolios used a significant amount of leverage (up to eight times, in some cases), which had a significant, negative impact on performance. [11]

2.3.2 Dedicated Short Bias

Dedicated short bias (DBS) hedge funds are directional[12] funds which take bets mainly on equities and derivatives, with a net short position in the market. This entails that a larger proportion of the portfolio is dedicated to short positions. Very few hedge funds carry a long-term short bias, since the equity markets tend to move up over time. Being net short is the opposite of being net long; hedge funds that maintain a net long position are dedicated long bias funds.

Connolly and Hutchinson (2010) documented strong results of DSB funds during the recent financial crisis due to their net short positions. They conclude that DSB hedge funds are a significant source of diversification for equity market investors and produce statistically significant levels of alpha. However, it is noteworthy to mention that their study was conducted on 35 DSB hedge funds. Dedicated short bias strategy is a lot less frequently used than other investment strategies. For this same reason, most DSB specific results have been omitted in this paper due to the small sample of data.

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[10]In another occurrence, many arbitrageurs made significant losses in 2005 by having long positions in General Motors (GM) convertible bonds and short positions in GM stock. In a short time period, GM's debt was downgraded at the same time when a billionaire investor tried to buy GM stock.

[11] JP.Morgan October 2013 Quarterly Investment Insights from Highbridge Hedge Fund Strategies

[12] Directional is a broad investing guidance in which the funds are required to move consistently in the desired direction whether market goes up or down. Market timers, long or short equity investors and trend investors all rely on directional investing strategies.

2.3.3 Emerging markets

As the name suggests, emerging market hedge funds specialize its investments in securities of emerging market countries. While there is no strict definition on what countries emerging markets entail[13], these countries usually carry a high level of risk due to their typically lower per-capita incomes and are in the process of moving from a closed market to an open market. Typical to emerging markets are these countries political and economic status which may result in lack of transparency, relative illiquidity and at times, extreme volatility.

Emerging market as a category consists of a wide range of nations, which makes it in fact a very heterogeneous group. For instance, China and Russia, two of the world's economic powerhouses, are lumped in the emerging market category with Peru, a much smaller country with fewer resources.

Emerging market hedge funds' significant advantage over mutual funds is that they have the freedom to invest to basically anything. While mutual funds may only invest in fairly liquid and transparent financial securities, hedge funds can offer exposure to more sophisticated investments, including commodities, real estate – while using leverage. However, since emerging market hedge funds carry the same emerging market risk as mutual funds, hedge funds have more opportunities to generate returns than their mutual fund counterparts.

The criticism towards Emerging Markets hedge funds is their role in disrupting local markets, as they rarely act as passive market observers. In the late 1990s, aggressive tactics were evident to different degrees in many East Asian markets. True or not, emerging markets hedge funds are seen as a volatile investment both in short- and long-term.[14]

2.3.4 Equity Market Neutral

Equity market neutral (EMN) hedge funds, as discussed earlier, is an equity long-short investment strategy seeking to minimize exposure to the systemic risk of the market. In order to conduct and maintain a perfect equity market neutral position requires high quantitative investment approach taking both long and short positions while aiming for a beta of zero. These funds aim to exploit investment opportunities presented by a specific group of stocks with the aim of being uncorrelated to rest of market movements and delivering pure alpha.

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[13] While only around 20% of the world's nations are considered emerging market countries, these countries constitute approximately 80% of the global population

[14] Hedge Funds in Emerging Markets by Gordon de Brouwer

EMN strategies were subject to significant errors in calculations in early August 2007 and many of the quantitative funds suffered record-high losses in the course of three days starting from the Lehman bankruptcy. However, it was documented that the funds that stayed the course and relied on their models experienced a strong recovery a few days later[15], while the ones that chose to liquidated suffered losses.

During the financial crisis, investors who were faced with illiquid hedge fund investments may be attracted by the fact that EMN managers mostly trade liquid securities such as stocks. The strategy's market neutrality essentially seeks to eliminate the problem of timing, which is the main problem with arbitrage strategies.

2.3.5 Event Driven

Event-driven strategy seeks to exploit pricing inefficiencies that may occur due to a corporate event, such as a bankruptcy, merger & acquisition activity or spinoff. An event-driven investor will analyze the potential acquisition (reasons for acquisition, the terms of the acquisition and any regulatory issues etc.) and determine the likelihood of the acquisition falling through. The event-driven investor will make its purchases and gains relying on their analysis and market discrepancies. Event-driven hedge funds often also practice "distressed-investing",[16] as these two strategies may be considered to be complementary to each other. Event-driven investing tends to work best when the economy is performing, where distressed-investing, on the other hand, tends to work best when the economy is performing poorly.

Traditional equity investors, including managers of equity mutual funds, do not have the expertise necessary to analyze many corporate events, which is why event-driven investing are typically limited to large institutional investors such as hedge funds and private equity firms.

While event-driven investing can be profitable, event-driven investors must be willing to accept fair amount of risk. Many corporate events do not occur as planned, which will ultimately reduce the target's stock price. As a result, a successful event-driven investor must have the knowledge and skills to accurately analyze corporate events and understand the business in which these companies operate in.

[15] 50% of the losses were recovered by Friday, August 10th according to Credit Suisse Asset Management LLC Sep 2009

[16] Investing in distressed securities. Distressed securities are securities (most often corporate bonds, bank debt and trade claims) of companies that are in some sort of distress, such as bankruptcy.

2.3.6 Fixed income arbitrage

Fixed income arbitrage is one of the most popular and long lasting hedge fund strategies. These arbitrageurs use a broad set of market-neutral strategies intend to exploit valuation differences between various fixed income securities. In terms of strategy, they may be divided into four main types: long-only, passive spread, trend following and convergence trading (Fung and Hsieh, 2002).

At their most basic level, fixed-income securities are simply debt instruments, issued by private companies or public entities, which promise a fixed stream of income. U.S. Treasuries, corporate bonds and municipal bonds are examples. There are, however, more sophisticated fixed-income securities, such as credit default swaps.

Fixed income arbitrage funds were under scrutiny during the financial crisis as its most common strategy was swap-spread arbitrage, which involves taking a bet on the direction of credit default swap rates. These credit default swaps (CDS) were financial instruments originally used as a hedge for investors holding mortgage backed securities (MBS) from the risk of default. However, it was the hedge funds that exploited the credit default swap arbitrages, beginning to heavily trading these securities and consequently providing the liquidity for the market (without necessarily trading the underlying assets). Once the financial institutions deteriorated because of losses related to subprime mortgages, also the likelihood increased that those providing the protection would have to pay their counterparties. As intermediary players in a market simply looking for returns, hedge funds may have had a crucial role in spreading the risk across the investors and financial institutions throughout the system, once the subprime mortgages began to default (Brunnermeier, 2009).

Fixed-income arbitrage strategy typically provides relatively small and steady returns if well managed, but can potentially lead to huge losses. In fact, when the convergence trading hedge fund LTCM went into crisis mode in 1998, its strategy was considered as one of the most toxic strategies around. Lowenstein (2000) reports that LTCM lost $1.6 billion by using swap spread positions.

2.3.7 Fund of funds

A "fund of funds" (FOF) is an investment strategy of holding a portfolio of other hedge funds rather than investing directly in financial securities.[17] For each individual FOF hedge fund, however, the reasoning for choosing underlying hedge funds may vary; the fund of hedge funds may invest only in hedge funds using a particular management strategy or a many different strategies in an attempt

[17] This may also be referred to as multi-manager or collective investment

to diversify their exposure from one specific strategy. Consequently, as a group, funds of funds may be considered as the benchmarks designed to reflect hedge fund industry performance (Fung and Hsieh, 2000).

The benefit of investing in FOFs is experienced management and diversification. In addition, given that most hedge funds have prohibitively high initial minimum investments, an investor may be able to theoretically gain access to a number of the country's best hedge funds with a relatively smaller investment through FOFs.

The disadvantage of investing in a fund of hedge funds is the fees. In addition to the fees charged by the underlying hedge funds, FOFs will also charge its own fees. In other words, each underlying hedge fund might charge a fee of 1% to 2% of asset under management and an incentive fee of 15% to 25% of profits generated, an incremental fee structure will be built up on top of that.

2.3.8 Global macro

Global macro is a macroeconomic investment strategy which uses economic theories to justify investment decisions on a large scale around the world. The strategy relies on forecasts and analyses on interest rates, expected flows of funds as well as political changes, government policies, relations and other broad systemic factors.

The financial and economic crisis had significant impact on the global macro hedge fund industry. The bickering between poor fundamentals as well as political and central bank intervention has created a range of mini-rallies followed by sudden changes in the economy, which are hard to trade. Historically, many macro funds benefited from being long on bonds during market shocks; however, it is harder for macro managers to be long bonds today given historical low interest rates. In addition, as liquidity dried up, some of the industry's biggest names chose to close their funds or returned considerable sums of money to clients, citing their inability to match historic 20%-plus returns. [18]

Historically, macro funds had one of the highest levels of dispersion of any hedge fund strategy. However, impact of so many macro managers following similar risk management models has evidently caused dispersion of returns to decrease dramatically in recent years. Analysis from the investment management team Neuberger Berman[19] concluded in 2014 that the average dispersion

[18] Hedge fund review Oct 2012

[19] "*2014 Hedge fund strategic outlook*" by Neuberger Berman Alternative Investment Management team

between the 75th and top 25th percentile of macro managers has declined from around 27% in 2009 to around 12% in 2012.

2.3.9 Long/short equity hedge

An equity long-short strategy is an directional investing strategy in which a hedge fund takes long positions in stocks that are expected to increase in value and short positions in stocks that are expected to decrease in value. At its most basic level, an equity long-short strategy consists of buying an undervalued stock and shorting an overvalued stock. Equity long-short strategies which hold equal dollar amounts of long and short positions are equity market neutral strategies. However, there are no requirements for equity long-short strategies to be market neutral.

Fung and Hsieh (2011) found in their empirical research that less than 20% of long/short equity hedge funds delivered significant, persistent, stable positive non-factor related returns. Their empirical analysis on long/short equity hedge funds found them holding persistently a net exposure to the spread between small and large cap stocks in addition to the overall market. Together, these factors account for more than 80% of return variation, with additional factors being price momentum and market activity.

Since hedge funds are not as liquid as mutual funds, equity long-short strategy may be challenged by the difficulty of selling their shares at the right time.[20] This could lead to significant losses. Additionally, equity long-short strategies may be challenged by some of its unique risks – the most significant being the fund manager's ability to pick stocks. Another fund specific risk results from what is referred to as the "beta mismatch"[21] of its positions. This may incur as uneven losses and profits when the market climate changes, even when the manager has aimed to keep its position market neutral.

[20] The infamous LTCM – which was more known for its convergence arbitrage in US Treasury bonds – suffered enormous losses due to forced liquidation of its equity positions at an unfavorable moment. LTCM had established an arbitrage position in the dual-listed company Royal Dutch Shell and Shell, with the former trading at an 8-10% premium relative to the latter. LTCM held short position on Royal Dutch and long position on Shell, however, they had to unwind their equity position at an unprofitable time due to losses accrued from their unfortunate bond trades.

[21] If the beta of the long position is larger than the short position, a market downturn should cause the long position to lose more, as market moves affect the long position more. Furthermore, if the beta of the short position is larger, a market upswing should increase the short position's loss more than the long position's gain.

2.3.10 Managed Futures (CTAs)

The term, managed futures, refers to the trading of futures and forward contracts on physical commodities and financial instruments by either institutions or investment advisors. Managed futures hedge funds thus invest mainly by going long or short in futures in areas such as metals, commodities, and grains, as well as equity indexes, foreign currency and bond futures. Managed futures hedge funds are managed by Commodity Trading Advisors (CTAs), a professional community of commodity investment managers that began offering investment advice to the public.

The major benefit of managed futures funds is that investing in futures contracts allows these funds to exhibit lower volatility while diversifying into a variety of instruments. As an additional benefit, managed futures has the ability to construct its portfolio with a negative correlation between its asset groups. For example, during periods with high expected inflation, investing in managed futures provides a hedge by holding investments in metals markets (gold and silver) against the damage that the economy may conversely have on equities and bonds.

Managed futures as a trading strategy became increasingly popular in the 1980s. Irwin et al. (1994) examined the returns of 363 CTAs for the 1979-89 period and that found virtually no correlation between returns from one two-year period to the next. While generally in the past managed futures have not shown to outperform stock indices such as S&P 500 or Nasdaq Composite Index, in in terms of risk-adjusted returns, the maximum drawdown – which is the difference between maximum peak-to-valley drop – was significantly lower in managed futures that those of the indices.

2.3.11 Multi-strategy

By definition, multi-strategy funds engage in more than one of the aforementioned strategies. The ultimate investment objective of multi-strategy hedge funds is to deliver consistently positive returns regardless of the directional movement in equity, interest rate or currency markets. The most common strategies adopted in a multi-strategy funds are convertible bond arbitrage, equity long/short, statistical arbitrage and event (merger) arbitrage. Successfully managing multi-strategy funds requires a deep knowledge and talent in various investment strategies.

Multi-strategy hedge funds aim to produce long-term results with their diversification of strategies. Hence, measured in short time windows, multi-strategy hedge funds are rarely the best performing category as the diversification of strategies will mitigate the returns of a single strategy. However, during a longer time period, the consistency and performance of multi-strategy funds should be able to deliver low volatility with high risk-adjusted returns. Multi-strategy funds may carry the lowest overall risk, as they reduce volatility by diversifying in asset-classes, while smoothing out single-strategy risks.

2.4 Hedge funds and financial crisis

2.4.1 Hedge funds' contribution to financial crisis

Hedge funds are often said to serve a purpose for providing liquidity and clearing market anomalies. This social function often also raise another question: if markets are prone to bubbles and crashes regardless of hedge funds, is it not possible that these wildest players actually contribute to these frenzies?[22]

The financial crisis in 2007 which was originally triggered by a complex interplay of policies that encouraged home ownership followed by questionable trading of these as "collateralized debt obligations" (CDOs) suddenly turned the focus of regulatory controls towards the hedge fund industry. Several academics (see e.g. Ben-David, Franzoni et al. 2012) have later argued that had it not been for hedge funds' intermediary position between the investors seeking yield and the banks creating these securities, the financial would have never reached the proportions of nearly collapsing the whole financial system. In fact, on the eve of the crisis at end-2006, it was registered by the Hedge Fund Research that all in all, hedge funds held about 47 per cent of the $3tn worth of CDOs while the banks held 25 per cent and insurance companies and asset managers held the remaining 28 per cent.[23] Consequently, it has been argued that had it not been for the vast supply, the proportions that were critical in precipitating the near collapse of the whole financial system may not have been reached.

Another important note on hedge funds riskiness is its capacity to leverage itself multifold. The fact that hedge funds imply themselves as market neutral and following low risk trading strategies, in reality its extensive use of leverage appears to suggest a high level of risk. In fact, during 2005 to early 2007, the gross hedge fund leverage stays between the ranges of 1.0–1.3. However, not long before the market crash, the cross-sectional leverage ratio increased to 1.6 in May (Ang, Gorovyy et

[22] In fact, during the Asian Financial Crisis, even the prime minister of Malaysia demonized Soros himself for causing the crisis.

[23] Financial Times, April 1, 2012 *The real role of hedge funds in the crisis* by Photis Lysandrou

al. 2011). While using leverage may boost profits, unexpected losses to a certain extent may wreak havoc once the leverage begins to transmit the losses to financial institutions granting the loan in the first place.[24]

Hedge funds have mainly used two arguments to deny any responsibility for causing the subprime crisis. The first one is that hedge funds had nothing to do with the creation of the toxic securities that were at the epicenter of the crisis. Hedge funds provided demand for supply, however, they did not structure nonconforming mortgages, repackage these mortgages into securities, bundle these securities together with other securities as collateral for yet other securities and give a rating to the structured credit securities. Secondly, hedge funds argued that other large financial institution such as pension and mutual funds, insurance companies and European and Asian banks were all similarly carrying the same toxic securities.[25]

Aragon and Strahan (2012) studied hedge fund liquidity from the Lehman bankruptcy and found that stocks held by Lehman-connected funds experienced greater declines in market liquidity following the bankruptcy than other stocks. It would thus seem that shocks to traders' funding liquidity reduce the market liquidity of the assets that they trade. Jylhä (2012) on the other hand, studied the role of hedge funds in supply and demand of market immediacy in the US market. They found that large funds with long lock up periods have higher propensity to supply immediacy than any other funds. In addition, the research suggests that hedge funds affect liquidity in general, the magnitude of return reversals and volatility in the market.

In April 2014, The Federal Reserve Bank of San Francisco published a new research stating that hedge funds fueled the global financial crisis in 2007-2009 by transmitting risk in the same fashion as banks and insurance firms.[26]

2.4.2 Financial crisis impact on hedge funds' performance

While generally the study has been focusing consistently on hedge funds impact on financial crisis, lesser amount of research has been conducted with an opposing point of view – that is, what was the impact of financial crisis on hedge funds?

[24] As for comparison, the LTCM had roughly \$4.8 billion in equity (early 1998) with which is reportedly managed to borrow more than \$125 billion from banks and securities firms, equaling up to a more than 20-to-1 leverage ratio. By the end of 1998, it had lost over \$4 billion of its equity interest rate swaps, leaving with only \$600 million of equity. These losses would force them to sell other large holdings at any price, which furthermore collapsed the value of the fund.

[25] Financial Times 2012, "*The real role of hedge funds in the crisis*" *by* Photis Lysandrou

[26] FRBSF Economic Letter, *"How Important Are Hedge Funds in a Crisis?"* by Reint Gropp, April 14th 2014

Following the suggestion of Fung and Hsieh (2000), Dai and Shawky (2013) studied Funds of Funds performance as a proxy for overall hedge fund performance during the financial crisis. They found that FOFs performance was brutally impacted by the crisis, with the largest funds taking the biggest hit. Additionally, their findings suggest that diversification (within the FOFs) did not have much of an impact on preventing poor performance caused by systemic risk.

Since mutual funds face an obligatory reporting requirement, Huang and Wang (2013) did an empirical study on the performance of "hedge-fund-like equity mutual funds" using directional strategies such as 130/30, market neutral and long/short equity funds during the 2007-2009 period. They examined the added value for investors during the 2007–2009 financial crisis and found that the top 90% of long/short funds and top 25% of 130/30 funds outperform a long-only passive index fund over the crisis period. Interestingly, these funds seemed to have the ability to generate alpha from their short positions, however, in the long run the gains were not sufficient to offset the losses from their long positions. Therefore it seems that at least some of the returns can be considered to be attributable to the managers' stock selection skills.

However, Market Neutral funds showed exceptional performance persistence in a study by Capocci, Corhay et al. (2005). The paper – using data obtained from MAR (Managed Account Reports) – also found significant outperformance in hedge funds during bullish markets. However, they reported no significant underperformance of individual fund strategies during bearish markets. In addition, apart from Market Neutral funds, they found weak persistency in general, with most predictability being found among middle performers.

An earlier paper written by Edwards and Caglayan (2001) studied commodity funds and hedge funds' performance through 1990-1998, the last few years of performance being severely impacted by the Asian financial crisis. Interestingly, they found that commodity funds are generally better at providing greater downside protection than hedge funds. Commodity funds had an inverse correlation with stock returns in bear markets, while hedge funds carried a positive correlation. Only three hedge fund styles - market-neutral, event-driven, and global macro - provide fairly good downside protection while still providing more attractive returns over all markets than do commodity funds.

An interesting finding by Joenväärä, Kosowski et al. (2012) showed that during the recent financial crisis illiquid funds experienced lower realized returns than liquid funds. This finding would suggest that – in contrast to previous studies – hedge funds styles applying high levels of leverage or strictly seeking long-term returns were unable to attain a market neutral position.

Based the previous research on hedge fund's performance during a financial crisis, it is not unlikely to perceive significantly different performance patterns between investment styles. Although the financial crisis had excruciating effects on the entire financial sector, its impact is not expected to be equally spread throughout the system.

2.5 Measuring hedge fund performance

2.5.1 Hedge fund databases

Due to hedge funds unregulated nature as well as their selective advertising[27], commercial databases often act as the sole marketing material available for potential investors. The most common hedge fund databases used are Morningstar, Eurekahedge, BarclaysHedge and LipperTASS – the latter being the most widely used among researchers and, consequently, the one used in this study.[28] These databases are consequently also the only source for obtaining information on hedge fund performance. Unsurprisingly, hedge fund performance obtained straight from the database is often highly skewed.

Joenväärä, Kosowski et al. (2012) thoroughly examined all the aforementioned databases and documented the fact that hedge fund performance studies are highly sensitive to database selection and biases associated with the ways data is inputted in the database. For example, EurekaHedge contains a relatively high proportion of Emerging Markets funds, possible because it is headquartered in Singapore. Also, in general, information on hedge funds' AUMs and coverage on defunct funds differ significantly among databases, with EurekaHedge and Morningstar being more likely to report a higher average fund performance than the other databases. In addition, Aragon, Liang, and Park (2013) document that onshore hedge funds registered in the United States deliver higher average performance than funds that are the registered in offshore locations.

The development of LipperTASS illustrates several biases that have arisen. London-based Trading Advisor Selection System (TASS) was founded in 1990. In March 2005, Lipper (now a subsidiary of Thompson Reuters) acquired TASS Research and the TASS database from Tremont Capital, which had purchased TASS in 1999. Aggarwal and Jorion (2010) report that pursuant the

[27] Hedge funds are for the mostly part prohibited from advertising to the public, as the instruments used in the vehicles were often considered too complex for non-professional investors. However, the regulative landscape has changed in the recent years in the US as a result of passing the JOBS Act in 2012.
[28] LipperTASS is considered to be generally the most reliable hedge fund database. In fact, Joenväärä, Kosowski et al (2012) showed that there are no significant differences between TASS database to aggregated database.

Tremont‘s purchase of TASS, the acquiring firm decided that its own hedge fund managers should contribute to the newly acquired database—in other words, the Tremont database was not absorbed directly into the TASS database. Hence a large number of Tremont funds were added to the TASS database between 1 April 1999 and 30 November 2001, a process that (according to Aggarwal and Jorion) induced a spurious survivorship bias.

However, Fung and Hsieh (2009) had pointed out another bias stemming from this database merger. Because the field for "date added to the database" refers to the date of entry into the TASS database and not the Tremont database, there are indications that some of those entries before that date are not necessarily backfill biased. Therefore, discarding such information may also unnecessarily reduce sample sizes.

2.5.2 Survivorship bias

A wide range of survival-related biases hinders in hedge fund databases. These biases arise because fund manager's self-selection tendencies as reporting to data vendors is voluntary. Studies showed that biases due to attrition and self-selection enforce each other and may lead to overestimating expected returns by as much as 8% per year (Ter Horst, Verbeek 2007).

Survivorship bias arises when information on defunct funds is unavailable and only the performance of surviving funds is investigated. This procedure will almost always ensure that the reported returns exaggerate the returns earned by the typical investor.

During times of poor performance, it is expected that hedge funds may be forced to liquate.[29] The liquidation process involves the sale of all of a fund's assets and distributes the proceeds to the fund shareholders. This means that at best, investors are forced to sell at a time not of their choosing; at worst, investors suffer a loss while ending up paying capital gains taxes too. In addition to liquidation, as data vendors often serve as their only marketing channel, many hedge funds will choose to exit the database in order to end their performance disclosure to the public.

Due to the nature of data, it is not self-evident whether the liquidation is forced or just an aesthetic procedure to mitigate further losses of a certain fund, and transferring those funds investment into another (new) hedge fund. Consequently, funds that stop reporting do not necessarily cease to exist outside the database. It is widely known that true failure rates for hedge funds are hard to determine because hedge funds are self-reporting (Aiken, Clifford et al. 2012).

[29] Liquidation rate generally accounts for over half of the attrition rate.

It is well understood that any database estimates are subject to a survivorship bias (Brown, Goetzmann et al. 1992). Survivorship bias is caused by the fact that poor performing funds are less likely to be observed in data sets that only contain the surviving funds because the survival probabilities depend on past performance (Brown and Goetzmann, 1995). A number of studies support this claim (see e.g. Liang (1999), Liang (2000), Brown et al (1999)), showing that poor performance is the main reason for a fund's disappearance.

Brown et al. (1999) studied hedge fund survival and performance on 1989-1995 offshore hedge fund data and found evidence on high liquidation rate, low covariance with the U.S. stock market, and consistently positive risk-adjusted returns over the time, but little evidence of differential manager skill.

However, there are also academics arguing for that *positive* survivorship bias may off-set the effects of survivorship bias. Positive survivorship bias suggests that well performing funds chose to close their funds to new investors and will choose to leave the database. Ackermann et al. (1999) studied hedge fund performance using from 1988-1996, and found evidence to support this claim.

Nonetheless, the prevailing academia in the last century have no longer found evidence to support positive survivorship bias. Malkiel (2005) showed the practice of voluntary reporting and back-filling appeared only on favorable past results, causing the reported results to be substantially upward biased. Jagannathan et al. (2010) reported similar findings in the database when evaluating hedge fund’s performance persistence.

2.5.3 Look-ahead bias

Another potential problem is the so called *look-ahead bias*, which arises when funds are included in the database for the first time, but are simultaneously included as instant history. Look-ahead bias is an ex-post conditioning bias, which arises when information that was not available at the time of the simulation is used in the test. In the case of hedge funds, the fact that these databases suffer from back-filling bias making historical performance seems like “up-to-date” return, simulation based on this data will diminish the accuracy of the fund manager’s true performance.

The reported numbers may greatly exaggerate the returns that typical investors have earned due to look-ahead bias, which can lead to spurious performance (Ter Horst, Nijman et al. 2001). Moreover, there are good reasons to believe that this phenomenon is even more common in hedge fund than mutual fund returns due to their complexity, higher liquidation rate and the manager's freedom in reporting standards.

Much of academic work on performance is based on using either one of the two measures: the Sharpe ratio (see e.g. Bollen and Busse (2005), Carhart (1997) and Jensen's alpha (see e.g. Edwards and Caglayan (2001)). Both of these persistence studies suffer from look-ahead bias, as data sets may be subject to backfilling biases, causing the funds dissolve in a nonrandom way during the evaluation period. This will eventually lead to spurious performance patterns.

Ennis and Sebastian (2003) examined the overall bias in numbers for the 1992–2002 period by comparing the reported 7.1% average return on the Hedge Fund Research Fund of Funds Index, which is the return earned by actual investors in funds of hedge funds, to the Hedge Fund Research Composite Index's reported average return of 11.3%. The 4.2% difference suggests a large bias in the industry's numbers.

Baquero, Ter Horst et al. (2005) found using US data that look-ahead bias can be as much as 3.8%. After correcting for look-ahead bias, the study found a positive persistence at short horizons of one and four quarters, although the statistical significance is weak. A similar study by Ter Horst, Verbeek (2007) showed that look-ahead bias can be as high as 8% annually due to liquidation and self-selection.

Given that the conventional method relies on the use of a single benchmark models, another common model – the pooled benchmark model – was introduced. The pooled benchmark model provides a standardized framework for identifying hedge fund performance by constructing benchmarks based on asset returns, which are free of the inherent biases in hedge fund databases. The pooled benchmark model is formed by optimally combining several well-known individual models including the Fung and Hsieh (2004) seven-factor model, the Fung and Hsieh (2001) five-factor model, the Agarwal and Naik (2004) model with four option-based factors, a three-factor international model, and the Carhart (1997) four-factor model.

Nonetheless, the pooled benchmark model merely introduces an alternative way of modeling hedge fund performance. While Funds and Hsieh (2004) found that over 90% of diversified hedge fund's monthly variations could be explained by their seven factor model, it simply provides the link between hedge funds risks and conventional asset-class risk and may be difficult to employ in practice.

When it comes to financial models, most would agree with the dictum of Box (1980) that "all models are false but some are useful". While the model is not perfect, it provided important insight and was widely used in the industry. Hence it is not atypical to employ models incorporating a dozen or more potential factors. [30]

2.5.4 Performance persistence

The existing academic literature questioning hedge funds returns and risks is vast. Given that the existence of hedge funds and mutual funds is largely based on the fact that investors believe in their ability to beat the market, a lot of research has been done regarding whether any true performance persistence exists in the fund industry.

There are several distinctive features that separate hedge funds widely from mutual funds. A study on hedge funds by Fung and Hsieh (1997) shows how dramatically hedge fund strategies differ from those of open-end equity mutual fund managers. Their application of Sharpe's (1992) style analysis to a sample of monthly hedge fund returns reveals that hedge funds actively shift their factor exposures, and this dynamic activity makes performance measurement difficult. In other words, while mutual funds' performance can always be measured against a relevant benchmark which they try to beat, hedge funds' performance cannot be measured in such a way.

While the general perception is that hedge funds follow a reasonably market-neutral investment style, hedge funds today are a very heterogeneous group when it comes to their investment approach. It is as such not surprising that there are a myriad of studies conducted on the importance and relevance of a hedge fund's investment style on its performance. Bali et al. (2012) investigates the extent to which market risk, residual risk, and tail risk explain the cross-sectional dispersion in hedge fund returns. They break up total risk of hedge funds into systematic and fund-specific or residual risk components. They found that, contrary to the popular belief, systematic risk is a highly significant factor explaining the dispersion of cross-sectional returns while at the same time residual risk and tail risk seemed to have little explanatory power. Hence, these supposed market-neutral funds are highly affected by systematic risk and in fact powerful determinants of the cross-sectional differences in hedge fund returns.

[30] According to Derman (2011), "It's impossible to make a correct financial model...In physics there may one day be a Theory of Everything; in finance and the social sciences, you have to work hard to have a usable Model of Anything."

Many estimates of persistence in mutual fund performance are based on data sets that only contain funds that are in existence at the end of the sample period.[31] Nonetheless, the evaluation of hedge fund performance continues to challenge both investors and researchers. By their very nature hedge funds' strategies are flexible in terms of their asset class exposure, leverage, and the choice of markets. Furthermore, the lack of operational transparency and performance reporting requirements makes it even more challenging to determine the investment strategy a particular hedge fund follows. Fung and Hsieh (2000) proposed using FOF hedge funds as proxy for market portfolio of hedge funds.

Several researcher have found evidence supporting the idea of hedge fund performance persistence. Edwards and Caglayan (2001) found evidence of hedge fund outperformance and concludes with that persistence may be as much as up to two years. In addition, many authors, such as Gruber (1996) and Carhart (1997) have reported persistence in the performance of mutual funds, meaning that funds with an above average performance in the recent past are more likely to continue to succeed in the future,. Although Agarwal and Naik's (2000) study also documented some evidence of persistence in hedge fund performance at quarterly horizons, they found that the longer the time horizons, the more ambiguous are the results.

However, academics opposing the view for observed persistence have noted that much of the persistence in fund returns can be explained by exposures to common factors such as size, book-to-market and momentum. Thus, on a risk-adjusted basis the performance even the best performing funds does not significantly differ from zero (Carhart 1997). Brown et al., (1999), Brown and Goetzmann, (2003) and Kosowski et al., (2007) have also concluded persistence diminishing in the long-term. Fung and Hsieh (2004) with a seven-factor model that incorporates asset-based style factors concluded similar results. Whether this persistence can be considered economically significant is yet up to debate.

In a more recent paper using a pooled distribution method, Bollen and Pool (2009) found a significant discontinuity in monthly hedge fund returns; the number of small gains far exceeds the number of small losses. However, this discontinuity disappears when using bimonthly returns, indicating a reversal in fund performance following small gains. This result suggests that the discontinuity is caused at least in part by temporarily overstated returns.

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[31] See Grinblatt and Titman, 1992

III. HYPOTHESIS DEVELOPMENT

In this section, I will build my hypotheses for this research based on the literature review in the previous section.

H1. Fund attrition is more severe during a financial crisis

As Ackermann, McEnally et al. (1999) noted, hedge fund were found to be more volatile than mutual funds or market indices to that matter. This results itself suggests that a volatile market – such as the 2007 financial crisis – hedge fund returns are expected to suffer even greater losses (as well as wins) than the market on the average. Previous academic literature and empirical research has proven that hedge funds frequently liquidate. Nonetheless, evidence for fund manager's self-selection and fund attrition due to poor performance is vast. As noted in many hedge fund performance studies (see e.g. Liang (1999), Liu and Loviscek (2009), Aiken, Clifford et al. (2012), Baquero, Ter Horst et al. (2005)), poor returns are often the biggest determinant for a hedge fund to liquidate or stop reporting. This finding combined with the fact that hedge funds are in fact more volatile than market indices would indicate the fund attrition occurs more frequently during a financial crisis period.

While it is commonly accepted that funds with a relatively bad performance are more likely to be dissolved, it is not clear a priori over which period historical returns are important to explain attrition. Therefore, although poor performance leads to fund attrition, the financial crisis effect is expected to be seen in the hedge fund industry within a delay.

Nonetheless, the problems arising from survivorship and back-filling bias would indicate that during a period of extreme poor performance such as the recent financial crisis, higher than average attrition rate would be present.

H2. Self-selection is more severe during financial crisis, which leads to spurious performance persistence in hedge fund returns

Strong historical returns on hedge funds are often advertised as an attractive feature, naturally causing biases in the self-reported returns. In addition, hedge funds may choose to report historical performance by back-filling, which distorts many academic studies as they suffer from look-ahead bias.

Following the hypothesis 1, I believe that fund managers self-select their reported returns even more rigorously during a financial crisis than they would in a generally bullish market environment. This, on the other hand, is expected to show up as spurious performance persistence.

H3. The longer the time horizon, the more ambiguous performance persistence becomes

Most academic studies have concluded that performance persistence – if such exists – is only short term by nature (see e.g. Brown et al., (1999), Brown and Goetzmann, (2003) and Kosowski et al., (2007). By sampling the data into separate time periods, I will test this assumption also with hedge fund returns rampaging through the financial crisis. I expect performance persistence to be even more short-termed during the financial crisis than on average.

H4. During a financial crisis period, certain investment styles may outperform others persistently

The hedge fund universe encompasses a range of different strategies and approaches and specialties. Some managers add value through knowledge of special asset markets, others through trading skills, and others through superior asset pricing models. It is this very variety that poses both a challenge and an opportunity. Given the extraordinary variety of hedge fund strategies, are there a few basic styles that they pursue? Second, are these styles meaningful to investors – that is, do they explain differences in performance? Third, are there any significant trends in these styles that investors and analysts should know about?

Many studies have shown that investment styles play a crucial role when measuring fund performance. Edwards and Caglayan (2001) found that manager skills contribute about 25% of overall hedge fund performance, and Brown and Goetzmann (2001) documented similar results. Nonetheless, it is be expected that during economic downturn, the ability to pick the correct investment opportunities becomes even more essential to the fund's performance. The 2007 financial crisis offers the unique environment to test hedge funds styles and their true ability to generate market neutral returns.

Following the hypotheses 1-3, a comparative analysis between performance measures during the financial crisis will be further explored specifically by investment style.

IV. DATA AND METHODS

In this chapter, I will describe the data and methods used in this research. Since hedge funds are a highly unregulated industry, reporting to a database is voluntary. Consequently, hedge funds may decide to start reporting to a database after some initial successful period, hence they enter a database with an instant history. Due to the unreliability of hedge fund data, it is not surprising that studies based on different databases have previously drawn conflicting conclusions and have founds different level survivorship biases in hedge fund returns.

4.1 Hedge fund data

The scope of this study consists of all global hedge funds – including hedge funds registered in offshore tax havens – using all available data collected from the period of 2000-2010. The popularity and importance of hedge funds have both increased dramatically in the past decade during which the financial markets have also globalized enormously. The period 2000-2010 includes important global events such as the dot-com bubble as well as the 2007 financial crisis, which both carried global effects.

Brown et al. (1999) used only offshore hedge fund data to measure survival and persistence. While the rationale behind using data on funds that have no or very little regulative involvement is valid, there is no evidence from return characteristics or other data to believe that the investment activities of offshore funds are different from U.S. hedge funds (Liang 1999). Nonetheless, using global data instead of data from one region only is justified in the sense that hedge funds are extremely unlikely to only invest locally.

The data used in this research was collected from Lipper TASS, which consists of monthly returns of all live and defunct hedge funds since January 1985.

During the 2007 crisis sources of liquidity in the economy and money market – mostly consisting of banks and the commercial paper market – severely reduced the number of loans they make. I believe that these occurrences further increased competition between hedge funds and, consequently, fund managers' incentives to provide superior results in order to attract investors. Therefore, it is a reasonable expectation that the impact of reporting bias in hedge funds causing predisposition in their survival, look-ahead bias and performance persistence will drive an even higher collision on the development of the financial markets.

TABLE 1
Summary on hedge fund data during 2000-2010

Total number of hedge funds		**9 165**
	Alive	6 423
	Dead	2 742

Primary investment style	Number of funds	Dead funds	Attrition rate (2007-2010)	% of total funds	N
Convertible arbitrage	107	49	46 %	1.2 %	**7 613**
Dedicated short bias	18	9	50 %	0.2 %	**1 500**
Emerging markets	544	135	25 %	5.9 %	**29 982**
Equity market neutral	281	121	43 %	3.1 %	**15 995**
Event driven	346	156	45 %	3.8 %	**24 477**
Fixed income arbitrage	213	65	31 %	2.3 %	**12 279**
Fund of funds	3 337	1061	32 %	36.4 %	**207 766**
Global macro	411	126	31 %	4.5 %	**16 997**
Long-short equity hedge	1 727	611	35 %	18.8 %	**113 211**
Managed futures	457	99	22 %	5.0 %	**31 199**
Multi-strategy	1 724	310	18 %	18.8 %	**74 379**
All funds	**9 165**	**2 742**	**29.9 %**	100.0 %	**535 398**

Table 1: Summary on hedge fund data during 2000-2010.
Hedge fund data 2000-2010 used for modeling attrition process divided into investment style.

Table 1 shows the summary of hedge fund data and their primary investment styles used in this research. The data in this research is organized as longitudinal data containing observations of multiple hedge funds over a 10 year period (*see Appendix 1 for more information*). The return data of funds extends starting from 2000 until 2010 and includes all funds that have stopped reporting during 2007-2010. Therefore, funds that have exited the database before 2007 have been excluded from this study. Given that many of these funds in this dataset have started operating after 2000 or died during 2007-2010, it is an unbalanced dataset.

Column “**N**” represents the number of individual monthly observations. Altogether 535,398 observations were included in this study. Compared to Baquero, Ter Horst et al. (2005), which uses quarterly data in their study, in this paper I use monthly returns. When Agarwal and Naik (2000) investigated persistence in the performance of hedge funds using a multi-period dataset, they found maximum persistence only at the quarterly horizon. This indicates that persistence among hedge fund managers is short-term in nature, hence I believe that by using monthly returns, the accuracy of short-term performance persistence can be captured more precisely.

TABLE 2 **Reasons for hedge funds exiting the database**		
Reason	No. Of funds	% of total
1. Fund liquidated	1 463	53.4 %
2. Fund dormant	1	0.0 %
3. Fund closed to new investments	9	0.3 %
4. Fund merged into another entity	142	5.2 %
5. Fund no longer reporting	640	23.3 %
6. Unable to contact fund	415	15.1 %
7. Program closed	17	0.6 %
8. Unknown	55	2.0 %
Total	2 742	100.00 %

Table 2: Reasons for hedge funds exiting the database
All reasons Lipper Tass offers as reasons for funds exiting the database. The most common is liquidation, followed by fund no longer reporting, which is an ambiguous reason.

Table 2 shows the main reasons each fund to stop reporting and exiting the LipperTASS database used in this research. The database offers eight different reasons for why a hedge fund has dropped from the database.[32]

Unlike previous studies focusing on specifically hedge fund liquidation (Brown et al. (1992), Baquero, et al. (2005), Ter Horst and Verbeek (2007)), instead of focusing solely on liquidation, the ultimate goal is to model the appropriate estimate for probability of any fund death capturing the database biases. This way, I can correct for all raw returns arising from self-selection and liquidation. The reasons for funds exiting the database are more or less equivocal, for example, in some cases where fund stops reporting may have been due to liquidation; similarly fund liquidation may also be due to self-selection. By including all aforementioned reasons, the probit model aims find the *true* performance of hedge funds within the database and correct the raw returns from any biases that arise from fund manager's self-selection. Therefore, for the purpose of this study, all fund deaths are considered relevant.

[32] Since 1985 – which was when the first observations were available to the public – altogether 11,363 hedge funds have dropped from the LipperTASS database. See Appendix for full fund data since 1985.

TABLE 3
Annual returns by investment style 2007-2010

Primary investment style	Return by year				
	2007	**2008**	**2009**	**2010**	**4y avg**
Convertible arbitrage	-5.95 %	-0.52 %	28.66 %	14.02 %	7.30 %
Dedicated short bias	12.37 %	-3.24 %	-0.71 %	6.82 %	3.86 %
Emerging markets	0.96 %	-9.90 %	27.79 %	12.94 %	7.00 %
Equity market neutral	2.63 %	-0.98 %	9.62 %	8.50 %	3.78 %
Event driven	-2.90 %	-7.46 %	24.74 %	14.00 %	2.85 %
Fixed income arbitrage	1.48 %	5.96 %	11.48 %	7.93 %	6.12 %
Fund of funds	-0.29 %	-7.40 %	6.96 %	5.18 %	0.04 %
Global macro	11.32 %	7.83 %	10.98 %	9.69 %	8.91 %
Long-short equity hedge	-0.30 %	-2.03 %	16.56 %	12.03 %	4.66 %
Managed futures	19.99 %	5.20 %	0.90 %	13.20 %	7.85 %
Multi-strategy	4.28 %	4.55 %	16.45 %	10.97 %	9.07 %
All funds	**1.81 %**	**-2.84 %**	**12.66 %**	**9.22 %**	**3.97 %**

Table 3: Annual returns by investment style 2007-2010

Table 3 represents the raw annual returns by investment style during the 2007-2010 period. The strategies that were able to generate a positive return in 2008 were Fixed Income Arbitrage, Managed Futures, Multi-strategy and Global Macro. The overall performance was negative and not coincidentally, all purely directional strategies failed. However, for comparison, in the year 2008 S&P 500 index fell by 38%, Dow Jones Industrial Average fell by 34%[33]. In addition, during the four year period of 2007-2010, both indices have overall decreased in value by 11.2% and 7.2%. A quick glance at the raw data in Table 3 would thus indicate that on average, hedge funds at least have the ability to outperform the stock market.

[33] Yahoo Finance: On Jan 1st 2008 S&P 500 closed at 1 447 and DJIA closed at 11 971. On Dec 31st 2008 S&P 500 closed at 903 and DJIA closed at 8 776.

TABLE 4
Number of hedge funds entering and exiting the database 2007-2010

Changes in number of funds in the database

Year	No. of funds Start Year	No. of funds End Year	Annual				
			Difference	*% Difference*	No. of funds entering	No of funds exiting	Total attrition rate
2007	5 723	6 271	548	*9.58 %*	1 010	462	**8.07 %**
2008	6 271	6 249	- 22	*-0.35 %*	874	896	**14.29 %**
2009	6 249	6 385	136	*2.18 %*	868	732	**11.71 %**
2010	6 385	6 511	126	*1.97 %*	778	652	**10.21 %**

Table 4: Number of hedge funds entering and exiting the database 2007-2010
Net number of funds has increased throughout the financial crisis apart from the year 2008, where more funds exited the database rather than entered

Table 4 shows the number of funds entering and exiting the database on an annual basis[34] during the period 2007-2010. It is noteworthy to see that the fund performance was at its worst in 2008 (Table 3), which is also the year that attrition rate was at its highest, 14.29 % on an annual level.

Overall, the rate of attrition of hedge funds is relatively high, and those funds who die rarely survive longer than four years. [35]

As mentioned earlier, a potential database problem is backfilling bias or instant history bias, which arises because when funds are included in the database for the first time, however they are included as instant history. My hypothesis is that this back-filling may be due to self-selection and fund manager's efforts to market their funds attractively. To correct for this bias, I will only include funds that have operated for more than 12 months; the total number of hedge funds during the period 2000-2010 drops to 11,500 of which 2,356 dies during this period.

The average annual attrition for this period was 11.05% and total attrition rate for the 2007-2010 period was 48%, excluding for new funds entering the database during this period. Note that this is concluded from a dataset which already excluded all funds that died within one year – the true level of attrition is thus even higher if all funds were included. Compared to data samples from older studies, the level of attrition has skyrocketed from those days. For example, a study on survivorship bias by Bing (2000) collected data from the TASS database and showed that average attrition rate for 1994-998 was 8.3%. [36] In addition, Kat and Gaurav (2002) documented attrition rates between 1994-2001 using Tremont TASS database, which showed an average attrition of 6.96%.

[34] See Appendix for monthly attrition rates for 2007 to 2010
[35] According to my own dataset
[36] The inconsistency in these figures different reasons selecting the data

Jagannathan et al. (2010) employing data from HFR documented an annual attrition of 12.34% between 1996-2004. Nonetheless, during this time period, the highest annual attrition 16.24% occurred in 2000, which coincidentally, is aligned with the occurrence of the dot com bubble and market crash.

4.2 Methodology

Modeling the attrition process and the method to correct for look-head bias is adapted from two similar studies on survival and look-ahead bias in hedge fund and mutual fund industry. The results are obtained through a two-stage process, of which the first part models the attrition process and the latter part corrects for look-ahead bias and measures performance persistence.

4.2.1 Attrition model[37]

The first part of this study which focuses on the attrition model is adapted from the study by Baquero, Ter Horst et al. (2005). The model analyses the variables that are likely to affect attrition rates of hedge funds; random-effects longitudinal probit is applied in order to attain this conditional probability of attrition.

$$y_{it}^{*} = \alpha + \sum_{j=1}^{J} \gamma_{ij}\, r_{i,t} + \beta' x_{i,t} + \delta_{it} \tag{1}$$

$$y_{it} = 0 \text{ , when the fund is liquidated in } t\text{+1}$$

$$y_{it} = 1 \text{ , otherwise}$$

where $r_{i,}$ indicated the return of the fund i in t, $x_{i,t-1}$ is the vector for fund and time specific characteristics including a set of fund specific dummies. The coefficient γ_{ij} shows the effect of lagged returns to the outcome of whether fund i survives over the period. The output of this model describes the conditional probability of fund attrition given the underlying conditions and is used to estimate the probability of hedge fund attrition based on its historical performance. Following the

[37] While this is noted as “attrition model”, it follows Baquero et al. (2005) liquidation model with the exception that it is extended to other fund deaths as well, not limited to only death by liquidation only. Fund liquidation however, is clearly the dominating reason for fund death, accounting for over 50% of all fund deaths.

Baquero, Ter Horst et al. (2005) approach, in the longitudinal data set hedge fund is defined to have become defunct the month prior its attrition.

The output of this attrition model also provides the necessary *conditional probabilities* required to obtain returns to test for true performance. Therefore, this attrition model will be modeled using all funds as one data sample, as well as modeled separately within each style sample. Due to the enormous differences between investment styles' characteristics, it is expected that the estimates for fund attrition also differ between investment styles. Therefore, two sets of conditional probabilities will be generated for each fund and time specific observation.

The results obtained from this attrition model (combined with the findings from Table 4) provides an answer to my first hypothesis:

H1. Fund attrition is more severe during a financial crisis.

4.2.2 Eliminating look-ahead bias for performance persistence

Many academic studies on performance studies suffer from this look-ahead bias. Many of these studies use a two-period framework. At the end of the first period, the ranking period, funds are ranked and assigned to portfolios on the basis of their past performance. In the second period, the evaluation period, the average performance of all portfolios is determined for the funds that survived this second period. This will usually lead to inaccurate results in the study or simulation, created by the use of information or data in a study or simulation that would not have been known or available during the period being analyzed. While the above-mentioned method controls for the effects of survivorship bias, it does not correct from look-ahead bias arising from fund liquidation.

To study performance persistence, it is useful to sort funds into decile portfolios by their monthly raw returns from 2000-2010. This ranking is done without correcting for look-ahead bias. However, look-ahead bias may cause exaggerated results for performance persistence, as fund managers may have selectively back-filled successful funds' performance into the database after they have observed performance persistence.

In order to eliminate look-ahead bias, I will use a weighting procedure based upon aforementioned probit regression in measuring performance persistence. The correction method implies a multiplication of the performance measure over a ranking period with a *weight factor* equal to *conditional non-attrition probability in the numerator and unconditional attrition probability in the denominator.* The conditional attrition probability defined is obtained from

$$(2) \qquad P\{Y_{it} = 1 \mid R_i, X_{it}\} = \prod_{s=t}^{t+11} P[y_{is} = 1 \mid r_{i,s-1,\dots,} x_{i,s-1}]$$

where $P[y_{is} = 1 \mid r_{i,s-1,\dots,} x_{i,s-1}]$ is defined as y_{it}^{*} and obtained from the probit model.

The unconditional non-attrition over time *t* is calculated as a forward looking probability, which is defined as the number of funds not liquidated during the ranking period *t-1* to the number of funds present in the sample at the beginning of the ranking period t. The unconditional probability is then estimated by the ratio of the number of funds that did not liquidate between month *t* and *t + 11* to the number of funds that were in the sample in month *t-1*. Hence, unconditional probability equals the ratio of the funds not liquidated during the ranking period to the number of funds present in the sample at the beginning of the ranking period.

Following the model introduced by Ter Horst, Nijman et al. (2001) the underlying interest are the unconditional distribution of returns multiplied by weight factor that is corrected by conditional attrition. The raw returns are then multiplied by the weight factor – which is fund and time specific – and another ranking into deciles based on corrected returns is done. A fund's true performance persistence over time will then be evaluated from the ranking derived from corrected returns.

As two sets of conditional probabilities will be obtained using the attrition model, there will also be two correction multipliers for each fund and time specific return observation; one that is based on conditional probability of attrition for all hedge funds and the second is conditional to investment style specific parameters.

Combined with the results obtained from the attrition process, this second part of my research provides results for examining hypotheses 2, and 3

H2. Self-selection is more severe during financial crisis, which leads to spurious performance persistence in hedge fund returns

H3. The longer the time horizon, the more ambiguous performance persistence becomes

By further examining the results investment style specifically, we can address my last hypothesis which is:

H4. During a financial crisis period, certain investment styles may consistently outperform others

4.3 Determinants for fund attrition

4.3.1 Independent variables

TABLE 5 Independent variables for modeling fund attrition					
	No. Of observations	Mean	Standard deviation	Min	Max
ln NAV	535 398	5.7	1.6	-13.8	17.6
ln Estimated Assets	273 905	17.4	2.1	0.0	56.9
ln Age	527 445	3.5	1.1	- 3.4	6.1
ln $(Age)^2$	527 445	13.4	7.0	0.0	37.3
St.dev	535 332	3.4	19.2	-0.0	1 816.1

Table 5: Summary statistics on independent variables used for probit regression

Net Asset Value, Estimated Assets, Age and Volatility

The independent panel data variables are in line with previous studies. **Age** is included in the model and defined in months, excluding funds that have operated less than one year. **Net Asset Value** changes over time, and is time and fund specific, as it is affected by fund performance. A hedge fund's value is calculated as a share of the fund's net asset value (NAV), meaning that increases and decreases in the value of the fund's investment assets (and fund expenses) are directly reflected in the amount an investor can later withdraw. NAV may be negative, as it is defined as fund's assets less its liabilities; since hedge fund may use leverage as a part of its investment strategy, it is possible that NAV becomes negative.

Estimated Assets (Assets under management, AuM) is either estimation provided by TASS or reported by the fund managers. Nearly half of the observations lack this observation. AUM is defined as fund's cash plus the difference between the fund's long and short positions and is equal to the value of all claims investors have on the fund. **Riskiness** of a fund is measured by its volatility and naturally expected to be highly correlated to fund performance and consequently affecting probability of attrition. This volatility is defined as fund specific standard deviation over the period of 2000-2010. It is assumed that NAV, Estimated Assets and Age at time *t* have a log-normal distribution.

4.3.2 Control variables

TABLE 6

Control variables for modeling fund attrition

	No. Of observations	Mean	Standard deviation	Min	Max
Management fees	535 398	1.4	0.8	0	22
Incentive fees	535 398	12.4	9.0	0	50
High watermark	535 398	0.6	0.5	0	1

Table 6:: Summary statistics on control variables used for probit regression

Management and incentive fees, high-water mark

Hedge fund managers are motivated to act by using strong incentives. Generally such incentives are largely based on performance. A high-water mark for is set for each investor participating the fund individually and it is set at the maximum share value of their investment in the fund. While all partners' funds are pooled so they earn the same rate of return, investors may have a separate high-water marks depending on their share value since their investment in the fund.

Hedge fund managers typically receive a fraction of the fund's return each year in excess of the high-water mark. The average basic management fee was 1.4%, varying between 0 - 22 %. Compared to previous papers, on average the incentive fees were much lower, only 12% of annual profits. The variance for this was, however, quite high and the incentive fees varied between 0 - 50%. As stressed in the previous section, incentive fees dropped significantly post-financial crisis. Note that not all funds had used a high-water mark, which may also reduce incentive fee values.

Several other control variables were considered for this study. Firstly, the geographic location of each fund were not included in the model. The location specific control variables had little impact on the overall results and are not at the focus of this research. Country-specific factors may cause fund attrition, such as tax regulatory changes, however the effect of geographic location for fund attrition seems low.

Proxies for illiquidity were not used as a control variable. In his study Joenväärä, Kosowski et al. (2012) showed after accounting for database selection biases, it seems that fund share restrictions (such as lock-up period) were insignificant factors to be associated with performance.

Another potential control variable considered was maximum leverage used within each fund. Firstly, the amount of leverage did not have a high explanatory power on whether fund was liquidated. Secondly, the use of leverage is often based on the investment strategy of the fund, therefore the investment strategy itself implies the amount of leverage used. On average, the leverage ratio was slightly below 1-to-1. Interestingly, in this study the fund with highest leverage ratios did not exit the database through liquidation, but due to the fund no longer reporting or inability to contact the fund furthermore,[38] suggesting that these funds may have suffered tremendous losses once their arbitrage positions closed. Nearly all funds with a leverage ratio above 30-to-1 were using fixed income arbitrage as their primary investment strategy.

[38] The highest leverage ratio during the 2000-2010 in this study was 8000, implying a debt-to-equity ratio of 80-to-1.

V. RESULTS

In this section, I will provide the results of the study and elaborate on the implications of the results obtained. Previous literature on hedge fund performance persistence all suggest that in cases where persistence is found, it is short term by nature. Therefore, in my paper I choose to use monthly returns in order to obtain results with shorter frequency.

5.1 Attrition process

For this research, I conducted two separate attrition models for obtaining two different sets of attrition probabilities. The first model is an all-inclusive model using all hedge fund data returns lagged up to 18 months. The output probabilities of this model (*Probit(All)*) are fund and time specific, however, the model does not take into account each fund's investment style. This model will be used to describe the overall hedge fund data used in this study.

Addition to the all-inclusive model, the attrition process is also modelled for each subsequent investment style. For this, hedge funds have been grouped into smaller subsamples according to their investment style. Each sub-samples' attrition probabilities are then estimated using monthly lagged returns up to one year. The output probabilities of this model $Probit(IS_y))$, are time, fund and investment style specific, and the approximation model differs between each subsample.

5.1.1 All funds attrition model *(Probit(All))*

The attrition process was conducted using two separate methods. The first set of results is obtained using all hedge fund data.

TABLE 7
Attrition estimates with last 18 month for All funds

Random-effects probit regression					All funds 2000-2010	
				Number of observations =	208 725	
				Number of groups =	5 019	
				Group variable product	Hedge fund ID	
				Return frequency	Monthly	
Parameters	**Estimate**	**Std. Error**	**z**	**P>|x|**	**{95% Confidence Interval}**	
Intercept	5.30	0.48	11.14	0.00	4.36	6.23
Return						
--.	0.02	0.00	8.34	0.00	0.01	0.02
L1.	0.02	0.00	7.08	0.00	0.01	0.02
L2.	0.01	0.00	5.55	0.00	0.01	0.02
L3.	0.01	0.00	3.08	0.00	0.00	0.01
L4.	0.01	0.00	2.62	0.01	0.00	0.01
L5.	0.00	0.00	0.94	0.35	0.00	0.01
L6.	0.02	0.00	6.44	0.00	0.01	0.02
L7.	0.01	0.00	3.91	0.00	0.00	0.01
L8.	0.01	0.00	4.67	0.00	0.01	0.02
L9.	0.00	0.00	2.09	0.04	0.00	0.01
L10.	0.01	0.00	3.69	0.00	0.00	0.01
L11.	0.01	0.00	2.05	0.04	0.00	0.01
L12.	0.01	0.00	3.56	0.00	0.00	0.01
L13.	0.01	0.00	2.41	0.02	0.00	0.01
L14.	0.00	0.00	1.45	0.15	0.00	0.01
L15.[39]	0.00	(omitted)	0	0.00	0.00	0.00
L16.	0.00	0.00	0.75	0.45	0.00	0.01
L17.	0.00	0.00	0.38	0.71	0.00	0.01
L18.	0.00	0.00	0.55	0.58	0.00	0.01
Other variables						
lnNAV	-0.01	0.01	-2.33	0.02	-0.03	0.00
lnEA	0.06	0.01	11.87	0.00	0.05	0.07
lnAge	-1.56	0.22	-6.92	0.00	-2.00	-1.11
ln(Age)^2	0.17	0.03	6.35	0.00	0.12	0.22
Std. Dev	0.04	0.00	7.96	0.00	0.03	0.05
Fee variables						
Management fee	-0.04	0.01	-3.57	0.00	-0.07	-0.02
Incentive fee	-0.01	0.00	-7.2	0.00	-0.02	-0.01
High watermark	-0.23	0.03	-7.93	0.00	-0.28	-0.17
Log likehood	-6903.38		χ^2 test	909.91	*(p = 0.00000)*	

Table 7: Attrition estimates for Probit(All), with 18 month lags in return observations

These results support the general consensus that *poor returns lead to fund attrition*. In fact, monthly returns up to one year are statistically significant determinants for fund attrition, after which the returns become clearly less significant. The estimated coefficient suggests that negative returns will cause funds to liquidate; returns that are within one quarter prior to attrition are both most significant and carry the most weight for fund attrition.

In the above specification explaining fund attrition, all other variables are also statistically significant. Following the finding of Brown, Goetzmann and Park (2001) reported, high risk funds experience a higher attrition probability.

[39] Returns lagged at 15 were omitted from the model due to collinearity with other returns.

Fee variables were all significant determinants for funds attrition – hedge funds with higher fees or high watermark had a smaller probability of disappearing. This is aligned with previous papers showing hedge fund fees being positively correlated with fund returns (see e.g. Liang, 1999). However, Schwarz (2007) documented that hedge fund fees seem to be unrelated to fund's ability to generate net alpha. Therefore, although higher fees could be a sign of better manager skills, this assumption is valid only to a certain level of performance.

Combined with the numbers obtained from the Table 4, these results reject null hypothesis for the first Hypothesis:

H1. Fund attrition is more severe during a financial crisis

5.1.2 Style specific attrition model *(Probit(IS_y))*

The attrition probabilities obtained from Table 7 examine hedge funds as a large homogenous group and may be used to examine the overall performance of hedge funds during financial crisis. Majority of all research conducted on hedge fund attrition model hedge funds as one group, where styles factors are included as control variables.

However, as argued by Brown and Goetzmann (2001), differences in investment styles attribute to about 20% of fund performance. Hedge fund's characteristics and investment patterns between styles are tremendously different, due to which probit analysis for each sub-sample explains determinants for attrition and liquidation more precisely. For example, different hedge fund strategies exhibit different levels of volatility, which would indicate that some funds are more prone to attrition due to poor performance more quickly, whereas other styles are better equipped to accept short-term poor performance. Therefore, I have come to the conclusion to use conditional probabilities generated from investment style specific models. [40]

While my first hypothesis concluded that poor returns cause fund attrition, the level of poor returns effect on attrition must be different within each investment style. In order to model true performance for each style specifically, hedge fund data was divided into style-specific subsamples and attrition models for each investment style were conducted.[41] Consequently, the correcting

[40] See Appendix List of Tables for full results
[41] Due to the lack of data and inconclusive results, Dedicated Short Bias was left out from this scope

returns using fund specific attrition model should capture this style specific sensitivity to poor returns.

TABLE 8 Attrition estimates with last 12 month for Fixed Income Arbitrage hedge funds						
Random-effects probit regression					Fixed income arbitrage	
				Number of observations =		5 547
				Number of groups =		138
				Group variable product		Hedge fund ID
				Return frequency		Monthly
Parameters	**Estimate**	**Std. Error**	**z**	**P>|x|**	**{95% Confidence Interval}**	
Intercept	3.8	2.1	1.79	0.07	-0.36	7.95
Return						
--.	0.024	0.0	2.17	0.03	0.00	0.05
L1.	0.040	0.0	4.03	0.00	0.02	0.06
L2.	0.052	0.0	4.81	0.00	0.03	0.07
L3.	0.006	0.0	0.38	0.70	-0.03	0.04
L4.	-0.003	0.0	-0.22	0.83	-0.03	0.03
L5.	0.018	0.0	1.14	0.26	-0.01	0.05
L6.	0.019	0.0	1.13	0.26	-0.01	0.05
L7.	-0.001	0.0	-0.05	0.96	-0.03	0.02
L8.	0.029	0.0	1.83	0.07	0.00	0.06
L9.	0.005	0.0	0.22	0.83	-0.04	0.05
L10.	-0.013	0.0	-0.73	0.46	-0.05	0.02
L11.	0.003	0.0	0.16	0.87	-0.03	0.04
Other variables						
lnNAV	-0.050	0.0	-1.32	0.19	-0.12	0.02
lnEA	0.143	0.0	4.85	0.00	0.09	0.20
lnAge	-1.631	1.0	-1.57	0.12	-3.66	0.40
ln(Age)^2	0.188	0.1	1.44	0.15	-0.07	0.44
Std. Dev	0.071	0.0	1.84	0.07	0.00	0.15
Fee variables						
Management fee	-0.234	0.2	-1.53	0.13	-0.54	0.07
Incentive fee	0.020	0.0	1.22	0.22	-0.01	0.05
High watermark	-0.295	0.3	-1.15	0.25	-0.80	0.21
Log likehood	-210.01662		χ^2test	90.4 *(p = 0.0000)*		

Table 8: Attrition estimates for Probit(IS) for Fixed Income Arbitrage, with 12 month lags in return observations

For illustrative purposes, Table 8 shows the output of attrition model for hedge funds practicing Fixed Income Arbitrage as their primary investment strategy (*see Appendix 2 for full set of attrition models constructed for each investment style)* Now, compared to Table 7, estimate coefficients for lags 4, 7 and 10 are now negative. Albeit being insignificant, these estimates do show the characteristics of Fixed Income Arbitrage as a more volatile strategy within the hedge fund performance as a whole. For Fixed Income Arbitrage, in fact, basically only the returns up to the past quarter are statistically significant for fund attrition and the impact of individual monthly observations decreases with time. As for other variables, only Estimated Assets (AuM) seems to have a significant positive effect on fund attrition.

For each investment style specific attrition model *(Probit(IS$_y$))*, I have only included returns for the past 12 months for estimation. This is due to both much smaller subsamples as well as imperfect data. In addition, as we can see from Table 7, returns lagging more than 12 months have significantly weaker explanatory power.

5.2 Fund returns

Based on the results obtained from the attrition models, hefty self-selection, survivorship and look-ahead bias may be expected from the reported returns during the financial crisis. These biases are expected to both exaggerate hedge fund's true returns as well as performance persistence

While survivorship has been frequently studied in academia, look-ahead bias has received less attention. In other words, most academic studies have simulated performance based on information that was not available at the time of the trade - such as a monthly earnings that was released six months later. Without correcting for the effect of look-ahead bias, the obtained results diminish the accuracy of the trader's true performance.

Using the method introduced in section 4.2.2, in order to eliminate survivorship and look-ahead bias, a weighting procedure based upon aforementioned probit regression results is used. The correction multiplier is equal to conditional non-attrition probability divided by conditional attrition probability (obtained from the probit) for each fund and time specific observation.

In order to test for true performance persistence, we will first need to examine the returns of the sample used. In the chart below I have sorted funds into decile portfolios according to their monthly performance with one month lag. These portfolios are conducted as equal-weighed portfolios as opposed to value-weighted due to the lack of AuM data in many observations.[42] In the first table (Table 9) funds have been sorted using raw returns and in the latter table (Table 10) returns have been corrected using fund and time specific multiplier.

[42] Tolonen et al. (2013) noted that the excess in reported returns for value-weighted portfolio compared to equal-weighted portfolio is also lower.

TABLE 9 Reported and corrected annual returns for decile portfolios 2007-2010						
Decile	**Raw returns**		**Corrected returns**		***Difference***	***P>|t|****
	Mean	Stdev	Mean	Stdev		
1	-24.10	16.10	-41.73	49.17	*-17.63*	*0.000*
2	-9.63	12.21	-9.44	12.11	*0.19*	*0.000*
3	-5.17	10.61	-5.02	10.26	*0.15*	*0.000*
4	-2.10	9.72	-1.84	9.52	*0.25*	*0.000*
5	0.44	9.08	0.61	8.59	*0.17*	*0.000*
6	3.32	8.24	3.25	7.90	*-0.08*	*0.000*
7	6.79	6.94	6.54	6.89	*-0.25*	*0.000*
8	11.22	6.77	10.83	7.09	*-0.39*	*0.000*
9	17.97	9.34	17.57	10.13	*-0.40*	*0.000*
10	40.95	20.19	39.36	20.94	*-1.60*	*0.000*
Total	**3.97**	**20.21**	**2.01**	**27.17**	***-0.40***	***0.000***

Table 9: Reported and corrected annual returns for decile portfolios 2007-2010
The difference between raw and corrected returns is heavily skewed towards the poor performing fund.

TABLE 10 Reported and corrected monthly returns for decile portfolios 2007-2010						
Decile	**Raw returns**		**Corrected returns**		***Difference***	***P>|t|****
	Mean	Stdev	Mean	Stdev		
1	-0.43	4.30	-0.51	4.65	*-0.07*	*0.000*
2	-0.11	2.51	-0.10	2.54	*0.00*	*0.015*
3	-0.03	1.95	-0.01	2.01	*0.02*	*0.000*
4	0.08	1.62	0.07	1.67	*-0.01*	*0.000*
5	0.16	1.55	0.17	1.55	*0.01*	*0.000*
6	0.29	1.51	0.28	1.58	*-0.01*	*0.000*
7	0.45	1.35	0.35	1.56	*-0.10*	*0.000*
8	0.72	1.48	0.63	1.76	*-0.08*	*0.000*
9	0.96	1.87	0.88	2.11	*-0.09*	*0.000*
10	1.71	3.41	1.80	3.82	*0.09*	*0.000*
Total	**0.38**	**2.42**	**0.36**	**2.61**	***-0.03***	***0.000***

Table 10: Reported and corrected monthly returns for decile portfolios 2007-2010

**T-test conducted using Newey-West estimator, which eliminates the problems arising with autocorrelation and heteroskedasticity in time series data.*

Table 9 shows each decile portfolio's annual average return during the 2007-2010 time period. The raw data indicates that worst performing decile on average in this three year period has made an annual loss of 24.1%, while the winning portfolio has generated a profit of nearly 40.95%. However, the returns corrected from survivorship and look-ahead bias indicate that in fact, the true performance of the loser portfolio seems to be as low as 41.73% on an annual level. This finding suggests that the difference between the reported returns and true performance on an annual level may be as high as 17.63%. Since the corrected returns take into account conditional attrition probability, it can be concluded that this phenomenon is due hedge fund's unregulated reporting as well as fund manager's ability to report historical performance by back-filling. At an annual level, all results are significant at 99% confidence level.

In addition, there is a staggering difference between standard deviation between raw and corrected returns in the loser portfolio – this suggests that losing portfolios take upon excessive amounts of risk and once the losses become inevitably large, they may choose exit the database. Therefore, apart from the fact that hedge funds have the ability to hide their poor performance, this involuntary reporting of hedge funds also hides their true riskiness.

The same data may be sorted on a monthly level, which is presented in Table 10. On a monthly level, the corrected average return of each decile portfolio (apart from the winning portfolio) is lower than reported returns. This on the hand suggests that nearly all funds (except the ones in the winning portfolio) have the tendency to exaggerate their performance.

Compared to previous academic research, these findings indicate that self-selection and look-ahead bias was more severe during the financial crisis. Using data from 1994-2000, Ter Horst et al. (2007) studied hedge fund liquidation and found that look-ahead bias and self-selection may lead to overestimating expected returns by as much as 8% per year. Baquero et al. (2005) – employing the same technique as used in this thesis found – fund liquidation due to look-ahead bias and self-selection overstated the returns by 3.8% in the same time period. Both these papers concentrated on fund liquidation as opposed to overall attrition, however, this still does not explain the fact that the difference between reported and corrected performance during financial crisis was as high as 17.6%.

There are several possible explanations for why over-reporting returns was even more severe during the financial crisis. Firstly, it is likely that during the financial crisis, competition for potential investors between hedge funds became much more tough during the financial crisis as liquidation in the market had dried up. Commercial databases often act as the only channel for hedge funds to promote themselves, self-selection and back-filling information became more common. In fact, from Table 4 one can see that number of new funds entering the database during 2008-2010 remained fairly stable. If poor returns cause fund attrition, it makes sense that positive returns are the cause for funds entering the database. Also, these finding do not support the claim that hedge funds would stop reporting due to good performance as they are no longer trying to attract new investors. The top performing funds exhibit no downwards biased reported returns on an annual level.

Secondly, hedge funds were largely blamed for the financial crisis. In addition to this, they were unable to generate their promised "market neutral" returns. In order to "save face", an aesthetic facelift for the industry was required. This could be done by back-filling returns of well-performing funds as well as liquidation those that could not continue to perform. This could, at least, give the impression that hedge funds were able to diversify away from the market risk despite of holding and trading large levels highly controversial instruments.

5.3 Performance persistence

Using the decile portfolios we can further examine performance persistence during the financial crisis. For each winning fund at time *t*, I have obtained the probability for each fund to be allocated to the winning portfolio at *t+1*. In order to examine whether true performance persistence exists, this two-period calculation is conducted both on a monthly and annual level, as it is expected that performance persistence diminishes through time. This two-period framework is done for both raw and corrected returns in order to test whether spurious returns also lead to spurious performance persistence.

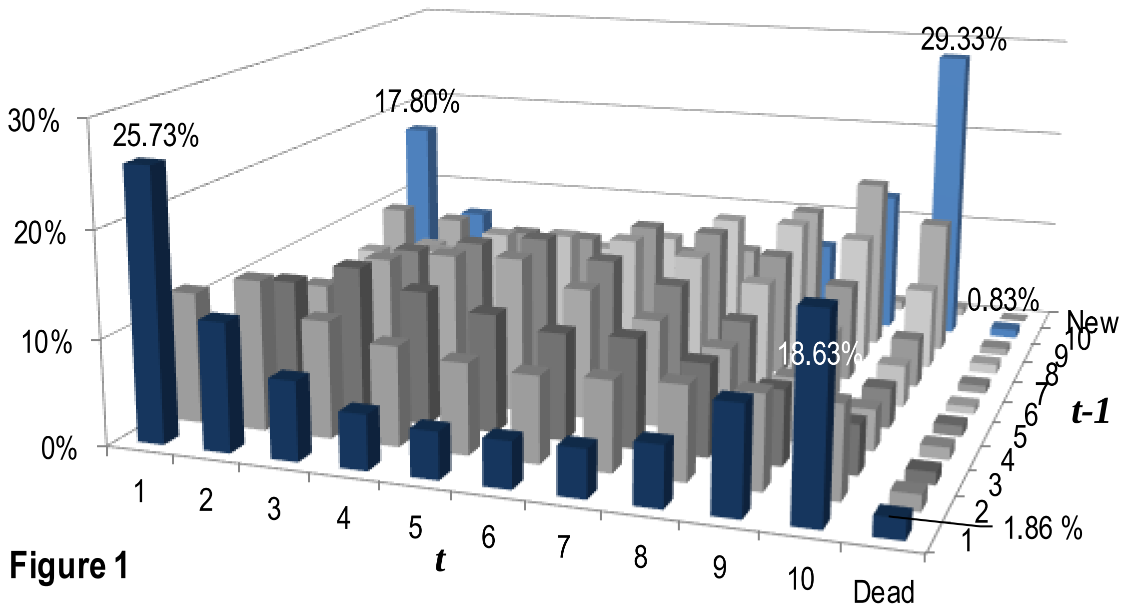

Figure 1: Monthly performance persistence (raw returns)

Unconditional monthly probability for funds to be allocated from one decile portfolio into another, computed from reported returns. Funds in extreme portfolios continuously exhibit the highest probabilities to be allocated into an extreme portfolio in the next month throughout 2007-2010.

Figure 1 shows the contingency for monthly raw performance. In each month, funds are ranked into 10 deciles and compared with their rank in the previous month. "Dead" indicates the probability of fund being removed from the database in the next month – the probability for a fund being ranked in the decile 1 (worst performing decile) to be removed from the database in the next period is 1.86%. The same probability for a fund performing in decile 10 (top performing decile) to die in the next month is 0.83%. New funds entering the database ("New") are also incorporated. Note that funds with age less than 1 year have been removed from this study in order to control for back-filling caused look-ahead bias, therefore probability for a new fund to exit the fund in the next period is 0%.

Funds in the top decile (decile 10) have a probability of 29.33% of being in the top decile in the next month and have a probability of 17.80% being in the worst performing decile (decile 1). Funds starting from the decile 1 have the probability of 19% being in the top performing decile in the next month and 25.73% probability for being in the worst performing decile for another month. It seems that funds exhibiting most volatility have the tendency to allocate into top and bottom decile portfolios, which is expected as risky funds have a more volatile performance pattern. This is also the reason why funds in decile 10 have a fairly high probability to die, despite of good performance. The results are similar to many previous studies showing short-term performance persistence (see e.g. Agarwal and Naik (2000), Edwards and Caglayan (2001))

TABLE 11

Difference in monthly performance persistence in corrected returns and raw returns 2007-2010

Decile	1	2	3	8	9	10
1	-1.35 %	-0.18 %	-0.84 %	0.46 %	0.72 %	0.60 %
2	0.21 %	-1.07 %	-0.14 %	-0.01 %	1.08 %	-0.23 %
3	-0.37 %	-0.26 %	-0.89 %	0.27 %	-0.10 %	0.30 %
8	-0.10 %	0.38 %	0.81 %	-0.59 %	-0.32 %	-0.16 %
9	0.47 %	0.02 %	-0.21 %	0.21 %	-1.32 %	0.46 %
10	-0.51 %	-0.22 %	-0.03 %	-0.04 %	0.66 %	-0.60 %

Table 11 : Difference between raw and corrected monthly performance persistence 2007-2010
Figures show the percentage point difference in unconditional probability when computed using corrected returns vs. reported returns. A positive number indicates that corrected returns generate a higher probability.

In order to see whether look-ahead bias and self-selection lead to spurious performance, Table 11 shows the difference between the reported and corrected performance persistence in the bottom 3 and top 3 deciles. The allocation at time *t-1* is shown in the row and the columns are the allocation at time *t*. Combined with Figure 1, Table 17 shows the change in performance persistence measured in corrected returns. For instance, the probability for a top 10 fund to be allocated in best performing decile measured in corrected returns is 28.73%, which is 0.60% less than measured in raw returns. This table shows several important findings.

Firstly, in most cases, the corrected returns show a weaker performance persistence than raw returns (red cells indicate weaker performance persistence by percent points). However, the weakening performance persistence is also found in bottom deciles; funds that performed worst in the last period now has a 1.35% smaller probability to be allocated in the worst performing fund also in next period, measured in corrected return. The explanation for this is due to the fact that corrected returns simulate the performance by excluding self-selection, which in turn skews the returns more to the left.

Secondly, there seems to be a higher probability for bottom funds to be allocated into top funds when measured in corrected returns. As discussed in the previous section, corrected returns implied a much higher volatility than found in reported returns. This effect – fund performance fluctuating between deciles can be seen in the predominantly green top right area in Table 16; the corrected returns exhibit a higher percentage of funds jumping from bottom deciles to top deciles. Increased tendency for funds to fluctuate between deciles indicate a lower persistency in corrected returns.

Finally, positive performance persistence in the top decile drops as hypothesized. However, by expanding the focus to decile 9, the corrected returns indicate a higher contingency. It would thus seem that reported returns do exaggerate performance persistence, however, some level of performance persistence is definitely observed in the short term. Nonetheless, this phenomenon may be easily attributed to to common factor exposures such as size, book-to-market and momentum, as argued by Carhart (1997).

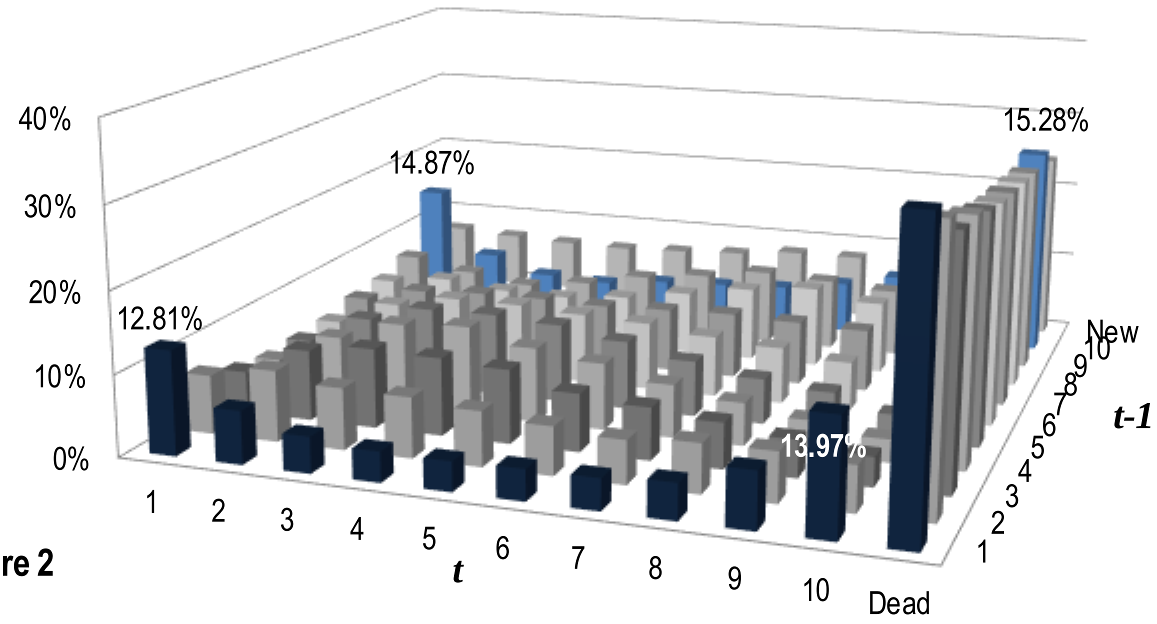

Figure 2: Annual performance persistence (raw returns)

Unconditional annual probability for funds to be allocated from one decile portfolio into another, computed from reported returns. Funds in extreme portfolios continue to exhibit a higher probability to be allocated into extreme folios, but are even more likely to be dead by the next year.

If short-term persistence is due to common factor exposures instead of managerial skills, in the long-term, performance persistence is expected to decrease. Figure 2 shows performance persistence measured using annual decile portfolio, computed using raw returns. Compared to the monthly data, it is evident that contingency diminishes with a longer time horizon. In fact, the probability for a top performing fund being allocated in the top performing decile in the following year is 15.28%, but has a simultaneously 14.87% probability being allocated in the bottom decile as well. The difference between these probabilities is a mere 0.39%, which can barely be considered as an indication for persistency in returns, but more as a sign of high volatility in extreme portfolio funds.

TABLE 12 Difference in annual performance persistence in corrected returns and raw returns 2007-2010						
Decile	**1**	**2**	**3**	**8**	**9**	**10**
1	-1.60 %	-1.01 %	-0.95 %	0.40 %	0.73 %	0.79 %
2	-0.43 %	-1.37 %	-1.84 %	0.12 %	1.12 %	1.36 %
3	0.41 %	-1.80 %	-3.35 %	1.77 %	0.84 %	0.51 %
8	-0.29 %	0.04 %	0.49 %	-2.04 %	-1.92 %	0.09 %
9	0.86 %	1.19 %	0.67 %	-1.19 %	0.18 %	0.52 %
10	-1.23 %	0.45 %	0.32 %	-0.74 %	0.64 %	-0.31 %

Table 12: Difference between raw and corrected annual performance persistence 2007-2010
Figures show the percentage point difference in unconditional probability when computed using corrected returns vs. reported returns. A positive number indicates that corrected returns generate a higher probability.

In fact, Table12 shows that performance persistence diminished even more measured in corrected returns. These findings are similar to those in Table 11, where corrected returns skew down performance persistence on an monthly level. Measured in corrected returns, the unconditional probability for top performing fund to continue its winning path into the following year is now 14.97%, while for a losing fund to achieve the winning status for the next year is 14.76%. As one can see, after correcting for self-selection, there are barely any signs of persistency in hedge fund performance.

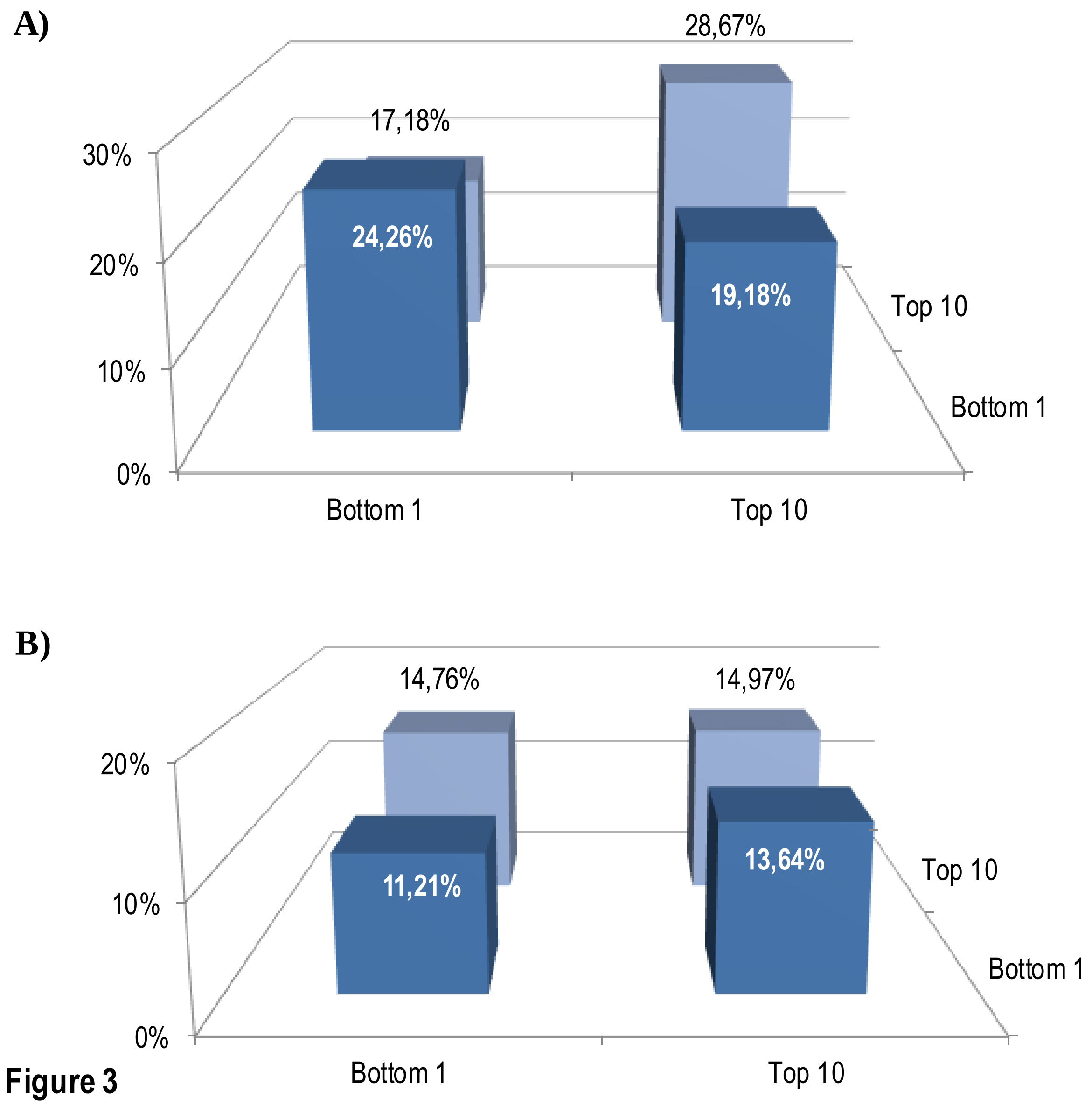

Figure 3

A) *Corrected performance persistence on top and bottom deciles monthly. Positive performance persistence (Top 10 -> Top 10) is evident on a monthly scale.*

B) *Corrected performance persistence on top and bottom deciles annually. Persistency found in short-term has clearly diminished on an annual level. Negative performance persistence (Bottom 1->Bottom 1) is slightly lower than positive persistency, which may be driven by poor performing funds dying.*

Figure 3: Corrected performance persistence on top and bottom deciles monthly and annually

Figure 3 further illustrates how corrected returns show performance persistence diminishing by focusing only on top and bottom performing deciles. The x-axis shows fund allocation at *t-1* and z-axis shows allocation at *t*. On the y-axis is the probability for this allocation. It is evident that persistency exists on a monthly level (top chart), as the probability for Top 10-Top 10 is significantly higher than any other probabilities at 28.67%. Although negative performance persistence is strong as well, it is still over 4% lower than positive performance persistence.

On an annual level, this persistence can be seen to have disappeared (bottom chart). The probability for a top fund to be allocated in the top decile is 14.97% while the probability for a bottom fund to become a top performing fund is 14.76%. The difference on an annual level has diminished into almost non-existent. Similarly, there is a slightly higher probability for a top fund to become a bottom fund than for a bottom fund to remain in the bottom decile, which furthermore shows that any performance persistence that was seen in short-term returns are more or less gone on an annual level.

These results reject null hypothesis for Hypothesis 2 and 3:

H2. Self-selection is more severe during financial crisis, which leads to spurious performance persistence in hedge fund returns

H3. The longer the time horizon, the more ambiguous performance persistence becomes

5.4 The winning and losing strategies

In the previous sections, fund returns and performance persistence were studied and tested using the whole cross-sectional data. In this section, hedge funds are broken down into investment styles and their respective performance during the financial crisis is investigated individually. Further, the hedge funds' returns and performance persistence between investment styles is studied. The ultimate goal is to find distinguishable differences between investment styles and – given the great level of debate as well as number of hedge funds dying during the financial crisis – see whether there was a winning strategy in the volatile crisis era.

5.4.1 Returns by style

For style specific results, I use the probabilities obtained from each investment style specific probit model $Probit(IS_y)$, and divide them by the unconditional attrition probability for the quotient as the correction multiplier.[43] The argument for using *Probit(All)* was due to its overall better fit, however, the model specification would not take into account investment style specific characteristics.

TABLE 13 Average annual return by investment style during 2007-2010						
Investment style*	Raw Mean	Volatility	Corrected Mean	Difference	P>|t|	α**
Convertible arbitrage	7.30	29.01	6.36	-0.93	0.000	0.12
Emerging markets	7.00	32.04	4.80	-2.20	0.000	0.06
Equity market neutral	3.78	15.92	2.77	-1.01	0.000	-0.01
Event driven	2.85	24.50	1.53	-1.32	0.000	-0.06
Fixed income arbitrage	6.12	17.29	4.66	-1.46	0.000	0.10
Fund of funds	0.04	14.54	-0.50	-0.54	0.000	-0.23
Global macro	8.91	18.88	7.60	-1.31	0.000	0.25
Long-short equity hedge	4.66	23.87	3.48	-1.17	0.000	0.02
Managed futures	7.85	17.54	6.47	-1.38	0.000	0.20
Multi-strategy	9.07	19.85	7.56	-1.52	0.000	0.23
All funds	3.97	20.21	2.90	-1.06	0.000	0.00

Table 13: Average annual return by investment style during 2007-2010
Investment Style specific average returns annually 2007-2010. Reported and Corrected average annual returns of each specific investment style.
**Dedicated Short Bias omitted from the table due to insignificant results.*
***Risk-adjusted excess return: All funds mean return used as the theoretical expected return*

Illustrative chart for returns shown in Table 13

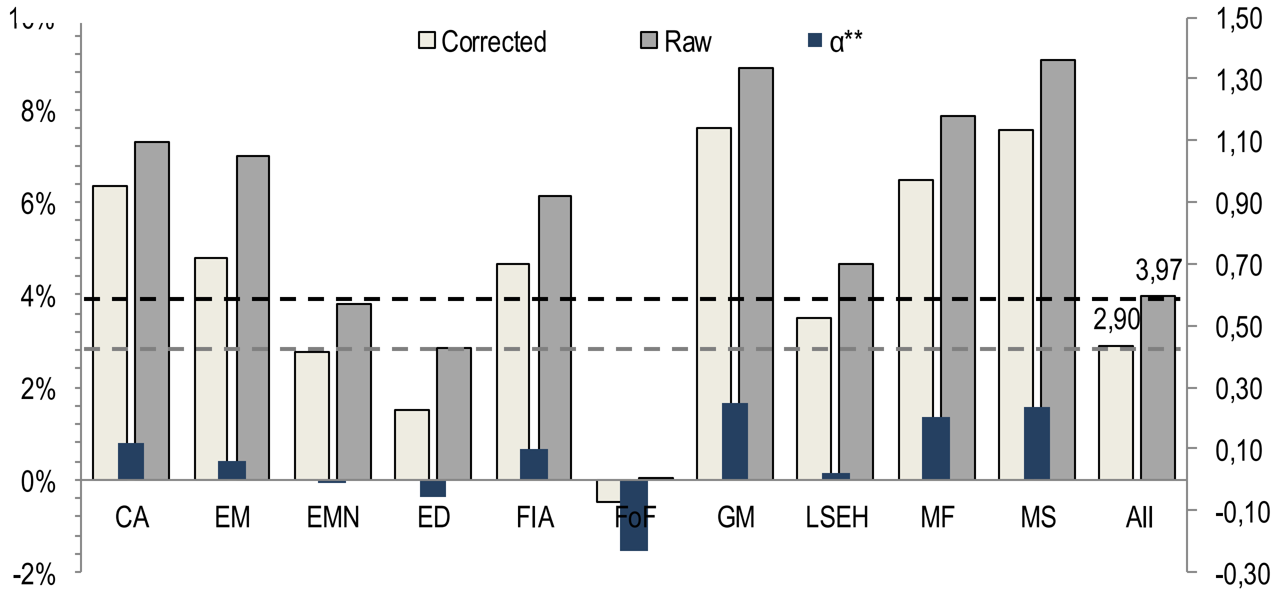

Table 13 shows annual mean returns – both straight from the database and corrected with the multiplier – of each returns investment style. By only comparing mean results, the best performing

[43] The non-conditional liquidation probability is same for Probit(All) and Probit(IS), however, due to different probit output for each fund and time specific observation, the multiplication quotient will be different and hence the corrected returns differ from the previous section

investment style would be either Global Macro or Multi-strategy. On the right hand side, Jensen's alpha for each specific style is calculated, has been calculated using sample mean as the theoretical expected return. The use of alpha enables us to compared each styles risk adjusted returns. Taking into account style-specific volatility, Global Macro and Multi-strategy seem to have been on average performing significantly better than other styles.

Fund of funds – despite of their popularity, has had clearly the worst performance on average. In addition, FOFs exhibits volatility that is lower than the whole data sample's. A possible explanation for this phenomenon could be that FOF managers tend to select funds in order to diversify, which results in selected hedge funds differing across certain dimensions such as size, age, or redemption frequency. The latter aspect may make Fund of funds unattractive during a financial downturn – investors with money tied in Fund of funds may be unable to withdraw their investments due to both underlying funds lock-up period as well and FOF's own restrictions. It is expected that during 2007-2010, investment opportunities generating returns were scarce, which would consequently require hedge fund managers acting quickly in order to make money. The diversification in FOFs decrease implied volatility, however, cumulated lock-up periods, longer redemption notice periods, and less frequent redemptions overall make FOF's investments not worthwhile. This finding contradicts Fung and Hsieh's (2000) argument for using FOFs as proxies in determining hedge fund performance.

TABLE 14
Average annual returns – both raw and corrected – of top and bottom decile portfolios by investment style

Investment style*	**Return for Bottom portoflio (1)**			**Return for Top portfolio (10)**		
	Raw	Corrected	*Difference*	Raw	Corrected	*Difference*
Convertible arbitrage	-29.94	-35.06	*-5.12*	55.82	54.15	*-1.67*
Emerging markets	-35.36	-43.26	*-7.90*	48.94	46.47	*-2.47*
Equity market neutral	-16.80	-19.97	*-3.16*	34.03	32.22	*-1.81*
Event driven	-27.77	-33.64	*-5.87*	47.07	44.47	*-2.61*
Fixed income arbitrage	-24.02	-27.72	*-3.70*	34.65	32.99	*-1.66*
Fund of funds	-20.17	-23.97	*-3.80*	38.95	36.91	*-2.03*
Global macro	-18.22	-20.84	*-2.61*	34.10	32.26	*-1.84*
Long-short equity hedge	-25.89	-30.24	*-4.35*	44.25	42.11	*-2.13*
Managed futures	-15.24	-17.60	*-2.36*	30.32	28.57	*-1.75*
Multi-strategy	-26.29	-31.74	*-5.45*	40.49	38.54	*-1.95*

Table 14: Investment style specific returns for funds ranked in the top and bottom portfolios 2007-2010. The raw returns are corrected using conditional probabilities obtained through Probit(IS_y)
**Dedicated Short Bias omitted from the results due to insignificance in the results*

To examine best and worst performers of the financial crisis, Table 14 presents the returns of top and bottom decile portfolios performance within each investment style (see Appendix for all decile portfolio returns). As expected, there is significant difference between the raw and corrected return. The difference between raw and corrected returns shows that the reported performance is clearly skewed towards both underestimating losses and highlighting returns, with again a greater difference seen in the losing portfolios.

Compared to Table 9 where bottom decile portfolio returns were upwards skewed by 17.63%, style-specifically corrected returns show that the bottom returns are much more moderately skewed. The equal-weighted average of the difference between reported and corrected returns for the losing portfolio is 4.35%. Nonetheless, the difference between reported and true performance is still significantly different. In other words, if the hedge funds were not allowed to liquidate or exit the database freely, the true performance of loser and winning portfolios are 4.35% and 2.05% lower than reported performance, respectively.

The correction multiplier's effect is much smaller when conducted using style specific attrition probabilities. The attrition model conducted investment style specifically showed that funds practicing different strategies had very different thresholds for fund attrition.[44] For example, the attrition model for Convertible Arbitrage showed much more sensitivity towards volatility and short-term returns than those of Emerging Markets. This is logical, as Emerging Markets funds expect their investments to be volatile, whereas Convertible Arbitrage aims minimize volatility while seeking returns. Therefore, it would also seem that for conducting a comparative analysis between investment styles, it is more useful to employ conditional probabilities obtained style-specifically.

The mean returns of extreme portfolios are aligned with implied volatility of each strategy were previously shown in Table 13. As seen from Table 14, while previously Global Macro hedge funds were on average better performing than others, its reported performance of top decile funds do not generate superior results compared to some other investment styles. Consequently, Global Macro's overall good performance stems from its better ability to control left tail losses.

[44] See Appendix 2 for investment style specific attrition model estimates

TABLE 15 Global Macro decile portfolio average annual returns 2007-2010							
Decile	**Raw returns**		**Corrected returns**		***Difference***	***Freq.***	***P>|t|***
	Mean	Stdev	Mean	Stdev			
1	-18.22	12.94	-20.84	16.91	*-2.61*	*10.8 %*	*0.000*
2	-6.97	11.43	-6.97	11.60	*-0.01*	*7.5 %*	*0.000*
3	-2.51	9.37	-2.55	9.20	*-0.04*	*5.3 %*	*0.001*
4	-1.55	10.46	-1.54	10.17	*0.02*	*4.6 %*	*0.010*
5	2.21	8.76	2.14	8.36	*-0.07*	*5.7 %*	*0.000*
6	5.15	7.50	4.92	7.17	*-0.23*	*8.9 %*	*0.000*
7	6.89	6.55	6.60	6.48	*-0.29*	*10.3 %*	*0.000*
8	10.19	6.05	9.82	6.45	*-0.38*	*12.5 %*	*0.000*
9	16.88	8.47	13.10	19.77	*-3.78*	*15.2 %*	*0.000*
10	34.10	15.20	32.26	14.97	*-1.84*	*19.0 %*	*0.000*
Total	**8.91**	**18.88**	**7.60**	**20.16**	***-0.40***	***100 %***	***0.000***

Table 15: Reported and corrected average annual returns of Global Macro funds in each decile portfolio during 2007-2010
'Difference' shows the upwards bias of raw returns compared to corrected returns. "Frequency" stands for the portion of Global Macro hedge fund observations to be categorized and allocated into each decile. Stdev shows the implied volatility within each decile GM funds.
T-test conducted using Newey-West estimator, which eliminates the problems arising with autocorrelation and heteroskedasticity in time series data.

As shown previously in Table 13, Global Macro on average delivered highest returns, both measured in corrected returns as well as in risk-adjusted terms. Table 15 shows the mean of all Global Macro funds that have been allocated into each subsequent decile The "Total" row illustrates the average annual return of Global Macro funds during the financial crisis (as shown in Table 13), which was 8.91% and 7.6% measured in raw and corrected returns, respectively.

The number of funds in each decile is different, since the initial sorting into decile was conducted with all funds in data sample; frequency (*Freq.*) shows the number of occurrences of the said investment style within each decile portfolio. The table above shows that 19% of Global Macro fund monthly returns observations would be considered as top performers, which is obviously above average. 65.9% of Global Macro funds were allocated in the top 50% decile portfolios. While 10.8% of Global Macro funds were allocated in the loser portfolio. Overall, it is safe to say that Global Macro funds emerged as one of the winning strategies from the financial crisis.

TABLE 16 Multi-strategy decile portfolio average annual returns 2007-2010							
Decile	**Raw returns**		**Corrected returns**		***Difference***	***Freq***	***P>|t|***
	Mean	Stdev	Mean	Stdev			
1	-26.29	16.79	-31.74	21.25	*-5.45*	*7.2 %*	*0.394*
2	-10.11	12.22	-10.10	12.42	*0.01*	*5.5 %*	*0.000*
3	-4.75	10.51	-4.74	10.31	*0.00*	*5.2 %*	*0.000*
4	0.53	9.63	0.37	9.29	*-0.16*	*6.1 %*	*0.000*
5	4.61	7.73	4.46	7.41	*-0.16*	*7.8 %*	*0.000*
6	6.48	6.93	6.19	6.67	*-0.29*	*10.4 %*	*0.000*
7	8.53	5.92	8.19	5.94	*-0.33*	*13.6 %*	*0.000*
8	11.05	6.44	10.66	6.78	*-0.39*	*15.2 %*	*0.000*
9	16.22	8.74	11.70	21.44	*-4.52*	*15.8 %*	*0.000*
10	40.49	20.81	38.54	20.71	*-1.95*	*13.1 %*	*0.000*
Total	**9.07**	**19.85**	**7.56**	**21.72**	***-1.52***	***100 %***	***0.000***

Table 16: Reported and corrected average annual returns of Multi-strategy funds in each decile portfolio during 2007-2010
'Difference' shows the upwards bias of raw returns compared to corrected returns. "Frequency" stands for the portion of Multi-strategy hedge fund observations to be categorized and allocated into each decile. Stdev shows the implied volatility within each decile MS funds.
T-test conducted using Newey-West estimator, which eliminates the problems arising with autocorrelation and heteroskedasticity in time series data.

Measured in absolute returns, Multi-strategy funds exhibited, on average, best performance during 2007-2010 (Table 13). Combined with the fact that at 18%, it also had the lowest attrition rate within the whole dataset (see Table 1), Multi-strategy appears as a lucrative investment style in the time period. Out of the entire data sample, 18.8% of all funds were labeled as practicing Multi-strategy as their primary investment style, making Multi-strategy one of the most popular investment styles.

Table 16 offers more insight into Multi-strategy funds' performance. Compared to Global Macro, its corrected returns show reported returns being more upwards skewed. In both cases, returns in decile 9 are remarkably more skewed than funds in the top decile, indicating that truly top performing funds are less likely to be reported selectively. Funds that are performing unusually well but do not reach the top 10th percentile are more likely to be exaggerated through self-selective reporting. Note that this effect was not found when the returns were corrected using the residual values of attrition model Probit(All) (see Table 9).

68.1% of all Multi-strategy hedge funds are allocated above the 50th percentile while less than 20% of funds were in the bottom 3 performing deciles. Although Multi-strategy's risk-adjusted returns were slightly behind those of Global Macro's, given its prevalence in the data set, overall Multi-strategy funds have outperformed other styles during the financial crisis.

TABLE 17 Emerging Markets annual return 2007-2010							
Decile	Raw returns		Corrected returns		*Difference*	*Freq*	*P>|t|*
	Mean	Stdev	Mean	Stdev			
1	-35.36	17.19	-43.26	21.02	*-7.90*	*17.9 %*	*0.087*
2	-17.70	13.13	-17.80	13.43	*-0.10*	*8.0 %*	*0.342*
3	-10.07	10.96	-9.95	10.76	*0.12*	*6.0 %*	*0.351*
4	-3.62	9.68	-3.50	9.38	*0.12*	*4.8 %*	*0.867*
5	0.12	8.46	0.20	8.03	*0.08*	*5.7 %*	*0.009*
6	3.11	7.99	3.00	7.64	*-0.12*	*6.2 %*	*0.911*
7	6.83	6.65	6.51	6.56	*-0.31*	*6.5 %*	*0.817*
8	13.15	7.15	12.67	7.41	*-0.48*	*9.4 %*	*0.000*
9	20.99	9.68	19.68	13.13	*-1.31*	*13.2 %*	*0.000*
10	48.94	21.52	46.47	21.72	*-2.47*	*22.2 %*	*0.000*
Total	**7.00**	**32.04**	**4.80**	**33.78**	***-2.20***	***100 %***	***0.000***

Table 17: Reported and coorrected annual returns of Emerging Markets funds found in each decile portfolio during 2007-2010
'Difference' shows the upwards bias of raw returns compared to corrected returns. "Frequency" stands for the portion of Emerging Markets hedge fund observations to be categorized and allocated into each decile. Stdev shows the implied volatility within each decile EM funds.
T-test conducted using Newey-West estimator, which eliminates the problems arising with autocorrelation and heteroskedasticity in time series data.

The winners of Emerging Markets funds were able to generate higher returns than any other strategy, even after correcting for self-selection and look-ahead bias. A quick glance at Table 17 reveals that Emerging Markets funds are highly volatile; while 22.2% over Emerging Markets returns wound up in the top portfolio, at the same time 17.9% of EM fund returns were in the loser portfolio. It would seem that the astounding returns generated by Emerging Markets funds are, in fact, driven by its high-risk high-return investments.

There is also a substantial upwards bias in the worst Emerging Markets funds; the difference between raw and corrected returns is 7.9%. Albeit the corrected return is significant at 90% confidence interval, this would still indicate that Emerging Markets hedge funds practice a high level of self-selection and back-filling of their returns. Given that many Emerging Markets funds wound up making tremendous losses, it is not surprising that EM managers are more likely to report their fund performance with a delay.

TABLE 18 Funds of funds decile portfolio average annual returns 2007-2010							
Decile	**Raw returns**		**Corrected returns**		***Difference***	***Freq***	***P>|t|***
	Mean	Stdev	Mean	Stdev			
1	-20.17	14.10	-23.97	18.39	*-3.80*	*6.5 %*	*0.000*
2	-8.69	11.76	-8.67	11.96	*0.02*	*11.8 %*	*0.000*
3	-4.96	10.55	-4.94	10.37	*0.02*	*15.0 %*	*0.001*
4	-2.67	9.76	-2.57	9.47	*0.09*	*15.6 %*	*0.010*
5	-0.81	9.36	-0.69	8.91	*0.12*	*14.3 %*	*0.000*
6	2.47	8.54	2.38	8.16	*-0.10*	*12.0 %*	*0.000*
7	6.82	7.16	6.49	7.05	*-0.33*	*9.9 %*	*0.000*
8	11.28	6.63	10.77	6.85	*-0.52*	*7.3 %*	*0.000*
9	16.39	8.17	12.54	19.41	*-3.85*	*5.1 %*	*0.000*
10	38.95	19.19	36.91	18.88	*-2.03*	*2.6 %*	*0.000*
Total	**0.04**	**14.54**	**-0.50**	**15.25**	***-0.54***	***100 %***	***0.000***

Table 18: Reported and Corrected Annual returns of Funds of Funds found in each decile portfolio during 2007-2010
'Difference' shows the upwards bias of raw returns compared to corrected returns. "Frequency" stands for the portion of Funds of funds hedge fund observations to be categorized and allocated into each decile. Stdev shows the implied volatility within each decile FOF funds.
T-test conducted using Newey-West estimator, which eliminates the problems arising with autocorrelation and heteroskedasticity in time series data.

The results for Funds of funds were unexpectedly disappointing. Commonly, considered as the "market portfolio of hedge funds", Funds of funds performance exceptionally bad during the financial crisis, significantly below the average. Its low risk strategic approach rarely placed them in the top performing decile as only 2.6% of FOFs were attributed as best performers.

A surprising fact is the high popularity of FOFs; within this data sample, 36% of individual funds and 39% of the individual observations were categorized primarily as FOFs. Given its extremely bad performance, one could argue whether FOFs increasing popularity is justified. It would seem that the popularity FOFs stems from the demand of individual investors, as hedge funds typically contain high degree of fund specific risks and the lack of transparency challenges investors to conduct proper due diligence. However, as Brown et al. (2003) already noted, the disappointing after-fee performance of some fund of funds may be explained by the nature of the "fees on fees" arrangement. The principal advantages of the FOF arrangement is that it allows for diversification, but in fact, the more diversified the fund is, the greater is the likelihood that an investor will incur an incentive fee regardless of overall fund performance.

Seeing as FOFs clearly underperforming all other strategies, one should also question whether it is reasonable to consider FOFs as benchmark proxies for hedge fund performance.

5.4.2 Performance persistence between styles

While the returns can offer an intuitive guess on the winning style, in order to conclude whether Global Macro and Multi-strategy are truly better strategies than others, it is important to test for their persistency. Agarwal and Naik (2000) concluded that performance persistence – if exists as such – is due to losers continuing to be losers, instead of finding evidence in neither positive performance persistence nor difference between styles. However, it is expected that in an exceptionally disastrous market environment such as the 2007 financial crisis, certain investment styles may have the ability to outperform others consistently.

TABLE 19

2007-2010	Monthly performance persistency on top and bottom deciles					
Investment Style	**Bottom 10 %**			**Top 10%**		
	Raw	**Corrected**	*Difference*	**Raw**	**Corrected**	*Difference*
Convertible arbitrage	26.32 %	22.30 %	*-4.02 %*	41.20 %	36.30 %	*-4.90 %*
Dedicated short bias*	38.82 %	42.35 %	*3.53 %*	23.30 %	21.90 %	*-1.40 %*
Emerging markets	33.33 %	31.55 %	*-1.78 %*	36.00 %	37.40 %	*1.40 %*
Equity market neutral	22.20 %	19.76 %	*-2.44 %*	19.80 %	13.40 %	*-6.40 %*
Event driven	25.39 %	21.90 %	*-3.49 %*	27.90 %	27.10 %	*-0.80 %*
Fixed income arbitrage	24.48 %	25.45 %	*0.97 %*	20.20 %	21.50 %	*1.30 %*
Fund of funds	19.01 %	16.77 %	*-2.24 %*	20.30 %	21.90 %	*1.60 %*
Global macro	28.04 %	24.83 %	*-3.21 %*	29.50 %	27.00 %	*-2.50 %*
Long-short equity hedge	25.02 %	23.79 %	*-1.23 %*	28.70 %	26.70 %	*-2.00 %*
Managed futures	30.09 %	29.96 %	*-0.13 %*	33.50 %	32.80 %	*-0.70 %*
Multi-strategy	26.34 %	20.94 %	*-5.40 %*	31.40 %	28.90 %	*-2.50 %*
All funds	**25.73 %**	**24.34 %**	***-1.39 %***	**29.33 %**	**28.75 %**	***-0.58 %***

Table 19: Investment style specific probabilities for being allocated to the same top or bottom decile for two consecutive months
**Data sample for Dedicated Short Bias not sufficient enough to produce significant results*

Short-term performance persistence between different fund styles is highlighted above (Table 19). As expected, performance persistence measured in corrected returns show a slightly lower contingency. Hedge funds practicing directional strategies or short-term arbitrages such as Convertible Arbitrage and Emerging Markets, exhibit very strong monthly persistence. This short-term persistence within these styles are easily attributed to momentum, which is inherent within their strategy. The fact that the negative persistence is also extremely high for Emerging Markets supports this argument.

Due to the nature of directional strategies, it is expected that they exhibit strong short-term persistency in returns; it's typical for the underlying asset to have a strong trend in its short-term performance, which often evens out in the longer term. Therefore, short-term persistence may be more related to the underlying investment strategy instead of attributed to any specific manager's skill.

2007-2010	TABLE 20 Annual performance persistency on top and bottom deciles					
Investment Style	Bottom 10 %			Top 10%		
	Raw	Corrected	*Difference*	Raw	Corrected	*Difference*
Convertible arbitrage	15.2 %	11.5 %	-3.7 %	13.7 %	16.8 %	3.1 %
Dedicated short bias*	27.3 %	35.8 %	8.5 %	1.2 %	0.0 %	-1.2 %
Emerging markets	13.5 %	10.5 %	-3.0 %	21.3 %	19.7 %	-1.6 %
Equity market neutral	16.0 %	12.2 %	-3.9 %	6.5 %	6.2 %	-0.2 %
Event driven	14.0 %	7.5 %	-6.5 %	15.2 %	12.6 %	-2.6 %
Fixed income arbitrage	13.7 %	14.6 %	0.9 %	10.5 %	15.1 %	4.7 %
Fund of funds	10.1 %	8.7 %	-1.4 %	10.8 %	8.8 %	-2.0 %
Global macro	10.2 %	5.8 %	-4.4 %	14.6 %	13.7 %	-0.9 %
Long-short equity hedge	12.9 %	12.5 %	-0.4 %	14.4 %	12.4 %	-2.0 %
Managed futures	13.0 %	12.4 %	-0.6 %	17.5 %	15.5 %	-2.0 %
Multi-strategy	15.2 %	6.6 %	-8.6 %	14.2 %	19.8 %	5.7 %
All funds**	**12.8 %**	**11.21 %**	**-1.6 %**	**15.3 %**	**15.0 %**	**-0.3 %**

Table 20: Investment style specific probabilities for being allocated to the same top or bottom decile for two consecutive years
**Data sample for Dedicated Short Bias not sufficient enough to produce significant results*

A smart fund manager has the skills the change their position before the turning point, which we would see as long-term performance persistence. Looking at Table 19, which presents the annual performance persistence of different styles, there are several findings that can be concluded. Firstly, as expected, performance persistence diminishes with all styles with a longer time horizon. Secondly, as opposed to Agarwal and Naik (2000) findings, performance persistence is effectively found on the positive returns and there are significant differences between styles even on the long term.

Measured in corrected returns, Emerging Markets and Multi-strategy have the highest positive persistency in returns. While Global Macro generated the best returns, its ability to perform persistently is slightly below average, which is unexpectedly disappointing due to its technical investment approach together with long-term investment horizon.

A closer look reveals that conducted on corrected returns decrease negative and increase positive persistency for Multi-strategy. This is most likely due to the fact that Multi-strategy funds exhibit lower than average attrition rates, indicating less self-selection actions from fund managers than in the other styles. The corrected ranking showed that Multi-strategists have been able to truly perform consistently well (Figure 5).

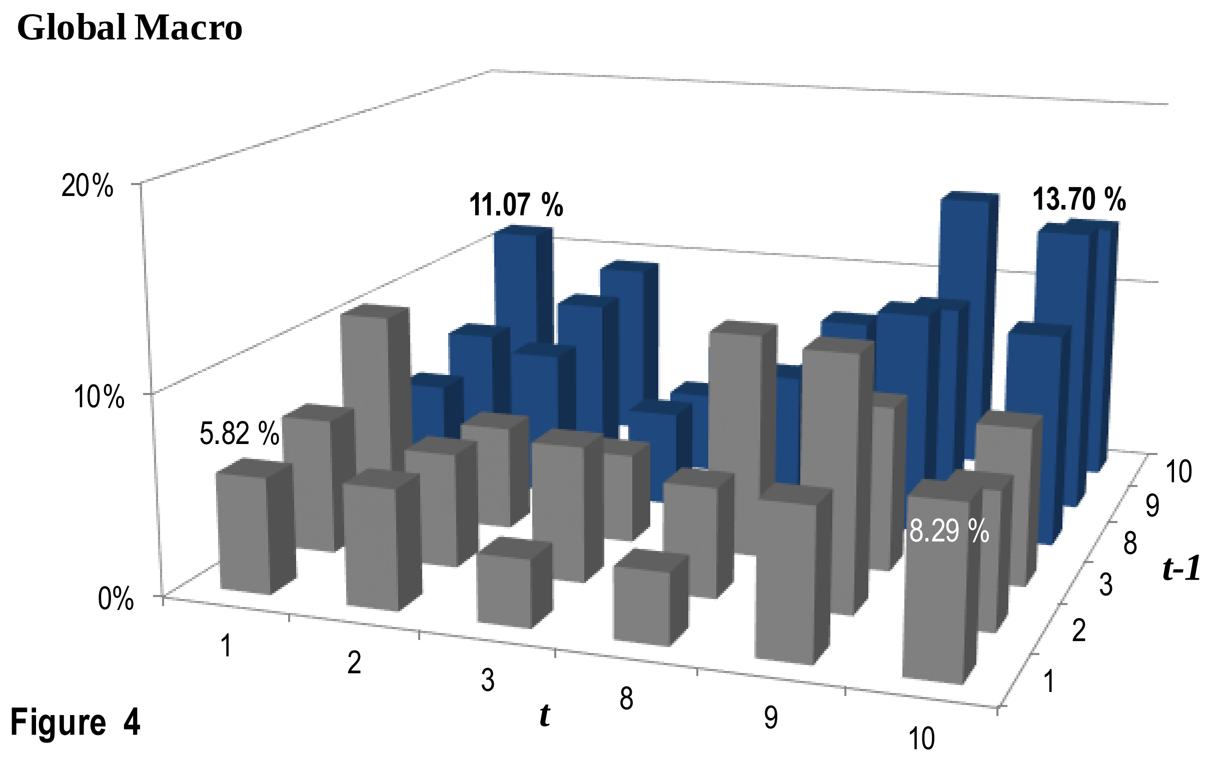

Figure 4: Corrected performance persistence for Global Macro hedge funds measured annually for top 3 and bottom 3 performing deciles.

Figure 4 illustrates Global Macro fund performance persistence of top 3 and bottom 3 decile portfolios. A certain level ofpositive performance persistence may be observed within the Global Macro funds, seeing as the probability positive persistence on annual level is at 13.70% in decile 10. Nonetheless, a higher performance persistence could have been expected from Global Macro as well, given the fact that 19% of all Global Macro fund observations were ranked in the winning portfolio (Table 15).

This level of persistency would indicate that exceptional performance by GM funds were coincidental and achieved by several different hedge funds instead of exceptional managerial skills by several fund managers. Nonetheless, these GM managers may have employed same strategies simultaneously, causing the high frequency of GM funds found in the winner portfolio. Nonetheless, the moderately high frequency of appearing in the losing portfolio (10.8%) also signals that Global Macro strategies failed very so often. This would not be surprising,, as many economic fundamentals did not drive the market into the anticipated direction during the financial crisis.

Based on the level of persistency found in the long-run, it does not seem that Global Macro funds managers were able to produce superior results consistently.

Multi-strategy

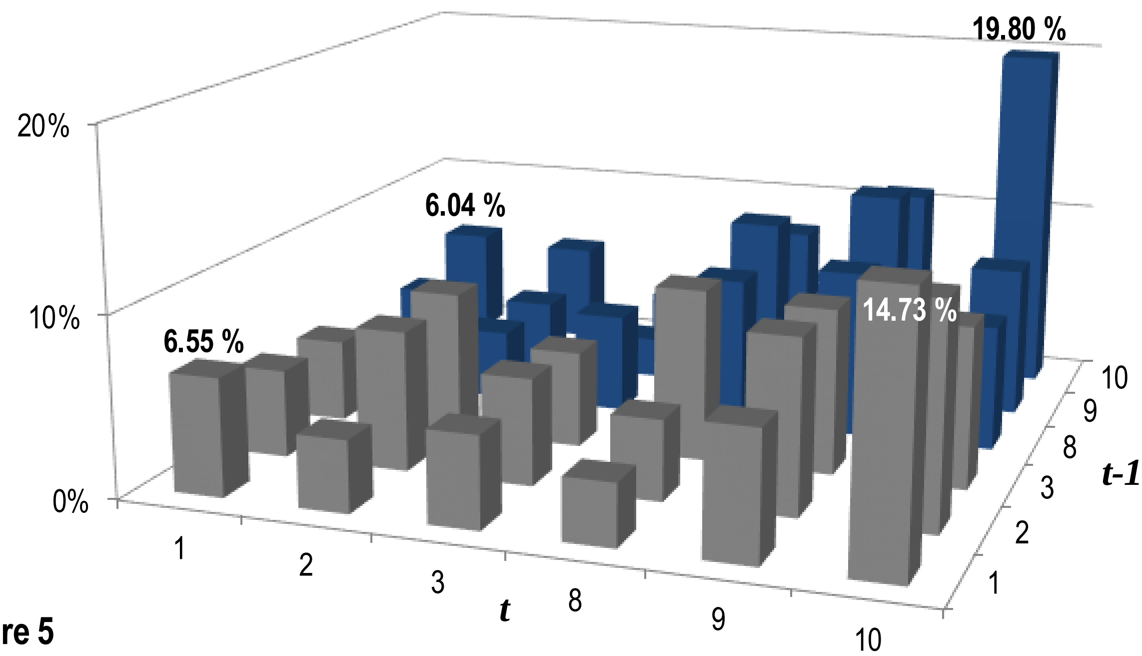

Figure 5

Figure 5:Corrected performance persistence for Multi-strategy hedge funds measured annually for top 3 and bottom 3 performing deciles.

Multi-strategy performance was an uplifting surprise in the financial crisis. From chart above (Figure 5) one can see that there is visibly long-term performance persistence in the Multi-strategy hedge funds. While certain level of persistency may be attributed to volatility, persistence in Multi-strategy funds is mostly positive. Negative performance persistence is extremely low 6.55% and on the other hand, the probability for a bottom fund being in the top the following year is 14.73%. It is also noteworthy to remember that attrition rate for Multi-strategy funds were 18% during the financial crisis, while the sample average was 29.9%; therefore this positive performance persistence is also unlikely be due to inability to correct for proper fund attrition.

The exceptional performance of Multi-strategy during the financial crisis is attributed to its ability to frequently change its position and strategy accordingly to the market. This would indicate that returns by Multi-strategy funds are, in fact, generated by truly skillful managers with the ability to predict the changes in the economy. In addition, it could expected that Multi-strategy managers are required to obtain a larger set of skills, as they undertake more than one strategic approach at a time.

As seen previously in Table 13, Multi-strategy had the ability to generate highest absolute returns and second highest returns on risk-adjusted terms. Taking performance persistence into account, Multi-strategy does seem to be the ultimate winning strategy in the financial crisis.

Emerging Markets

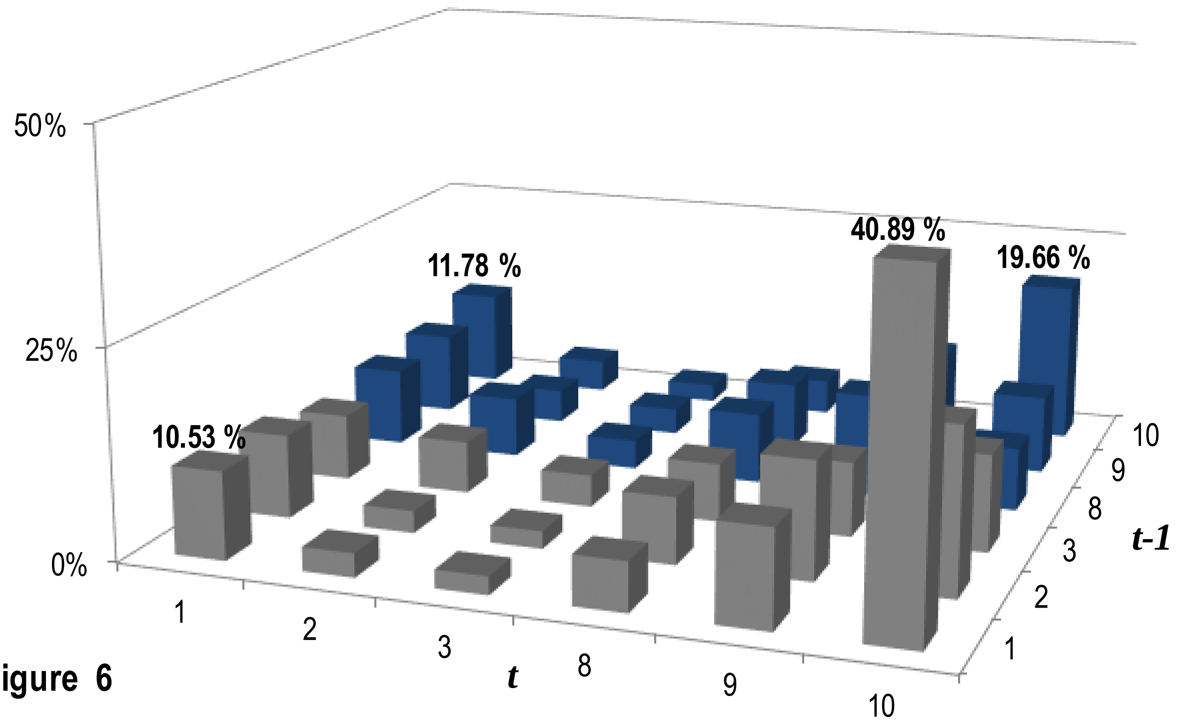

Figure 6

Figure 6: Corrected performance persistence for Emerging Markets hedge funds measured annually for top 3 and bottom 3 performing deciles.
Emerging markets perceived performance persistence is mostly due to extreme volatility and cannot be considered as persistence performance

From Table 19 we saw that Emerging Markets exhibited some level of performance persistence in the top decile (19.7%). However, as Emerging Markets funds persistency is further investigated, one can see from Figure 6 that this positive performance is most likely coincidental and driven by its extremely high levels of volatility. For example, as seen from the chart, there is a 40.89% probability for a loser fund becoming a winning fund after one year. The high prevalence of Emerging Markets funds being allocated in the top and bottom deciles also indicates that there is no real persistency in performance in EM funds.

Nonetheless, over the period of financial crisis, Emerging Markets average annual fund return was 7.00% and 4.80% measured in raw and corrected returns, respectively. While these returns were above average, compared to the implied volatility of Emerging Markets funds, EM funds do not prove to be a stable investment opportunity, especially during a financial crisis.

Fund of Funds

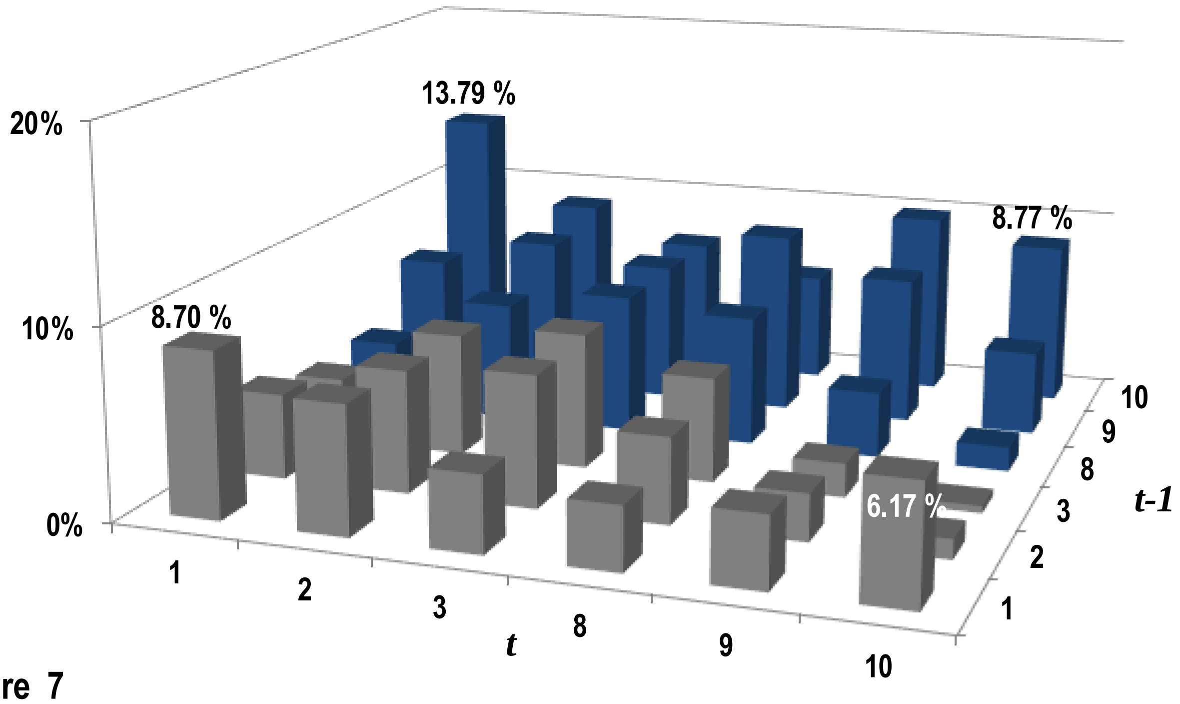

Figure 7

Figure 7: Corrected performance persistence for Funds of Funds hedge funds measured annually for top 3 and bottom 3 performing deciles.

In addition to disappointing returns generated by Funds of funds, there is no indication of FOFs exhibiting any sort of persistence in performance ether. For example, there is a 8.77% probability for a winning fund to be allocated again in the winning portfolio the next year. Given that the expected probability of reoccurrence the same decile should be at least 10% for every fund[45], FOFs underperform even this minimum expected value. To make matters worse, the winning funds have a 13.79% probability to be allocated in the loser portfolio in the next year, suggesting that FOFs performance during the financial crisis can be categorized as chaotic at best.

[45] Although, a number of funds will be dead by the next year, therefore the expected probability should be even higher than 10%. Performance persistence may be present only if the probability clearly exceeds 10%.

These results reject null hypothesis for the last Hypothesis:

H4. During a financial crisis period, certain investment styles may outperform others persistently

5.5 Robustness check

Contradicting views on survivorship for hedge funds have also been posed. Easterling (2007)[46] illustrates that compared to mutual funds, the dynamics for attrition in hedge funds may be completely opposite. He argues furthermore that in fact, hedge funds are twice as likely to stop reporting due to good performance rather than poor performance when they are no longer trying to attract new investors.

There is a common assumption in the hedge fund literature that both the worst and the best funds are missing from the databases. Aiken, Clifford et al. (2012) formally test commercial database returns for hedge funds to see for this effect and they find that delisting and underreporting is heavily truncated to the worst performing funds, and they as average selection bias is heavily driven by extreme poor performance. While positive survivorship bias may exist, it has not been documented to impact hedge fund returns as significantly as poor returns do. Especially during the financial crisis period, it is highly unlikely that certain hedge funds close down or shut to new due to success instead of liquidity crisis.

Naturally, there are a broad set of data that has never been reported. Therefore, it is entirely possible that the true performance of all hedge funds would generate different results, if all hedge funds could be observed. In fact, Aiken, Clifford et al. (2012) studied commercial databases and hedge fund returns from SEC filings, the latter including hedge funds that did not report to databases. They found non-reporting funds performing significantly weaker and concluded that investors should simply avoid investing in non-database hedge funds and in fact, treat the fund's decision to report to a database as a certification for manager skills.

In this paper, survivorship and look-ahead bias were aimed to be corrected by probit analysis as well as excluding all funds with less than 1 year of age. Despite the best of efforts, some level of instant history bias possibly still exists in this dataset. Generally, only successful strategies will go public revealing their historical records; the records of the unsuccessful strategies are not made

[46] Author of the book "Hedge Fund: Myths & Facts", 2007

public. Given that the worst performing funds often do not report at all, even the corrected returns in this paper possibly exaggerate true hedge fund performance.

Nonetheless, Derman, Park et al. (2010) discusses the distinction between “theories” that aim to accurately describe a phenomena and “models” conducted in finance and the social sciences that can be at best viewed as empirical suggestions guided by our best understanding with limited applicability. Therefore, when faced by an incomplete model space, model selection – namely the choice of one model to the exclusion of others – is an inherently flawed strategy.

VI. DISCUSSION OF IMPLICATION OF RESULTS

The hedge fund industry's historical development has been widely studied as it has played a crucial part of the fast development of financial markets in the last century. Many money market participants anticipate seeing further growth in the hedge fund industry as a corollary of financial development, as both individual and institutional investors wish to diversify their investments in a way that the returns are not correlated to the market. The constantly growing client base willing to participate in the hedge fund style of investing suggests that these vehicles are expected to further increase their importance in the market.

Despite of the issues with hedge fund reporting, it is useful to see how far the data available can provide insight to the hedge fund industry. One of the key findings in this paper was the significantly weaker performance of Funds of funds compared to the rest of the hedge fund. As mentioned, Fung and Hsieh (2000) had proposed that using data on FOFs as a proxy for hedge fund performance would mitigate the biases in hedge fund data. Under the light of results generated in this paper, FOFs do not seem to disclose true hedge fund performance. In fact, even if corrected returns were unable to remove all self-selection biases, in most cases the difference between a specific style and FOFs is at 7-9%. In addition, Funds of funds suffered from selection-bias as well.

Following the recommendation of Fung and Hsieh (2000), Dai and Shawky's (2013) study on hedge fund performance during financial crisis using Funds of Funds performance as a proxy for overall hedge fund performance looks flawed. Not surprisingly, they concluded that the impact of the financial crisis on fund performance was severe. However, as shown in section 5.4.1 "Returns by style" poor performance was characteristic for Funds of funds especially and does not truly represent hedge fund performance as a whole.

As an interesting contrast to poor returns by Funds of funds, the best performing hedge fund strategy was Multi-strategy funds. In many ways, FOFs and Multi-strategy funds operate under the same philosophy; both strategies aim to diversify from single-strategy risks and change their positions accordingly to the development in the market. How is it then possible that FOFs and Multi-strategy ended up the in opposite ends of the spectrum?

One explanation could be that exponentially increasing demand and popularity for Funds of funds in the market made that specific hedge fund industry such a lucrative market to enter that also the unskilled and incompetent managers have been able to penetrate it. This has diminished the returns of the handful of talented managers, reducing the overall performance of Funds of funds.

Compared to Funds of funds, Multi-strategy hedge funds may require a more active approach to investing. While FOFs may, in theory, invest in funds that openly share their underlying investments and their alphas, Multi-strategists do not have this same luxury. A Multi-strategy hedge fund manager must make the initiative to actively gain knowledge and skills to fully analyze their target investments. In addition, multi-strategists need often to be familiar with more than one investment strategy, they may face higher professional requirements, and hence it is highly probable that manager skills are present. Furthermore, these requirements would prevent unskilled and lazy managers to consider Multi-strategy as their primary investment style.

Thorough studies on Multi-strategy funds are rare, and in light of the results of this thesis they should definitely receive more focus in the academic field. Actually, it is still quite unclear what strategies do Multi-strategists undertake in reality. It is often said that "hedge funds may invest in anything", including unusual illiquid investments such as art, PIPE deals, real estate and other investment vehicles that are not highly correlated with the general market at all. Nonetheless, most strategies eventually invest predominantly in the (liquid) financial markets such as equities, fixed income, currencies or derivatives. Whether or not it is a possibility that Multi-strategists carry a larger exposure to set of peculiar investments remains unknown.

The final note of this discussion is on how media addressed the financial crisis. Interestingly, when it comes to the financial crisis, in the media it is often proclaimed that the financial crisis has diminished economic fundamentals. On the other hand, "professionals" continue to offer their opinions regarding near-future events, implying a directional recommendation or suggestion.

In fact, directional strategies during the financial crisis more or less failed. My results imply that despite of the financial crisis, technical analysis on economic fundamentals generated the best returns. Although Global Macro funds' growth stagnated after the financial crisis r as pure economic fundamentals disappeared[47], it generated the best adjusted returns on its risk level. Therefore, it seems that while its performance has relinquished from its prime years, it remains as a well-performing investment style.

Finally, and in retrospect, during an economic crisis, investors who participated in Multi-strategy and Global Macro hedge funds came out from the financial crisis as winners. In addition, as argued

[47] HFR Hedge Fund Industry Report 2011

by Aiken and Clifford (2012), worst hedge funds probably do not ever enter the database. During a financial crisis where most investments went south, this is possibly even more accurate.

VII. CONCLUSION

Traditional studies focusing purely on financial market fundamentals and their effect on hedge funds have often put less emphasis on the database problems. The aim of this research was to close this gap between traditional performance studies with respect to the financial crisis' effect on the hedge fund industry.

This paper provided further insight on hedge fund performance during the financial crisis, with an emphasis on examining the differences between investment styles during the financial crisis. As expected, fund attrition was much more severe during the financial crisis, as poor returns drove fund managers to more frequently dissolve the fund. Additionally, performance was clearly exaggerated by funds managers' back-filling of historical data, causing look-ahead bias.

The attrition model for hedge fund data clearly indicates that poor returns cause fund attrition. This finding is aligned with a paramount of previous studies, which explain fund managers' abilities to self-select and backfill data, resulting in an upwards bias in reported returns. However, once the attrition model was applied separately to each investment style, there was a clear distinction between the level of significance of past returns. Generally, investment styles that were more volatile were less affected by short-term poor returns than styles that aimed to keep market neutral position.

Using conditional probabilities obtained from the attrition model, the reported returns were corrected for self-selection and look-ahead bias. Employing the conditional probability of all hedge funds, the corrected returns show that hedge funds use self-selection to hide both their poor performance as well as true volatility. In fact, on average, the worst performing decile during 2007-2010 was 17.36% worse than reported after accounting for fund selection. However, correcting returns using investment style specific conditional probabilities proved the skewness of reported returns to be much more moderate, approximately between 2.36%-7.9% at worst.

Despite arguments for positive self-selection bias (Easterling, 2007), findings of this research did not discover any evidence to support this argument; there were no returns that were upward skewed due to self-selection. This may also be explained by the gloomy market environment, during which liquidity and good returns were hard to come by.

Based on raw and corrected returns, the best performing styles during 2007-2010 were Global Macro and Multi-strategy. The fact that Multi-strategy generated better than average returns over other strategies showed that active investing and diversifying strategies was a good approach in a volatile economy. Since Multi-strategists have the flexibility to shift and alter between different investing styles depending on the market, those funds were better equipped for an economic turmoil. Nonetheless, the strong prevalence of Multi-strategy hedge funds in the top performing deciles show their ability to consistently perform well, making it the most lucrative style to invest in.

A surprising result was Global Macro's better than average risk-adjusted performance compared to the rest of the group. As discussed in section 2.4.4, Global Macro funds have been in decline due to the financial crisis effecting interest rates and wiping out pure economic fundamentals used for modeling. Nonetheless, it seems that even in a crisis era Global Macro continued to outperform other hedge funds despite of doubts. While Global Macro did not show as strong performance persistence as Multi-strategy, Global Macro's performance showed that an investment strategy relying on economic fundamentals is a good one even when the economy is not at its best.

Funds of funds were clearly the underdog in the financial crisis 2007-2010. Incremental fees, restrictions in redemptions and long lock-up periods stipulated FOFs tying up large sums of money in funds that were not necessarily making any money. The "fees of fees" structure would additionally force investors to incur incentive fees regardless of overall fund performance. Despite the fact that Funds of funds invest under a similar ideology to Multi-strategy funds, it seems the structure of FOFs causes them to be too stiff during a financial crisis and, consequently, unable to reach their full potential. The severe underperformance of FOFs in the financial crisis raises the question on whether the use of them as proxies for hedge fund market portfolios in academic research is sufficient to generate truthful results.

The recent global financial crisis of 2007 has led to a renewed focus on the issue of the hedge fund industry. Hedge funds were, after all, one of the intermediaries between financial institutions and investors for securing and supplying these securities. The results of this paper indicate that the hedge fund are in fact an immensely heterogeneous group, as the effect of the financial crisis were incredibly different between investment styles.

From an investor's point of view, this paper has shown that investment strategies are an essential element in determining hedge fund performance. Certain hedge funds styles also proved their ability to continue to generate profits despite of the financial crisis, suggesting that a thorough analysis on investment styles and manager's skills may account for a big portion of expected fund performance.

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APPENDIX

Appendix 1: Summary of LipperTASS data

Summary of all data variables used in this study. Monthly average returns and attrition is also shown during the 2007-2010 period.

APPENDIX 1						
Summary of variables and data						
Variable	**Type**	**Number of observation**	**Mean**	**Std.Dev**	**Min**	**Max**
Fund ID	long	535 398	60017	28512	1	99175
Alive	byte	535 398	0.995	0.0710	0	1
Net Asset Value	float	535 398	5389	283520		
Estimated Assets	float					
Age (monthly)	float	535 398	51.90	48	0	499
Time (monthly)	int	535 398	564.16	32	480	611
Return	float	535 398	0.66	20	-100	13950
lnNAV	float	535 398				
lnEA	float	273 905	17.38	2.1	0.0	57
lnAge	float	527 445	3.49	1.1	-3.4	6
Std. Dev (Return)	float	535 332	3.36	19.2	0.0	1816
lnAge2	float	527 445	13.44	7.0	0.0	37
incentivefee	float	535 398	12.37	9.0	0.0	50
high watermark	float	535 398	0.56	0.5	0.0	1
management~e	float	535 398	1.43	0.8	0.0	22

	Monthly returns				Monthly attrition			
	2007	**2008**	**2009**	**2010**	**2007**	**2008**	**2009**	**2010**
January	1.24 %	-2.08 %	0.54 %	-0.25 %	0.35 %	0.53 %	1.04 %	0.77 %
February	0.62 %	1.83 %	-0.44 %	0.49 %	0.28 %	1.18 %	0.99 %	0.90 %
March	0.82 %	-2.07 %	0.93 %	2.13 %	0.45 %	0.62 %	1.15 %	0.55 %
April	1.91 %	1.12 %	2.31 %	1.00 %	0.19 %	0.77 %	1.41 %	0.91 %
May	1.99 %	1.69 %	3.67 %	-2.15 %	0.83 %	0.98 %	0.69 %	0.31 %
June	0.94 %	-0.47 %	0.41 %	-0.56 %	0.78 %	0.70 %	1.38 %	0.73 %
July	0.45 %	-2.14 %	1.93 %	1.02 %	0.68 %	0.79 %	0.88 %	0.77 %
August	-1.78 %	-1.29 %	1.40 %	0.41 %	0.59 %	1.49 %	0.93 %	0.96 %
September	2.37 %	-5.07 %	2.27 %	2.36 %	1.28 %	1.90 %	0.48 %	0.85 %
October	2.81 %	-5.33 %	-0.09 %	1.71 %	0.80 %	1.54 %	0.71 %	0.88 %
November	-1.25 %	-1.42 %	1.16 %	0.21 %	0.32 %	2.01 %	0.90 %	0.94 %
December	0.63 %	2.16 %	0.94 %	2.17 %	1.13 %	1.68 %	1.19 %	1.58 %
AVERAGE	**0.90 %**	**-1.09 %**	**1.25 %**	**0.71 %**	**0.64 %**	**1.18 %**	**0.98 %**	**0.85 %**

Appendix 2: Attrition models by style

APPENDIX 2

Investment style	Convertible arbitrage			Emerging Markets			Equity Market Neutral			Event Driven			Fixed Income Arbitrage		
Number of observations =			**4 875**			**16 364**			**8 539**			**14 744**			**5 547**
Number of groups =			**72**			**342**			**163**			**251**			**138**
Log likehood			-173.56			-405.58			-371.18			-580.75			-210.02
χ^2 test		49.50	(p = 0.0003)		82.99	(*p* = 0.0000)		67.05	(*p* = 0.0000)		96.96	(*p* = 0.0000)		90.4	(*p* = 0.0000)
Parameters	**Estimate**	**Std. Error**	**P>|x|**	**Estimate**	**Std. Error**	**P>|x|**	**Estimate**	**Std. Error**	**P>|x|**	**Estimate**	**Std. Error**	**P>|x|**	**Estimate**	**Std. Error**	**P>|x|**
Intercept	5.743	3.189	0.072	4.193	1.556	0.007	5.356	1.899	0.005	6.759	1.403	-	3.794	2.119	0.073
Return															
--.	0.056	0.019	0.003	0.014	0.006	0.019	0.044	0.012	0.000	0.023	0.008	0.007	0.024	0.011	0.030
L1.	0.029	0.023	0.210	0.000	0.006	0.966	0.024	0.017	0.165	0.032	0.009	0.001	0.040	0.010	0.000
L2.	0.032	0.025	0.194	0.006	0.006	0.353	0.021	0.017	0.221	0.011	0.010	0.281	0.052	0.011	0.000
L3.	0.041	0.033	0.210	-0.004	0.006	0.564	0.017	0.018	0.349	0.005	0.010	0.602	0.006	0.016	0.704
L4.	-0.081	0.029	0.005	0.013	0.007	0.045	0.046	0.018	0.011	0.015	0.012	0.204	-0.003	0.015	0.826
L5.	0.040	0.031	0.193	0.001	0.006	0.907	-0.011	0.020	0.574	0.000	0.012	0.985	0.018	0.016	0.255
L6.	-0.011	0.037	0.758	0.015	0.006	0.022	0.018	0.018	0.319	0.022	0.011	0.047	0.019	0.017	0.258
L7.	-0.006	0.032	0.845	0.005	0.006	0.442	0.010	0.018	0.585	-0.001	0.012	0.909	-0.001	0.013	0.958
L8.	0.012	0.029	0.686	0.019	0.006	0.003	0.032	0.018	0.073	0.006	0.011	0.575	0.029	0.016	0.068
L9.	0.043	0.023	0.054	-0.003	0.007	0.603	0.030	0.018	0.096	0.003	0.012	0.779	0.005	0.021	0.827
L10.	-0.007	0.028	0.811	0.010	0.007	0.156	0.020	0.019	0.288	0.006	0.009	0.540	-0.013	0.018	0.464
L11.	-0.002	0.027	0.934	-0.008	0.007	0.216	0.004	0.019	0.853	-0.016	0.012	0.199	0.003	0.019	0.873
Other variables															
lnNAV	0.017	0.062	0.789	-0.016	0.027	0.557	0.009	0.029	0.767	-0.052	0.028	0.066	-0.050	0.038	0.186
lnEA	0.083	0.038	0.030	0.058	0.022	0.009	0.066	0.023	0.004	0.092	0.018	0.000	0.143	0.029	0.000
lnAge	-1.837	1.488	0.217	-0.408	0.752	0.587	-1.625	0.930	0.081	-2.427	0.649	0.000	-1.631	1.038	0.116
ln(Age)^2	0.169	0.177	0.339	0.010	0.094	0.917	0.163	0.115	0.156	0.287	0.079	0.000	0.188	0.131	0.151
Std. Dev	0.300	0.074	0.000	0.023	0.015	0.133	0.073	0.042	0.079	0.024	0.021	0.258	0.071	0.038	0.065
Fee variables															
Management fee	-0.571	0.205	0.005	-0.446	0.126	0.000	-0.138	0.101	0.170	-0.329	0.087	0.000	-0.234	0.154	0.127
Incentive fee	0.008	0.016	0.632	-0.004	0.011	0.700	0.029	0.014	0.036	-0.006	0.010	0.527	0.020	0.016	0.224
High watermark	-0.212	0.166	0.200	-0.315	0.122	0.009	-0.953	0.310	0.002	-0.021	0.109	0.849	-0.295	0.257	0.252

Investment style specific attrition estimates. L indicates the number of lags in months.

APPENDIX 2 cont.															
Investment style	**Funds of funds**			**Global Macro**			**Long-short Equity hedge**			**Managed Futures**			**Multi-strategy**		
Number of observations =			**78 335**			**7 677**			**56 966**			**17 220**			**22 971**
Number of groups =			**2 030**			**229**			**1 013**			**300**			**808**
Log likehood			-1968.30			-310.06			-1977.24			-321.99			-484.35
χ^2 test			438.64 (*p = 0.0000*)			71.79 (*p = 0.0000*)			230.33 (*p = 0.0000*)			40.36 (*p = 0.0045*)			114.36 (*p = 0.0000*)
Parameters	**Estimate**	**Std. Error**	**P>|x|**	**Estimate**	**Std. Error**	**P>|x|**	**Estimate**	**Std. Error**	**P>|x|**	**Estimate**	**Std. Error**	**P>|x|**	**Estimate**	**Std. Error**	**P>|x|**
Intercept	5.544	0.714	0.000	13.551	2.858	0.000	5.287	0.708	0.000	5.287	0.708	0.000	5.224	1.360	0.000
Return															
--.	0.036	0.005	0.000	0.014	0.013	0.259	0.011	0.003	0.002	0.005	0.009	0.542	0.016	0.008	0.041
L1.	0.018	0.006	0.001	0.031	0.014	0.030	0.019	0.003	0.000	0.012	0.008	0.145	0.014	0.009	0.121
L2.	0.024	0.006	0.000	0.027	0.015	0.061	0.003	0.004	0.352	0.012	0.009	0.156	0.021	0.011	0.053
L3.	0.020	0.006	0.001	0.042	0.015	0.004	0.006	0.004	0.126	0.010	0.009	0.250	0.024	0.012	0.041
L4.	0.011	0.006	0.075	0.022	0.015	0.141	0.007	0.004	0.074	0.008	0.009	0.338	0.000	0.010	0.993
L5.	0.022	0.006	0.000	-0.022	0.014	0.118	0.000	0.004	0.935	0.015	0.009	0.085	-0.013	0.010	0.195
L6.	0.004	0.007	0.521	0.048	0.014	0.001	0.017	0.004	0.000	0.018	0.009	0.042	0.001	0.012	0.954
L7.	0.014	0.006	0.029	0.006	0.014	0.651	0.010	0.004	0.018	0.002	0.009	0.825	0.037	0.012	0.001
L8.	0.012	0.006	0.059	0.036	0.014	0.011	0.007	0.004	0.089	0.007	0.009	0.443	-0.008	0.007	0.263
L9.	0.028	0.006	0.000	0.022	0.015	0.131	0.007	0.004	0.111	0.015	0.009	0.096	-0.008	0.007	0.226
L10.	0.024	0.006	0.000	0.037	0.014	0.009	0.009	0.004	0.032	-0.010	0.009	0.257	0.017	0.011	0.126
L11.	0.007	0.007	0.347	0.012	0.013	0.365	0.002	0.004	0.689	0.031	0.009	0.001	0.041	0.010	0.000
Other variables															
lnNAV	-0.031	0.012	0.009	0.016	0.041	0.702	-0.004	0.011	0.728	-0.028	0.036	0.434	-0.052	0.024	0.028
lnEA	0.064	0.009	0.000	0.025	0.025	0.307	0.052	0.009	0.000	0.074	0.025	0.003	0.075	0.019	0.000
lnAge	-1.669	0.344	0.000	-5.763	1.409	0.000	-1.406	0.331	0.000	-2.569	0.900	0.004	-1.310	0.650	0.044
ln(Age)^2	0.182	0.042	0.000	0.705	0.177	0.000	0.145	0.040	0.000	0.299	0.106	0.005	0.138	0.081	0.090
Std. Dev	0.074	0.016	0.000	0.106	0.036	0.003	0.032	0.009	0.000	0.061	0.021	0.004	0.103	0.027	0.000
Fee variables															
Management fee	-0.012	0.022	0.589	-0.091	0.078	0.241	-0.192	0.050	0.000	-0.069	0.044	0.121	-0.182	0.062	0.003
Incentive fee	-0.020	0.003	0.000	0.000	0.012	0.985	-0.006	0.006	0.321	-0.009	0.009	0.333	-0.012	0.006	0.070
High watermark	-0.189	0.046	0.000	-0.486	0.268	0.070	-0.219	0.059	0.000	-0.019	0.118	0.873	-0.470	0.123	0.000

Appendix 2: Liquidation models by style (cont'd)

APPENDIX 3

i) Monthly	Convertible arbitrage			Emerging Markets			Equity Market Neutral			Event Driven			Fixed Income Arbitrage		
Decile	Raw	Corrected	P>|t|	Raw	Corrected	P>|t|	Raw	Corrected	P>|t|	Raw	Corrected	P>|t|	Raw	Corrected	P>|t|
1	-2.655	-2.963	0.001	-1.579	-1.695	0.299	-0.179	-0.246	0.776	-0.758	-0.838	0.271	-0.250	-0.401	0.000
2	-0.949	-0.997	0.056	-0.327	-0.336	0.001	0.147	0.155	0.225	-0.506	-0.520	0.047	-0.024	-0.033	0.013
3	-0.312	-0.343	0.008	-0.131	-0.115	0.000	-0.019	-0.016	0.170	-0.184	-0.199	0.000	0.242	0.249	0.000
4	0.205	0.178	0.001	-0.001	-0.002	0.312	0.048	0.007	0.000	0.169	0.143	0.075	0.442	0.382	0.143
5	0.170	0.135	0.350	0.256	0.234	0.000	0.221	0.204	0.645	0.223	0.205	0.000	0.411	0.421	0.000
6	0.315	0.318	0.047	0.374	0.405	0.000	0.274	0.267	0.000	0.389	0.384	0.000	0.529	0.504	0.895
7	0.556	0.474	0.001	0.375	0.214	0.000	0.335	0.115	0.000	0.424	0.250	0.164	0.301	0.043	0.000
8	0.678	0.590	0.220	0.796	0.740	0.091	0.649	0.558	0.000	0.759	0.669	0.000	0.671	0.545	0.267
9	1.363	1.159	0.588	1.124	0.339	0.017	0.960	-0.177	0.000	1.021	0.307	0.022	0.812	-0.471	0.431
10	2.252	2.359	0.994	1.906	1.953	0.000	1.198	1.243	0.000	1.893	1.948	0.119	1.657	1.803	0.769
Total	0.256	0.184	0.000	0.380	0.255	0.000	0.371	0.195	0.000	0.362	0.246	0.000	0.464	0.260	0.000

i) Monthly	Funds of funds			Global Macro			Long-short Equity hedge			Managed Futures			Multi-strategy		
Decile	Raw	Corrected	P>|t|	Raw	Corrected	P>|t|	Raw	Corrected	P>|t|	Raw	Corrected	P>|t|	Raw	Corrected	P>|t|
1	-0.243	-0.291	0.000	0.022	-0.034	0.351	-0.311	-0.340	0.000	0.180	0.187	0.000	-0.766	-0.875	0.000
2	-0.066	-0.047	0.000	0.149	0.150	0.192	-0.194	-0.182	0.000	0.112	0.138	0.146	0.014	0.018	0.000
3	-0.057	-0.028	0.000	0.092	0.125	0.002	-0.071	-0.047	0.000	0.099	0.132	0.000	0.103	0.109	0.000
4	0.026	0.030	0.028	0.137	0.122	0.000	0.017	0.017	0.000	0.216	0.198	0.000	0.256	0.212	0.000
5	0.093	0.089	0.000	0.301	0.303	0.601	0.036	0.007	0.153	0.338	0.336	0.534	0.353	0.365	0.000
6	0.233	0.227	0.000	0.287	0.287	0.913	0.181	0.179	0.000	0.359	0.366	0.000	0.458	0.458	0.000
7	0.443	0.284	0.000	0.468	0.322	0.078	0.407	0.194	0.013	0.434	0.250	0.000	0.547	0.400	0.000
8	0.691	0.607	0.000	0.812	0.759	0.000	0.797	0.737	0.000	0.535	0.419	0.000	0.708	0.588	0.000
9	0.776	-0.229	0.000	1.033	-0.506	0.000	1.172	0.389	0.000	0.839	-0.996	0.000	0.899	-0.561	0.000
10	1.592	1.692	0.872	1.611	1.718	0.000	1.851	1.908	0.000	1.316	1.419	0.000	1.699	1.840	0.000
Total	0.245	0.156	0.000	0.563	0.374	0.000	0.484	0.376	0.000	0.557	0.379	0.076	0.491	0.275	0.000

Appendix 3: Raw and corrected returns by style and decile

APPENDIX 3

ii) Annually	Convertible arbitrage			Emerging Markets			Equity Market Neutral			Event Driven			Fixed Income Arbitrage		
Decile	Raw	Corrected	P>|t|	Raw	Corrected	P>|t|	Raw	Corrected	P>|t|	Raw	Corrected	P>|t|	Raw	Corrected	P>|t|
1	-29.945	-35.061	0.019	-35.361	-43.262	0.087	-16.803	-19.967	0.000	-27.770	-33.642	0.875	-24.016	-27.717	0.000
2	-19.952	-20.145	0.008	-17.703	-17.805	0.342	-6.811	-6.771	0.000	-14.562	-14.637	0.000	-4.802	-4.826	0.000
3	-9.369	-9.321	0.000	-10.074	-9.954	0.351	-2.653	-2.662	0.000	-8.371	-8.329	0.172	-0.815	-0.879	0.000
4	-5.108	-4.977	0.245	-3.620	-3.501	0.867	-2.042	-1.938	0.000	-2.527	-2.465	0.259	3.388	3.170	n.a
5	-1.027	-0.880	0.023	0.122	0.204	0.009	1.244	1.255	0.000	0.630	0.690	0.039	4.590	4.459	0.000
6	1.541	1.460	0.007	3.114	2.997	0.911	2.099	2.005	0.000	2.702	2.625	0.364	5.861	5.665	0.032
7	6.156	5.814	0.000	6.826	6.512	0.817	4.795	4.572	0.080	5.820	5.612	0.006	6.274	6.001	0.000
8	11.729	11.227	0.002	13.154	12.672	0.000	9.350	8.828	0.040	11.929	11.540	0.131	9.183	8.729	0.000
9	23.259	22.334	0.054	20.993	19.683	0.000	16.874	12.862	0.058	22.500	20.726	0.002	15.179	9.591	0.000
10	55.824	54.151	0.000	48.936	46.470	0.000	34.031	32.224	0.000	47.073	44.467	0.000	34.653	32.989	0.000
Total	7.299	6.365	0.000	7.003	4.804	0.000	3.781	2.770	0.000	2.849	1.526	0.000	6.119	4.656	0.000

ii) Annually	Funds of funds			Global Macro			Long-short Equity hedge			Managed Futures			Multi-strategy		
Decile	Raw	Corrected	P>|t|	Raw	Corrected	P>|t|	Raw	Corrected	P>|t|	Raw	Corrected	P>|t|	Raw	Corrected	P>|t|
1	-20.172	-23.970	0.000	-18.224	-20.837	0.000	-25.892	-30.240	0.000	-15.237	-17.601	0.000	-26.290	-31.740	0.394
2	-8.690	-8.671	0.000	-6.965	-6.972	0.000	-10.554	-10.572	0.000	-3.096	-3.089	0.003	-10.105	-10.098	0.000
3	-4.956	-4.938	0.000	-2.512	-2.551	0.001	-5.786	-5.744	0.000	-1.035	-1.032	0.309	-4.747	-4.744	0.000
4	-2.666	-2.572	0.000	-1.554	-1.537	0.010	-1.996	-1.924	0.000	1.407	1.345	0.000	0.530	0.374	0.000
5	-0.813	-0.694	0.000	2.212	2.141	0.000	0.355	0.411	0.000	3.681	3.631	0.000	4.614	4.456	0.000
6	2.472	2.375	0.000	5.152	4.920	0.000	2.097	2.050	0.000	4.566	4.383	0.000	6.480	6.192	0.000
7	6.821	6.487	0.000	6.891	6.604	0.000	5.415	5.183	0.000	5.577	5.385	0.004	8.525	8.192	0.000
8	11.281	10.765	0.000	10.194	9.816	0.000	11.643	11.193	0.000	10.146	9.732	0.000	11.053	10.664	0.000
9	16.393	12.539	0.000	16.880	13.103	0.000	20.720	18.752	0.000	14.297	10.352	0.000	16.215	11.695	0.000
10	38.946	36.912	0.000	34.096	32.257	0.000	44.246	42.115	0.000	30.318	28.568	0.002	40.486	38.541	0.000
Total	0.044	-0.497	0.000	8.911	7.601	0.000	4.657	3.482	0.000	7.847	6.471	0.000	9.074	7.555	0.000

Appendix 3: Raw and corrected returns by style and decile (cont'd)

APPENDIX 3										
Frequency of each hedge fund style in monthly and annual decile portfolio										
	Convertible Arbitrage		**Emerging Markets**		**Equity Market Neutral**		**Event Driven**		**Fixed Income Arbitrage**	
Decile	Monthly	Annually	Monthly	Annually	Monthly	Annually	Monthly	Annually	Monthly	Annually
1	8 %	9 %	17 %	18 %	12 %	10 %	11 %	14 %	9 %	10 %
2	11 %	12 %	10 %	8 %	13 %	12 %	11 %	12 %	10 %	9 %
3	9 %	10 %	7 %	6 %	9 %	8 %	10 %	10 %	11 %	7 %
4	9 %	8 %	6 %	5 %	9 %	8 %	9 %	7 %	9 %	6 %
5	9 %	8 %	5 %	6 %	7 %	9 %	8 %	9 %	10 %	8 %
6	9 %	7 %	6 %	6 %	8 %	11 %	8 %	9 %	10 %	10 %
7	10 %	6 %	7 %	7 %	9 %	11 %	8 %	9 %	12 %	12 %
8	12 %	8 %	9 %	9 %	10 %	12 %	11 %	9 %	10 %	16 %
9	13 %	16 %	13 %	13 %	12 %	12 %	11 %	11 %	12 %	14 %
10	10 %	15 %	21 %	22 %	10 %	8 %	12 %	11 %	8 %	10 %

APPENDIX 3										
Frequency of each hedge fund style in monthly and annual decile portfolio										
	Funds of Funds		**Global Macro**		**Long-short Equity Hedge**		**Managed Futures**		**Multistrategy**	
Decile	Monthly	Annually	Monthly	Annually	Monthly	Annually	Monthly	Annually	Monthly	Annually
1	5 %	6 %	15 %	11 %	16 %	14 %	23 %	18 %	7 %	7 %
2	9 %	12 %	10 %	8 %	13 %	11 %	10 %	9 %	8 %	6 %
3	13 %	15 %	7 %	5 %	8 %	8 %	6 %	5 %	9 %	5 %
4	14 %	16 %	7 %	5 %	6 %	7 %	5 %	5 %	9 %	6 %
5	14 %	14 %	7 %	6 %	6 %	7 %	5 %	5 %	10 %	8 %
6	14 %	12 %	7 %	9 %	6 %	8 %	5 %	6 %	11 %	10 %
7	12 %	10 %	8 %	10 %	7 %	9 %	6 %	7 %	12 %	14 %
8	9 %	7 %	11 %	13 %	9 %	10 %	7 %	10 %	13 %	15 %
9	7 %	5 %	12 %	15 %	12 %	12 %	10 %	11 %	13 %	16 %
10	3 %	3 %	15 %	19 %	17 %	13 %	23 %	24 %	9 %	13 %

Appendix 3: Raw and corrected returns by style and decile (cont'd)

Appendix 4: Performance persistence by style **(corrected returns)**

Tables below show the probability of a fund being allocated in each decile portfolio depending previous allocation on a monthly basis. E.g. Emergin Markets fund that was allocated at decile 1 (bottom) in January 2008 has a 22.96% probability to be allocated in the decile 10 (top) portfolio in February 2008.

APPENDIX 4											
Monthly performance persistence											
Convertible arbitrage	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Dead**
1	22.82	11.41	8.05	13.42	6.71	9.40	4.03	4.70	2.01	12.75	4.03
2	9.74	7.79	22.08	13.64	7.14	3.90	9.74	3.25	10.39	5.84	4.55
3	9.91	11.32	17.45	10.85	12.26	8.96	14.15	6.13	4.72	2.36	1.89
4	9.00	11.00	17.00	12.50	9.50	10.50	7.00	10.50	9.00	2.00	2.00
5	3.97	9.27	11.26	4.64	9.27	18.54	11.92	15.23	7.28	6.62	1.32
6	2.46	8.37	11.82	14.78	9.36	12.81	13.79	11.82	11.33	0.49	1.97
7	4.46	9.41	9.90	7.43	7.92	13.37	13.37	14.36	12.38	5.45	0.99
8	6.42	8.26	5.96	11.01	7.80	12.39	9.17	15.60	13.76	8.26	0.92
9	4.22	4.22	3.80	8.44	5.49	8.02	9.70	19.41	20.25	14.35	1.27
10	8.70	1.63	1.63	0.00	5.43	5.43	7.07	8.15	22.28	38.04	0.54
New	0.00	0.00	0.94	0.00	0.00	0.00	0.47	0.47	0.94	0.94	0.00
Emerging Markets											
1	31.24	9.81	4.21	3.14	3.00	2.87	3.27	5.81	11.62	22.96	1.07
2	16.76	11.31	8.00	5.76	6.40	7.26	7.36	6.83	13.13	15.26	0.53
3	9.33	9.33	10.26	7.62	7.93	7.78	9.02	10.73	12.60	13.22	1.24
4	11.45	8.40	7.63	9.16	7.44	11.64	12.40	9.35	10.50	10.50	0.95
5	7.67	10.28	10.45	12.20	7.84	7.32	9.41	13.07	10.45	8.89	1.22
6	6.00	12.35	9.17	8.47	9.88	6.35	10.41	13.93	11.99	10.05	0.35
7	7.49	9.18	6.92	6.50	8.33	8.47	11.44	13.84	11.30	14.55	0.14
8	9.27	8.94	6.54	5.67	5.34	6.87	10.47	12.54	16.79	15.59	0.87
9	13.47	10.37	5.96	4.80	7.35	6.73	7.82	8.51	12.15	20.98	0.54
10	16.73	7.38	4.82	2.22	3.33	2.70	3.18	6.51	15.04	36.69	0.53
New	0.48	0.41	0.13	0.06	0.25	0.35	0.22	0.57	0.51	0.67	0.00
Equity Market Neutral											
1	20.40	18.63	4.88	8.43	4.43	5.10	7.54	8.20	10.86	8.87	2.44
2	13.07	15.28	14.09	8.83	5.94	8.66	8.66	8.83	7.47	6.62	2.21
3	9.96	15.98	11.62	10.79	7.26	4.77	10.37	9.96	12.24	4.77	1.66
4	10.19	14.93	10.43	8.06	8.77	10.90	9.24	10.43	9.95	5.21	1.42
5	5.52	8.59	11.66	10.12	9.20	12.27	10.12	10.74	13.50	5.83	1.53
6	8.40	13.49	8.91	10.69	7.38	10.43	10.43	10.43	14.50	3.31	1.27
7	6.78	11.38	11.16	9.63	8.10	10.72	11.60	8.53	12.47	6.78	1.09
8	6.96	8.15	9.15	7.75	7.36	7.95	11.53	16.90	14.51	6.96	1.79
9	5.63	12.68	11.09	8.63	7.04	6.87	10.21	14.26	14.79	6.69	0.70
10	13.18	9.00	6.75	7.72	4.18	9.00	9.32	9.97	13.83	13.83	2.25
New	0.07	0.29	0.44	0.07	0.37	0.29	0.15	0.29	0.44	0.29	0.07

APPENDIX 4

Monthly performance persistence

Event Driven	1	2	3	4	5	6	7	8	9	10	Dead
1	23.43	14.13	6.98	6.98	4.65	4.29	5.19	5.19	9.12	14.85	3.94
2	11.11	12.39	10.11	10.26	9.26	10.54	9.12	9.69	8.40	5.13	3.56
3	9.33	13.17	15.09	13.17	10.01	8.64	8.50	9.47	6.04	4.66	1.51
4	6.72	13.88	13.43	13.43	9.55	9.70	11.19	8.81	7.61	3.43	0.90
5	2.79	10.80	16.90	13.24	8.54	8.36	11.32	12.37	8.36	4.88	1.74
6	4.44	8.89	14.70	12.31	9.23	10.09	8.38	15.73	10.26	3.42	0.51
7	4.34	11.19	8.68	8.18	9.18	12.85	11.19	13.19	13.86	5.84	1.34
8	4.90	8.00	7.87	9.94	7.61	9.03	8.90	15.61	16.13	9.42	1.81
9	6.34	6.21	8.15	7.50	9.31	6.47	10.61	14.10	18.24	11.90	0.52
10	12.33	7.67	7.83	3.67	5.33	4.00	4.33	10.17	15.67	26.50	1.33
New	0.40	0.40	0.00	0.50	0.60	0.20	0.60	0.50	0.30	0.60	0.00
Fixed Income Arbitrage											
1	25.94	8.19	6.14	10.24	9.22	3.41	9.22	3.41	8.19	10.58	5.46
2	9.56	12.29	12.97	6.48	12.29	14.68	8.53	7.51	6.83	6.83	1.71
3	5.82	21.09	14.91	11.64	7.27	7.27	10.18	6.18	6.55	6.55	1.82
4	7.39	17.51	12.45	11.28	6.61	8.56	15.56	7.39	7.39	3.89	1.56
5	9.62	12.31	9.62	8.85	10.00	11.15	18.08	7.31	7.31	4.62	1.15
6	19.11	12.89	8.00	8.44	8.44	9.78	11.11	8.44	6.22	4.44	0.44
7	11.25	5.63	9.06	10.31	10.94	5.31	15.00	12.50	9.06	6.25	0.00
8	10.43	5.76	6.12	6.83	10.79	7.91	7.55	10.79	17.63	14.75	1.44
9	5.82	6.85	8.22	6.51	7.88	6.16	8.56	22.60	16.44	9.93	0.68
10	8.50	6.88	4.86	7.69	4.86	6.07	11.34	11.74	15.38	20.65	1.62
New	0.52	0.31	0.82	0.31	0.41	0.41	0.31	0.00	0.10	0.10	0.00
Funds of funds											
1	17.79	13.65	9.77	8.56	6.80	5.77	5.68	6.62	9.59	12.52	1.53
2	7.67	13.29	13.07	12.90	10.56	10.03	10.18	9.25	6.26	3.65	1.34
3	3.75	11.06	16.24	16.84	14.69	12.40	11.13	6.90	3.82	1.09	0.86
4	2.59	8.05	15.56	17.03	18.05	13.56	11.85	6.93	2.99	0.87	0.55
5	1.96	6.03	13.08	16.88	18.61	17.43	12.50	6.79	3.56	0.71	0.61
6	1.66	5.52	10.86	14.90	18.43	18.12	14.78	9.28	3.60	0.82	0.40
7	2.45	4.92	9.42	13.14	15.75	17.84	15.91	11.58	5.33	1.26	0.53
8	3.62	7.21	11.19	9.67	10.57	15.57	15.33	12.98	8.85	2.52	0.37
9	7.55	8.90	7.45	6.90	8.87	11.18	10.76	16.07	13.63	6.35	0.59
10	17.92	9.28	4.28	5.00	3.93	4.57	6.21	9.14	15.42	22.06	1.07
New	0.22	0.34	0.49	0.61	0.47	0.44	0.33	0.28	0.23	0.12	0.05

APPENDIX 4

Monthly performance persistence

Global Macro	1	2	3	4	5	6	7	8	9	10	Dead
1	24.61	12.37	5.41	2.96	4.77	4.12	3.99	7.99	11.47	20.88	1.03
2	17.93	15.98	10.33	7.02	4.68	5.07	5.65	9.94	9.75	10.53	2.73
3	20.38	11.78	9.87	5.41	5.73	5.41	7.01	9.87	8.60	12.74	3.18
4	12.61	11.34	13.03	7.56	7.56	6.30	6.30	13.45	11.76	7.14	0.84
5	11.86	16.21	11.46	9.88	5.53	4.74	8.70	5.14	9.49	16.60	0.40
6	10.32	15.87	7.94	9.52	6.35	6.75	9.92	10.71	9.52	9.52	0.79
7	9.97	8.97	8.97	9.97	7.64	10.30	4.98	12.29	15.61	5.98	1.99
8	13.21	9.96	7.72	5.69	6.71	5.69	8.33	11.38	14.43	12.20	2.44
9	15.28	10.19	4.75	4.58	6.62	4.24	6.11	14.77	17.15	14.09	0.85
10	20.20	7.57	4.49	2.24	2.52	4.63	5.19	10.24	14.59	27.49	0.42
New	0.24	0.20	0.32	0.16	0.44	0.32	0.52	0.40	0.56	0.44	0.00
Long-short Equity hedge											
1	23.90	12.27	6.79	4.21	3.45	3.69	4.61	6.67	11.99	19.65	1.72
2	16.21	13.41	9.16	6.48	6.31	6.23	7.10	8.77	11.34	12.24	1.56
3	11.54	14.04	9.77	8.37	6.77	7.40	7.40	10.61	12.14	9.98	1.01
4	11.21	14.15	9.15	7.51	8.00	8.27	8.17	11.32	10.56	9.25	1.31
5	8.86	14.14	10.01	9.47	7.34	8.19	7.77	10.74	12.26	8.62	1.70
6	10.78	11.28	10.28	9.27	7.32	8.49	10.17	9.44	10.78	9.61	1.01
7	9.64	12.01	8.97	7.45	7.08	9.45	8.78	11.25	12.68	10.59	1.04
8	10.49	11.61	7.96	6.59	6.63	7.16	9.01	13.22	14.14	10.80	1.23
9	12.73	10.95	6.79	4.71	4.90	5.91	7.38	11.16	15.93	17.77	0.59
10	17.22	9.52	5.19	3.85	3.22	3.47	5.91	7.66	15.16	26.94	1.04
New	0.45	0.40	0.29	0.23	0.23	0.14	0.26	0.45	0.39	0.60	0.05
Managed Futures											
1	29.74	10.02	5.11	2.91	2.39	2.67	3.44	4.77	10.36	27.16	0.53
2	18.46	12.97	9.18	5.39	4.09	4.89	6.09	6.39	14.47	15.37	0.80
3	16.06	12.75	7.28	5.13	6.46	6.95	10.93	9.11	8.11	14.40	0.66
4	12.11	15.70	6.73	6.50	6.73	6.28	7.62	10.09	10.99	15.25	0.00
5	17.59	11.33	8.67	6.75	6.02	5.54	8.43	8.19	12.53	12.29	0.72
6	17.42	10.61	9.85	7.83	6.57	4.04	7.32	8.84	9.85	14.90	0.76
7	15.47	12.77	6.83	8.99	5.58	5.22	7.55	8.99	13.49	12.05	0.36
8	17.45	11.58	8.94	4.99	7.04	7.62	7.62	5.87	11.73	15.10	0.88
9	20.38	8.88	4.35	3.99	6.52	4.26	5.34	10.96	13.77	19.93	0.63
10	24.16	7.64	4.14	2.86	2.22	2.47	4.49	6.56	12.18	32.00	0.59
New	0.40	0.17	0.06	0.45	0.17	0.06	0.34	0.34	0.40	0.62	0.00

APPENDIX 4											
Monthly performance persistence											
Multi-strategy	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Dead**
1	19.92	11.27	9.14	5.64	5.54	6.12	6.03	5.93	8.16	18.85	1.07
2	10.13	12.79	12.16	8.46	6.99	8.46	10.06	10.97	11.74	5.52	0.70
3	5.46	11.77	11.90	13.15	11.70	7.30	11.18	11.77	9.53	4.14	0.39
4	4.64	10.89	11.47	13.27	12.18	11.28	9.86	11.53	8.05	3.99	1.03
5	3.81	9.95	9.63	10.47	11.89	12.02	13.90	13.32	9.24	2.91	0.58
6	3.47	8.14	11.11	9.85	11.81	12.82	12.82	12.31	8.59	4.17	0.69
7	3.56	7.72	9.94	12.44	11.50	10.44	11.11	9.22	9.94	4.39	0.06
8	3.36	6.67	7.57	9.07	10.93	10.78	12.03	13.58	11.88	6.67	0.45
9	3.92	6.04	5.78	7.10	7.05	9.54	9.70	17.34	18.66	11.40	0.32
10	10.86	6.98	4.96	4.24	3.67	5.32	7.27	9.21	16.26	28.99	0.36
New	0.15	0.21	0.22	0.13	0.21	0.21	0.16	0.22	0.36	0.22	0.02

Tables below show the probability of a fund being allocated in each decile portfolio depending previous allocation on an annual basis. E.g. Emergin Markets fund that was allocated at decile 1 (bottom) in January 2008 has a 40.89% probability to be allocated in the decile 10 (top) portfolio in January 2009.

APPENDIX 4

Annual performance persistence

Convertible arbitrage	1	2	3	4	5	6	7	8	9	10	Dead
1	11.54	4.4	2.75	1.1	3.85	8.24	10.99	10.99	10.44	7.69	28.03
2	3.38	3.38	1.93	2.42	9.66	7.73	5.8	6.28	11.11	14.01	34.3
3	7.05	4.56	8.71	7.88	7.47	4.98	7.47	8.3	9.54	5.81	28.21
4	2.25	4.95	11.26	6.31	6.31	11.26	6.31	6.31	10.36	6.76	27.93
5	2.3	5.99	7.83	12.44	5.07	8.76	6.45	8.76	11.52	4.61	26.27
6	5.12	6.98	11.63	13.02	6.51	3.72	6.05	3.72	12.09	7.91	23.26
7	1.4	13.02	18.14	6.51	5.12	2.79	2.79	5.58	10.23	0.93	33.49
8	1.21	7.69	8.1	6.48	7.29	8.5	3.24	7.29	10.12	4.86	35.22
9	2.7	4.05	4.39	5.74	7.77	2.7	3.04	8.78	9.12	6.76	44.93
10	4.93	2.46	1.48	4.93	1.97	0.99	12.32	12.32	10.84	16.75	31.03
New	2.05	1.37	2.73	2.73	4.44	2.05	4.78	3.07	1.71	2.05	73.03
Emerging Markets											
1	10.53	2.85	2.18	1.61	2.56	1.90	1.61	5.88	11.57	40.89	18.40
2	10.06	2.66	2.09	4.17	4.93	6.26	4.74	7.97	14.04	19.73	23.34
3	7.99	6.30	3.87	4.36	9.69	7.51	6.78	7.02	8.96	11.62	25.90
4	9.61	6.41	3.66	6.18	6.64	5.03	6.64	8.01	9.84	6.41	31.58
5	8.07	5.73	7.22	5.31	7.86	4.88	5.10	7.86	5.52	7.22	35.24
6	7.63	5.98	4.33	6.39	6.60	7.84	4.95	7.84	8.25	8.87	31.34
7	11.83	4.36	4.77	4.36	5.39	5.81	6.64	7.68	8.30	9.34	31.54
8	9.46	7.36	3.55	4.07	3.15	4.86	3.29	8.54	12.35	7.62	35.74
9	9.98	4.13	3.18	4.48	3.96	3.53	4.22	8.00	7.23	9.47	41.82
10	11.78	3.99	2.19	2.10	1.97	2.28	3.00	4.25	9.40	19.66	39.37
New	1.66	0.93	1.01	1.16	1.01	1.40	1.45	2.12	3.28	5.46	80.53
Equity Market Neutral											
1	12.16	6.88	1.83	2.75	5.50	3.90	3.67	5.28	5.73	3.21	49.08
2	7.16	10.56	7.16	6.81	5.96	3.07	9.20	6.81	9.54	1.70	32.02
3	5.45	10.91	7.73	5.23	7.27	6.82	6.82	8.86	7.27	2.50	31.14
4	8.59	8.85	10.42	5.73	8.59	6.77	7.03	12.50	6.25	3.13	22.13
5	8.14	9.77	7.21	7.67	5.58	7.67	3.95	8.84	6.98	0.93	33.26
6	4.72	5.19	6.37	8.25	6.13	7.31	4.95	10.85	7.31	3.30	35.62
7	4.01	11.56	3.30	5.42	6.13	9.20	10.85	8.73	10.38	2.36	28.06
8	4.45	7.42	6.78	5.30	7.63	8.05	10.81	6.78	9.11	1.91	31.77
9	7.68	6.61	6.40	4.26	7.04	8.53	8.53	8.53	8.10	5.33	29.00
10	3.11	6.83	6.83	4.35	9.94	9.32	9.94	3.11	14.91	6.21	25.46
New	2.09	4.47	2.43	1.75	1.02	1.36	1.02	1.30	1.92	0.74	81.89

APPENDIX 4											
Annual performance persistence											
Event Driven	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Dead**
1	7.51	11.62	7.99	3.39	3.63	4.36	5.81	2.91	7.26	12.35	33.17
2	6.10	10.92	5.53	6.52	5.11	3.26	6.24	5.96	9.65	11.63	29.08
3	3.70	7.82	7.97	5.26	3.84	4.13	9.67	8.68	11.38	4.69	32.86
4	4.52	7.42	6.29	5.32	5.32	6.29	6.94	7.74	10.65	5.48	34.03
5	3.59	8.58	5.30	3.28	7.80	7.18	5.77	12.32	9.36	6.40	30.42
6	3.43	6.39	8.88	5.30	5.76	6.39	9.50	11.37	11.84	4.98	26.16
7	4.18	8.73	7.22	5.19	5.57	6.33	9.75	11.39	11.27	3.92	26.46
8	2.05	6.16	7.00	8.70	8.21	6.04	8.57	10.99	7.61	3.26	31.40
9	4.43	7.35	7.35	6.88	7.82	7.23	6.07	4.90	7.00	5.83	35.12
10	4.65	4.65	7.05	4.35	3.15	3.90	3.60	4.35	3.75	12.59	47.98
New	2.55	1.66	1.53	2.17	1.79	2.23	1.79	2.81	2.30	2.87	78.28
Fixed Income Arbitrage											
1	14.61	9.55	5.06	5.06	5.62	2.81	5.06	8.15	5.34	6.74	32.02
2	5.48	10.14	10.41	4.93	5.21	2.47	3.01	7.12	3.56	3.84	43.83
3	8.02	8.33	7.10	6.17	8.33	6.79	4.94	5.86	4.32	1.85	38.27
4	6.06	8.59	10.61	2.02	5.56	6.57	2.02	9.60	5.56	3.03	40.40
5	16.48	8.24	6.59	4.95	3.85	6.59	2.20	5.49	8.79	3.30	33.52
6	9.66	3.45	8.97	2.76	6.21	2.76	1.38	12.41	10.34	2.76	39.31
7	12.96	6.17	4.32	3.70	3.09	2.47	5.56	6.79	9.88	4.94	40.12
8	11.01	7.05	5.73	3.08	0.00	3.52	9.69	4.85	11.01	18.06	25.99
9	5.64	4.89	1.88	4.14	6.39	8.27	7.14	10.53	14.66	7.14	29.33
10	5.95	5.95	5.95	3.24	6.49	3.24	3.78	5.41	6.49	15.14	38.38
New	2.34	1.69	1.03	1.22	0.28	0.37	0.84	0.75	4.50	1.31	85.66
Funds of funds											
1	8.70	6.74	4.03	3.63	3.34	3.86	2.54	3.34	3.75	6.17	53.89
2	4.49	6.46	6.94	6.99	6.21	5.62	3.88	4.52	2.47	1.04	51.38
3	3.37	6.46	7.17	8.68	8.70	8.19	5.67	5.53	1.79	0.37	44.08
4	2.07	5.71	8.28	10.84	10.47	9.93	7.65	4.80	1.24	0.44	38.58
5	1.54	5.47	9.03	11.93	11.46	9.48	8.53	4.12	1.58	0.46	36.40
6	1.56	6.17	9.71	10.80	10.71	9.32	8.38	4.25	1.71	0.52	36.87
7	2.06	5.60	8.30	10.99	9.62	9.35	8.12	3.93	2.54	1.02	38.47
8	3.54	6.37	7.45	9.03	8.59	8.56	8.93	6.91	3.50	1.28	35.84
9	6.67	8.30	7.48	5.60	6.60	7.55	7.99	9.81	7.92	4.47	27.61
10	13.79	9.05	7.24	4.04	4.74	6.82	5.15	5.85	9.89	8.77	24.66
New	0.66	1.27	1.74	1.76	1.59	1.83	1.49	0.89	0.63	0.16	87.97

APPENDIX 4											
Annual performance persistence											
Global Macro	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Dead**
1	5.82	6.00	3.35	3.88	3.17	2.47	3.53	3.53	7.41	8.29	52.56
2	6.82	5.77	6.82	4.20	4.46	2.62	2.36	5.51	12.60	6.82	42.00
3	10.57	5.28	4.53	2.64	2.64	3.02	4.53	11.32	8.30	7.92	39.24
4	9.87	6.28	2.69	5.38	2.24	4.04	4.93	9.42	7.17	6.28	41.71
5	5.96	6.38	4.68	1.28	3.40	3.40	3.83	6.38	9.79	10.21	44.68
6	8.40	4.96	4.20	1.15	4.58	3.05	5.34	7.25	8.78	11.83	40.46
7	7.80	7.09	4.61	3.90	3.19	4.26	7.80	6.03	9.93	10.64	34.75
8	5.17	7.49	4.91	2.84	4.39	6.46	8.79	7.49	11.37	10.85	30.23
9	6.48	8.76	4.20	4.55	7.01	8.23	7.53	5.78	10.16	14.71	22.60
10	11.07	9.38	5.25	3.38	5.07	3.38	5.82	7.32	14.82	13.70	20.83
New	3.59	1.23	0.55	0.72	0.80	1.10	0.63	1.86	3.55	1.78	84.18
Long-short Equity hedge											
1	12.54	5.61	3.66	2.99	2.50	3.17	3.60	4.85	8.73	14.71	37.63
2	8.74	8.74	4.62	4.48	4.04	5.90	5.54	8.01	9.61	8.45	31.86
3	7.82	6.90	5.61	4.69	4.09	4.87	8.55	10.02	7.82	6.48	33.15
4	6.63	6.94	5.14	6.06	4.98	7.25	7.09	6.83	7.45	4.27	37.36
5	5.98	6.25	9.03	6.77	5.35	6.46	8.24	8.14	7.45	4.36	31.97
6	6.46	7.41	8.77	6.87	5.56	4.74	8.90	7.68	8.31	6.46	28.83
7	5.41	7.91	6.47	5.52	6.21	7.68	7.00	10.22	8.40	5.94	29.24
8	6.08	7.84	6.83	5.96	5.44	5.99	6.92	9.82	6.58	6.73	31.81
9	8.10	7.79	5.94	5.32	4.84	5.35	6.27	7.51	8.38	7.54	32.95
10	12.78	7.28	4.19	3.68	3.54	4.49	4.37	6.03	7.16	12.36	34.11
New	1.99	1.65	1.23	0.96	1.17	1.60	1.80	2.23	2.96	2.14	82.28
Managed Futures											
1	12.41	4.05	2.32	1.29	1.58	2.27	4.05	5.39	7.17	15.67	43.79
2	10.43	5.06	4.03	3.41	3.93	4.44	4.34	6.30	7.44	12.71	37.92
3	12.41	6.90	4.31	3.45	2.59	3.28	3.79	6.55	8.62	14.31	33.79
4	10.42	6.02	6.94	4.63	3.01	3.94	3.24	6.02	9.03	14.35	32.41
5	12.98	6.97	4.81	5.05	3.85	3.13	5.29	3.85	11.30	12.26	30.53
6	10.28	7.92	4.28	2.78	4.07	4.50	5.35	9.21	7.92	11.13	32.55
7	12.01	8.07	3.38	4.88	3.94	4.32	4.13	8.63	11.44	11.07	28.14
8	16.27	8.76	6.12	4.59	3.89	5.29	6.12	5.42	9.60	13.49	20.45
9	18.47	9.18	5.51	4.18	3.98	5.41	3.67	6.63	7.65	18.06	17.24
10	29.83	9.04	5.20	2.95	2.48	4.13	4.78	5.79	9.10	15.53	11.16
New	2.92	2.77	1.96	1.24	1.53	0.81	1.10	1.91	2.44	3.87	79.44

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APPENDIX 4

Annual performance persistence											
Multi-strategy	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Dead**
1	6.55	4.00	5.09	3.82	3.64	4.73	3.64	3.45	7.09	14.73	43.27
2	4.89	7.79	5.94	4.76	4.23	3.96	5.42	4.49	9.64	12.29	36.59
3	4.60	8.06	5.37	5.12	7.29	4.48	5.63	9.59	9.21	8.95	31.71
4	4.35	5.20	5.62	5.20	5.90	8.71	9.83	5.20	6.88	7.72	35.39
5	3.30	5.17	4.74	7.61	7.04	8.33	7.61	7.47	5.46	6.90	36.35
6	3.15	4.09	5.02	4.67	6.31	8.88	9.46	9.93	7.94	5.37	35.17
7	2.55	2.45	5.75	5.66	5.00	7.83	8.11	7.74	7.55	7.17	40.19
8	2.40	3.93	5.56	5.47	6.04	5.47	6.42	8.34	9.40	7.00	39.99
9	4.06	3.88	2.29	3.35	3.44	6.53	7.14	10.05	12.26	8.47	38.54
10	6.04	5.68	3.20	2.75	2.49	3.29	4.62	7.90	10.83	19.80	33.39
New	0.43	0.64	0.67	0.59	0.49	0.68	1.09	0.73	1.21	0.73	92.75