Hedge Fund Performance

Ph.D. Thesis

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by

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Hedge Fund Performance

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Le doyen

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I dedicate this dissertation to my newborn son, Ethan.

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"One only understands the things that one tames"

Antoine de Saint-Exupéry, *the fox in The Little Prince, ch. 21, p. 51 (1943)*

Introduction

Collective investment schemes have long been an important part of many investors' portfolios. However, hedge funds, a category of investment funds specifically aimed at institutional investors and wealthy individuals, were widely overlooked until relatively recently. Even though academics have been studying the investment fund industry for over half a century, hedge fund research dates back twenty years at most. Early research focused in particular on the drivers and strategies behind the returns of hedge funds, whose typical performance objective is to deliver a steady return rather than following or slightly outperforming a market index. Fung and Hsieh (2006) present hedge funds as "*an industry in its adolescence*". Six years later, this industry is more alive than ever and entering *its young adulthood*. As such, it is still certainly immature and evolving, and a number of questions need to be addressed or re-addressed to apprehend and understand its peculiarities.

This dissertation predominantly focuses on the drivers behind hedge fund performance and analyzes them in three distinct chapters. Chapter one draws a picture of current knowledge by reviewing the existing literature about hedge fund performance and information reliability. It documents a mostly beta-driven persistent performance of hedge funds to which investors react asymmetrically; they bring money to well performing funds but do not necessarily rush out of bad ones. These money inflows tend in turn to deteriorate funds' performance because of decreasing returns to scale. Additional performance drivers emerge from the specific remuneration structures hedge funds deploy, from fund-level characteristics, and from the limited legal reporting requirements they face. There appears, however, to be a number of issues when relying on hedge fund data. Indeed, virtually all databases suffer from multiple sources of errors, biases, and misreporting, which added to the fact that hedge fund reporting is mostly voluntary, are all reasons of concern.

Chapter two[1] analyzes the role of remuneration structure in hedge fund performance. It rationalizes the persistent performance of hedge funds with a simple model that takes into account the peculiarities of this industry. The combination of a performance-linked remuneration with the lack of benchmarking opportunities results in the necessity for managers to keep outperforming in order to maximize their income. Managers manipulate their attractiveness toward investors to control the size of their fund. Thus, performance-diluting flows do not occur and the fund keeps outperforming. Therefore, the hedge fund-like remuneration structure emerges as an effective way to align investors' and managers' interests when no straightforward benchmark is available. The predictions of the model are consistent with the literature and are confirmed by the analysis of a unique dataset of management fee modifications.

Chapter three documents the uses and the effects of long equity holdings in the portfolios of equity-focused alternative investment firms that are subject to periodical holdings disclosures by the SEC. Specifically, it analyzes the information content of mandatorily reported long equity holdings by contrasting the returns that could be obtained by mimicking these holdings to the net total returns firms voluntarily report. A large majority of the firms do not appear to produce any risk-adjusted outperformance solely with their long equity positions but one third of them outperform in terms of net total returns. This underlines that secrecy about positions and investment strategies might be at the core of the return generating capacities of alternative investment firms. Stock picking, when measured on long equity holdings changes conditioned on public information, is absent among most managers. Though, two equivalently sized groups are particularly good, respectively particularly poor, at picking stocks. Market timing is also scarce and, in the few cases it is significantly present, it is generally negative. Further analysis permits to rank long equity positions as a diversifying portfolio component rather that as an

[1] A collaboration with Ivan Guidotti.

additive one. The implication being, that long equity holding choices are not an investment strategy on their own but are part of a more global investment strategy.

This dissertation sets itself within the global regulatory-changing trend toward the financial industry in general and toward hedge funds in particular. In 2012, hedge funds' assets have reached their highest ever level at USD 2.13 trillion—about one tenth of the size of the mutual fund market—[2] and cannot any longer be considered as marginal players. Actually, they do not anymore only concern institutional investors and wealthy individuals, but are now also reaching *naïve* investors as part of collective investment schemes proposed by banks and pension funds or via easily investable exchange traded funds. Moreover, because of the highly concentrated—and leveraged—bets or investment strategies a number of hedge funds put in place, there are concerns about their potential effect on financial stability, and as such, they are now a public concern. As a consequence, they are at the center of the financial regulatory revisions currently deployed by the American government, the European Commission, and even by the Swiss government.

In this context, understanding the drivers of hedge fund performance is of first-order importance to implement efficient and well-focused regulatory measures. I believe that this dissertation gives novel and valuable insights in that respect. Chapter one underlines the fact that the current, mostly voluntary, reporting scheme is prone to errors and biases, and is thus not sufficiently reliable. On this ground, there appears to be a necessity to amend the type and extent of mandatory reporting required, without publicly disclosing potentially performance-hurting information. The regulatory eyes-only mandatory reporting, out of which a two-compartment anonymous dataset for researchers could be extracted, as proposed at the end of the chapter, is an example of an easily implementable solution that could permit to draw a more accurate picture of this industry.

[2] See, for instance, Chung, J., *Hedge-fund assets rise to record level*, The Wall Street Journal, 19/04/2012, http://online.wsj.com/article/SB10001424052702304331204577354043852093400.html and *2012 Investment company fact book*, The Investment Company Institute, http://www.icifactbook.org/2012_factbook.pdf.

The long-debated effect of performance-based asymmetric remuneration schemes treated in chapter two underlines the fact that, in the specific context of hedge funds, it is a contractual term that is not only in the best interest of managers but also of investors. It also shows that the performance fee in itself is not sufficient and that such a fee applied in the context of mutual funds would not have the same interest-aligning effect. Thereby, it points out the importance of considering an industry in a global framework and with all its specificities when envisaging new regulatory measures. As a matter of fact, a regulation that has one effect in a particular context might have another effect, or no effect, in a different context.

Finally, by showing that alternative investment firms' long equity holdings are only part of a more global investment strategy, chapter three highlights the limited usefulness of current mandatory reporting requirements when it comes to understanding the investment strategies put in place. Moreover, it rejoins the conclusions of chapter one with respect to the need to be cautious when implementing new rules. Indeed, under the present reporting requirements, global strategies remain hidden, and sometimes profitable, but regulators must be careful not to require disclosures that would potentially bring any remaining return for the investors to zero.

Chapter 1: Hedge Fund Performance, a Review

1.1 Introduction

Once only familiar to a very limited number of sophisticated investors, hedge funds have gradually become part of many institutional portfolios. However, because of their opacity and the loose regulation under which they exercise, many myths still follow them. In addition, in the last decades, a series of public affairs—such as the L.T.C.M.[3] debacle, the 2008 sub-prime crisis, the Madoff[4] scandal, and a relatively poorer performance—further contributed to build a biased image of hedge funds. Combined with wide and often ill-informed media coverage, this resulted in many pre-conceived ideas, and hedge funds are often considered to be maverick investment firms, seen essentially as a plague to investors, financial markets, and the economy in general.[5] In a time where governments and citizens are pushing towards greater regulation of financial markets, certain characteristics of the hedge fund industry need to be re-examined. In this paper, I review the literature about two interconnected topics, hedge fund performance persistence and data reliability. Indeed, since any results regarding performance or persistence rely on the quality of the underlying data, it is important to consider these topics together. Both have been widely studied and have been shown, or have at least been thought, to have certain hedge fund specific features, which I propose to examine here. Specifically, I first document the drivers of hedge fund performance and how investors react to and affect this performance. Second, I review the reliability of financial data in general and of hedge fund data in particular.

Hedge funds have built their reputation on their supposed ability to produce positive returns consistently, regardless of financial market performance. This is also the main argument they

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[3] Long Term Capital Management was a hedge fund which, after its highly leveraged investment strategy failed, had to be bailed out in 1998 to avoid contagion to financial markets. See, for instance, Lowenstein (2000).

[4] Bernard Madoff was (or pretended to be) a hedge fund manager who financed investors' returns through a Ponzi scheme that collapsed at the end of year 2008 as he registered massive redemptions from investors in the follow-up of the sub-prime crisis. See, for instance, Henriques (2011).

[5] See, for instance: Tim Rayment, *Hedge-Fund Managers, Lords of Lucre*, Timesonline, 20/01/2008, http://business.timesonline.co.uk/tol/business/movers_and_shakers/article3196956.ece

advance in favor of the high fees they charge. From the literature, it emerges that this argument is only partially justified. While hedge fund managers are apparently able to generate performance over mutual funds and multifactor risk models, the persistence of this outperformance varies greatly among studies and is found to range from one month to three years. Multiple factors, such as the period under study or statistical procedures used, seem to influence the results, but it emerges that one of the main issues is the lack of a well-defined benchmark to measure performance against. In the absence of such a benchmark, it is understandable that both the length and extent of outperformance remain debated.

Benchmarks should reflect the risk, thus allowing evaluating hedge fund risk and understanding its sources. It is, therefore, perhaps more important to know the drivers of hedge fund returns. Contrarily to what is commonly thought, the literature shows that most of hedge fund returns are actually explained by common or strategy related factors. In addition to these (common) factors, advanced risk exposures emerge. Higher moment exposures and non-linearities, as well as liquidity risk, all participate to explain hedge fund returns. Although complex, all of these sources are identifiable and can be categorized as beta exposures. Thus, the biggest part of hedge fund returns does not come from alpha, as usually thought. Some fund-level characteristics also play a role, so there appears to be a concave relation between size and returns, and a positive relation between share restrictions and returns (explained by an illiquidity premium paid to the investors). Next, I consider another factor, opacity. It is generally thought that secrecy is a necessary condition for hedge funds to apply their strategy and to keep making money. In reality, the conclusions of the literature on this subject are limited and conflicting. Although it is clear that the funds which put a specific emphasis on secrecy have good reasons to do so—because it helps them generate performance—it is not possible to conclude that all funds take advantage of this. This topic remains debated for the moment, and there is a need for further studies on the matter. The part of returns which remains unexplained by the above-mentioned drivers is generally called alpha, or skill. Since there is hedge fund outperformance not explained by any other factors, it seems clear that skill is present. The literature, however, conflicts about the nature of this skill. Whether it comes from a superior ability to access information, from a superior ability to process this information, from stock-picking skills, or from market-timing skills, the source of alpha is yet to be confirmed. Future researches will certainly be able to answer this question by analyzing hedge fund holdings and identifying what value is added by hedge fund managers over all publicly available information.

I then review the interactions between investors and hedge funds. The reaction of fund performance to investors' flows confirms the investment capacity hypothesis.[6] As a matter of fact, studies find opposing results between small and large funds; smaller funds tend to benefit from flows, while for larger funds, it is the opposite. Furthermore, differences also appear depending on the time horizon considered. Indeed, at first, fund inflows have a tendency to increase performance, but later on, the effect disappears or even reverses. The relation investors have towards performance appears to be ambiguous. On the one hand, it is obvious and clearly shown that investors try to invest in the best performing funds, but on the other hand, the literature also demonstrates that they tend to keep their money in poorly performing funds too. As one might expect, this partially stems from the fact that they not only consider pure returns, but elements such as risk also factor into their equation. This includes not only pure quantitative risk but also perceived risk, based on personal traits of the fund manager, for instance. Additionally, they also consider liquidity risk in the sense that they take share restrictions into account in their investment decisions. It would, therefore, be interesting to further study the state and the evolution of investors' reactions towards various perceived risk

[6] The hypothesis states that there is only a limited amount which can be invested within a particular strategy without impacting returns negatively.

factors along with quantitative risk factors to identify what the real drivers are in their decision process.

Further analyzing the literature, I pinpoint why there are discrepancies between hedge funds and mutual funds in terms of performance and persistence. It seems that the difference does not customarily come from a drain of talents in the mutual fund industry. Indeed, the best mutual fund managers are offered to start in-house hedge funds to keep them from leaving. So, there is an aspect of hedge funds which attracts them and allows them to further outperform. I identify one single feature which seems to explain most of the performance differences: asymmetric remuneration structure. Indeed, from the papers I review, it emerges that hedge funds' combination of incentive fees and high watermarks are linked with superior performance and help in limiting the risks they take. Hedge fund managers therefore seem to outperform their mutual fund counterparts because they are *motivated* to do so. However, it would be interesting to clarify a point. Hedge funds modify their fee structure from time to time, but it is yet relatively unclear exactly how and why they do so. Indeed, up to now, studies have tried to link these changes with fund-level and performance related factors. However, since remuneration structures' intent is to reward well-performing managers, there is potentially another explanation which relates remuneration scheme changes to how they motivate managers by making them better off.

All of the above results are, however, subject to the validity of the data that has been used. By reviewing the literature about financial data reliability, I shed light on the reliability of current research and come to the conclusion that one must be cautious when using third party data. Indeed, the sources of errors are numerous. Data definition and construction, entity classification, coverage, and reporting errors are all present in most of the well-known datasets. In hedge fund datasets, in addition to the problems shared by all financial databases, other biases arise because of the voluntary reporting regime this industry is subject to. Luckily, many of these hedge fund specific biases can be mitigated. Nevertheless, an additional issue seems to plague hedge fund figures: misreporting. As the literature shows, misreporting is not rare among hedge funds. Also, figures reported in multiple databases do not always match. Finally, database revisions are not uncommon and do not have a random pattern, so some funds tend to be revised more often than others. This suggests that data has to be treated very carefully because it might contain errors, differ between databases, or even be revised from time to time. Several questions, however, remain open. It would, for instance, be interesting to verify to what extent misreporting is voluntary and how its presence in databases actually affects research results. Additionally, one could check whether the errors come from data vendors or are strategically done by hedge fund managers by comparing multiple snapshots of multiple databases.

In Sections 1.2 to 1.5, I review the literature about hedge fund performance. Section 1.6 discusses the reliability of current research, and Section 1.7 concludes this chapter.

1.2 Presence and Persistence of Performance

Whether fund managers are able to deliver a persistent performance—that is, consistently outperform their benchmark—is probably *the* central question in the investment management literature and also in investors' minds. Indeed, while anyone can be lucky or have a specific information advantage that lets her outperform once, investment managers supposedly exist to repeat this performance over and over again. Of course, they also provide investors with additional advantages, such as diversification or delegation, but the hefty fees they are able to charge seem to plead in favor of at least some sort of persistence in the performance they deliver. Jegadeesh and Titman (1993) show that a very simple investment strategy, buying past winners and selling past losers, can generate persistence up to a one-year horizon. Therefore, on the one hand, it seems reasonable to expect that fund managers should be able to do this as well. But on the other hand, the efficient market hypothesis suggests they should not be able to persistently outperform, once all fees and costs have been accounted for. In the hedge fund industry, the question is even more central since most funds justify their high levels of fees by an ability to deliver absolute return, regardless of market conditions. In this context, I review the literature on performance persistence and shed light on the presence of persistence in hedge fund returns.

The literature on performance persistence goes back to Sharpe (1966), who finds little evidence of persistence in the outperformance of mutual funds. Since then, numerous authors have investigated the issue. If anything, the evidence in favor of performance persistence in mutual funds is weak. Grinblatt and Titman (1995) propose an in-depth review of the corresponding literature and conclude that there is little evidence in favor of persisting abnormal performance, and the benchmark against which the funds are evaluated greatly affects the conclusions. They, however, underline that there is a subset of mutual funds that have sufficient skills to collect and process financial information in a profitable way. More recently, Fama and French (2010) reach similar conclusions, at least when all costs have been accounted for. Therefore, if persistence in some mutual fund returns may exist, it is not the case in general.

While mutual fund performance is usually measured against a market index, such as the S&P 500, hedge fund performance is measured in risk adjusted terms over the risk free rate. Therefore, while a mutual fund can outperform with a return of minus ten percent, provided that the market return is even lower, hedge funds can only outperform with positive returns. This is the source for a new area of financial literature, which I review below. Table 1.1 describes the corresponding papers and summarizes the main findings.

Table 1.1: Literature about Hedge Fund Performance Persistence

This table summarizes the articles about performance persistence in hedge funds. It describes the methods and the samples used, along with a summary of the key results, the performance measures, and the conclusions about the presence of outperformance and performance persistence. When not precised, the method is archival.

Reference	Method / Sample	Key results	Performance Measure	Outperformance	Persistence
Ackermann, McEnally, and Ravenscraft (1999)	HFR, MAR, 1988-1995	Hedge funds outperform mutual funds but not market indices in terms of Sharpe ratio and absolute return.	Excess Sharpe ratio and alpha over 1) mutual funds, 2) equity market index	Yes	-
Brown, Goetzmann, and Ibbotson (1999)	U.S. Offshore Funds Directory, 1989-1995	Offshore hedge funds have positive outperformance as a group in terms of Sharpe ratio or Jensen's alpha, but there is no evidence of persistence.	Sharpe ratio and single factor Jensen's alpha	Yes	No
Agarwal and Naik (2000b)	HFR, 1982-1998	Hedge fund performance persists at quarterly horizon, before and after fees. There is very limited persistence after one year or more.	Alpha over hedge funds of the same strategy and appraisal ratio	-	Yes, 1Q
Agarwal and Naik (2000c)	HFR, 1994-1998	Hedge funds outperform their benchmark consistently. There is persistence in hedge fund performance at the quarterly level.	Alpha over an 8 factor model: 3 equity, 3 bond, 1 currency, and 1 commodity	Yes	Yes, 1Q
Edwards and Caglayan (2001)	MAR, 1990-1998	Both positive and negative hedge fund performance persists up to two years when alpha is measured against a six factor model.	Simple return, excess return, Sharpe ratio, and alpha over a 6 factor model: equity market, HML, SMB, MOM, term spread, default premium	Yes	Yes, 2Y
Bares, Gibson, and Gyger (2003)	FRM, 1992-2000	There is evidence of short-term performance persistence of hedge fund portfolios and long-term performance reversal. Persistence does not stem from volatility.	Alpha over investment strategy peers	-	Yes, 1-3M
Brown and Goetzmann (2003)	TASS, 1989-1999	Evidence of return persistence is very limited at the yearly level. There is persistence in risk levels in the different investment styles.	Simple return	-	No
Kat and Menexe (2003)	TASS, 1994-2001	Hedge fund returns do not persist much, but risk and correlations with the market do.	Simple return	-	No

Koh, Koh, and Teo (2003)	AsiaHedge, EurekaHedge, 1999-2003	Asian hedge funds' performance persists at the monthly and quarterly horizon but not longer.	Simple return and alpha over a 7 factor model: Asian, Japanese, and US equity markets, Japanese bond market, SMB, HML, MOM	-	Yes, 1Q
Capocci and Hübner (2004)	HFR, MAR, 1994-2000	No performance persistence in extreme decile hedge funds but some persistence in average funds.	Alpha over market index, over Carhart's factors, and over an 11 factor model: 6 equity, 4 bonds, and 1 commodity	Yes	Yes, but only average funds
Harri and Brorsen (2004)	LaPorte, 1977-1998	There is evidence of hedge fund performance persistence at the quarterly horizon, but most persistence is observed at a one-month horizon.	Simple return, Sharpe ratio, and an 8 factor model: 3 equity, 2 bond, 1 cash, 1 commodity, and 1 currency	Yes	Yes, 1-3M
Baquero, ter Horst, and Verbeek (2005)	TASS, 1994-2000	Hedge fund performance persists at horizons from one to four quarters. There is performance reversal at the two-year horizon.	Simple return and alpha over strategy index	-	Yes, 1-4Q
Malkiel and Saha (2005)	TASS, 1994-2003	Hedge fund return persistence at the yearly horizon is limited and greatly varies from year to year.	Simple returns	-	Yes, but not every year
Kosowski, Naik, and Teo (2007)	TASS, HFR, CISDM, MSCI, 1990-2002	Hedge fund outperformance persists at annual horizon and cannot be explained by luck. The best results are obtained when using the Bayesian alpha as a performance proxy.	Bayesian alpha over the Fung and Hsieh (2004) 7 factor model	Yes	Yes, 1Y
Boyson (2008)	TASS, 1994-2000	Hedge fund performance persists at a quarterly horizon if managers are selected on past performance and manager tenure.	Alpha over a 19 factor model: 1 equity, 2 bond, 1 currency, 2 commodity, SMB, HML, MOM, and 10 strategy indices	-	Yes, 1Q
Zhong (2008)	CISDM, 1994-2005	Hedge fund aggregate alpha has been decreasing over time. This is due to a small right tail of the returns distribution rather than to a bigger left tail.	Alpha over the Fung and Hsieh (2004) 7 factor model	Yes, but decreasing	-

Eling (2009)	Review and archival, CISDM, 1996-2005	Depending on the methodology used and the strategy analyzed, performance persistence might, or might not be found in hedge fund returns. Biases push returns and persistence upward.	Simple return, alpha over 2 multi-factor models, 2 appraisal ratio, and Sharpe ratio	-	Technique and strategy dependent
Manser and Schmid (2009)	CISDM, 1994-2005	Hedge fund risk-adjusted performance persists at the 1 year horizon, less so when only raw returns are considered.	Alpha over a 6 factor model, equity market, SMB, HML, MOM, and 2 option factors	Yes	Yes, 1Y
Aggarwal and Jorion (2010b)	TASS, 1996-2006	After inception, individual hedge fund performance persists up to five years.	Alpha over style index	-	Yes, 5 Y
Ammann, Huber, and Schmid (2010)	TASS, CISDM, 1994-2008	There is evidence of performance persistence in hedge fund returns up to 36 months. Strategy distinctiveness systematically improves on persistence up to 24-month horizons. Other characteristics are partially explicative.	Alpha over a 7/23 factor model selected via stepwise regression	Yes	Yes, 3Y
Jagannathan, Malakhov, and Novikov (2010)	HFR, 1996-2005	There is performance persistence in hedge funds with respect to their style benchmark. One quarter of the 3-year outperformance persists in the next 3 years. Evidence is strong for good performers but not for poor performers.	Alpha over strategy index and over the Fung and Hsieh (2004) model	Yes	Yes, 3Y
Diez de los Rios and Garcia (2011)	CS/Tremont, 1994-2008	Taking into account non-linearities and public information, only two hedge fund strategies and the hedge fund overall index outperform.	Alpha over a 16 factor model	Strategy dependent	-

Among the first to tackle the issue of hedge fund performance, Ackermann et al. (1999) find that, over the 1988-1995 period, hedge funds outperformed mutual funds but not market indices, both in terms of Sharpe ratio and absolute returns. It is important to note that the market returns were exceptional in the period under study. The S&P 500 accumulated a return of over 220 percent over the eight years considered. Over a similar period, Brown et al. (1999) document positive outperformance of off-shore hedge funds in terms of Sharpe ratio and Jensen's alpha but find no evidence that this outperformance persists. Similarly and over a longer time period, Brown and Goetzmann (2003) observe very limited evidence of performance persistence at a yearly level, but they find that risk levels are persistent within the various investment strategies. They also underline the fact that hedge funds are not a homogenous investment class. Additionally, Kat and Menexe (2003) identify persistence in risk and market correlations, not in returns, but underline that the predictive power of return track records is strongest for evaluating risk profiles relative to strategy peers rather than in absolute terms. After taking into account the effect of a number of risk exposures, Capocci and Hübner (2004) only find performance persistence in average hedge funds, but nothing in the best or the worst funds, thus pointing towards a short term nature of performance. Malkiel and Saha (2005) find limited persistence at the one-year horizon and a great variation from year to year, so performance appears to persist in some years and not in some others. Moreover, they highlight higher risks and lower returns than what is usually thought. Confirming this lower performance, Zhong (2008) shows that the hedge fund alphas have been decreasing over time and that this is mainly due to extremely good performers reversing towards the mean while the number of poor performers remains constant. Finally, Eling (2009) and Diez de los Rios and Garcia (2011) underline the variation of performance and persistence levels across hedge fund strategies and suggest that, if present, the identification of performance persistence is very sensitive to the statistical technique employed.

Contrarily to the above-mentioned literature, Agarwal and Naik (2000b, 2000c) find strong evidence of persistence at a quarterly horizon, both before and after fees, although they observe that it is mainly due to poor performers continuing to perform poorly rather than to good performers continuing to outperform. Edwards and Caglayan (2001) identify that, after controlling for risk exposures with a six-factor model, approximately one quarter of the hedge funds outperform and that both positive and negative persistence is present at horizons of up to two years. Further studies debate on the length and extent of the persistence. On the short-term side, Bares et al. (2003) document that persistence is strongest at the one-month horizon, that it is decreasing with holding period, and that there is reversal towards the mean at long-term horizons; also see Koh et al. (2003), Harri and Brorsen (2004), Baquero et al. (2005), and Boyson (2008) for similar conclusions. On the long-term side, Kosowski et al. (2007) compute hedge fund alphas with the methodology introduced by Pastor and Stambaugh (2002) and report that hedge fund portfolios, selected on the basis of Bayesian alphas, persistently outperform up to a yearly horizon. Manser and Schmid (2009) make a case in the same direction and document persistence at a one-year horizon when performance is measured on a risk-adjusted basis and especially with a multifactor model. Over the longer term, Ammann et al. (2010) extend the persistence to three-year horizons and show that strategy distinctiveness with respect to other funds significantly participates in the persistence; i.e., funds that are less correlated with their peers persist more. Jagannathan et al. (2010) corroborate these findings and observe that one quarter of the managers who outperform during a three-year period also outperform in the subsequent three-year period, and they add that this is only true for good performers. Finally, taking an alternative route, Aggarwal and Jorion (2010b) show that after inception, the initial performance of hedge fund managers persists up to five years. This suggests that when hedge fund managers enter the market, they have an investment idea that they are able to exploit in the subsequent years before it dries up, either because it has been arbitraged away or because of the cyclicality in investment opportunities.

Overall, performance persistence in hedge funds is still under debate, but it is more about its length than its existence. The source of the debate is twofold. First, the methodology used has its own importance and can greatly influence the conclusions, depending on the horizons considered, on the classification technique that has been applied, or on the time-period under study. Second, in hedge funds, contrarily to mutual funds, there is never a clear consensus over what benchmark to use. Since there is no market index against which the fund is benchmarked, there cannot be a unique way of measuring performance. It may be represented by returns that remain unexplained by risk or market factors, by the returns over other hedge funds, by a risk-adjusted measure, or by many other measures. In this context, any performance measure is, by definition, subjective, and it seems unlikely that any study could give the final call to the debate about hedge fund performance persistence. Therefore, in the following, rather than trying to identify the most appropriate measure of performance, I review the various characteristics, market factors, and risk exposures that have been shown to affect hedge fund returns in the literature.

1.3 Sources of Returns

Understanding the sources of returns is fundamental for analyzing the risks involved in an investment. Carhart (1997) shows that mutual fund returns are almost entirely explained by common market factors and that persistence is mostly driven by the momentum factor; also see Jegadeesh and Titman (1993). While it is clear that such simple exposures are partially explanatory of hedge fund returns, there are other more sophisticated factors and characteristics which participate in the variations of their returns. In this context, the task is then to identify which are the risks and which are the corresponding risk premia that explain hedge fund returns, to finally establish whether there is something left that can only be explained by the manager's skill. In the following, I draw a representative picture of the different return drivers and classify them into five categories: common and investment strategy-based factors, advanced risk exposures, non-market related factors, secrecy, and skill. The corresponding literature is summarized in Table 1.2.

1.3.1 Common and Investment Strategy-Based Factors

In the early days of hedge fund performance measurement, Fung and Hsieh (1997) were among the first to understand that common risk factors are not sufficient to describe hedge funds' returns and propose an augmented version of the Sharpe (1992) model, which includes five investment-style factors extracted from hedge funds' time-series. In the same vein, Schneeweis and Spurgin (1998) also augment the Sharpe (1992) model with trend-following factors and show its power in explaining commodity trading advisor and hedge fund returns.

Table 1.2: Hedge Funds' Sources of Return and Risk: a Review

This table summarizes the articles about the sources of return and risk in hedge funds. It describes the methods and the samples used, along with a summary of the key results. When not precised, the method is archival. The papers are order by year of publication and author.

Reference	Method / Sample	Key result
Fung and Hsieh (1997)	Morningstar, Paradigm, TASS, ~1990-1995	Identify five prevailing investment strategies in hedge funds that can be added to Sharpe (1992) factors to explain hedge fund returns.
Schneeweis and Spurgin (1998)	Morningstar, MAR, HFR & others, 1990-1995	A set of factors based on trend-following rules explain returns in managed futures and hedge funds, along with the Sharpe (1992) model. Alternative investments can sometimes provide diversification to mutual fund portfolios.
Liang (1999)	HFR, 1992-1996	Size and length of lockup period (illiquidity) are positively related to hedge fund returns.
Agarwal and Naik (2000a)	HFR, 1994-1998	Hedge funds are significantly exposed to equities, bonds, and currencies. Exposition varies from one investment style to another.
Agarwal and Naik (2000c)	HFR, 1994-1998	Hedge funds can help diversify a traditional portfolio because their risk loading is relatively different from standard asset classes.
Fung and Hsieh (2001)	TASS, ~1990-1998	Create (non-linear) trend-following factors, using traded options, which better explain hedge fund risk exposures and returns than standard asset-based factors.
Mitchell and Pulvino (2001)	CRSP, DJ News Service, Wall Street Journal, 1963-1998	Estimate the returns and risks of risk-arbitrage strategies using M&A data. In positive market return months, the strategies have a market beta of zero and positive return, but in negative market return months, market beta increases. So, the strategy can sometimes have large negative returns.

Fung and Hsieh (2002a)	HFR, TASS, 1994-2001	Show that trend-following asset-based style factors are appropriate to measure hedge fund performance on a risk-adjusted basis. The model has out-of-sample predictive power.
Gregoriou and Rouah (2002)	Zurich, LaPorte, 1994-1999	Size of hedge funds and funds of hedge funds do not impact the performance they are able to generate.
Bacmann and Scholz (2003)	TASS, HFR, 1994-2003	Show that two risk measures (Omega and Stutzer), which take into account the non-normality of the distribution of returns, better rank hedge funds by riskiness.
Brown and Goetzmann (2003)	TASS, 1989-1999	Investment style (strategy) differences account for 20 percent of cross-sectional variation in returns.
Cerrahoglu, Daglioglu, and Gupta (2003)	CISDM, 1992-2002	Allowing for time-varying betas does not impact hedge fund alpha estimation. Managers have skill, but most do not show market-timing.
Kat and Miffre (2003)	MAR, 1990-2000	Static models are misspecified for hedge funds. Time varying parameters give better measure of abnormal performance. Managers perform better in down markets.
Kazemi, Martin, and Schneeweis (2003)	TASS, HFR, 1990-2000	No single set of factors can explain the performance of the various hedge funds. Fund level characteristics partially affect performance. It is important to allow for time-varying sensitivities.
Koh et al. (2003)	AsiaHedge, EurekaHedge, 1999-2003	Fees (management or performance) or systematic risk do not explain Asian hedge fund performance. Performance is positively related to size (confirming economies of scale) and length of lockup period.
Agarwal and Naik (2004)	HFR, TASS, 1990-2001	Left tail risk is large and underestimated under mean-variance framework. They have non-linear exposure to financial markets and also to Fama and French (1993) and Carhart (1997) factors.
Brunnermeier and Nagel (2004)	SEC 13F, 1998-2000	During the technology bubble, hedge funds were more loaded on technology stocks than the market and were good at timing the market.
Capocci and Hübner (2004)	HFR, MAR, 1994-2000	A model combining Carhart (1997), Agarwal and Naik (2004), and Fama and French (1998), plus an emerging markets factor, explains a significant proportion of equity hedge fund returns.
Fung and Hsieh (2004b)	HFR TASS, 1994-2002	A seven factor asset-based model explains up to 80 percent of the performance of hedge funds. Applying a Kalman filter backward identifies several break points in factor loadings.
Getmansky, Lo, and Makarov (2004)	Theoretical model and archival, TASS, 1977-2001	Serial correlation in hedge fund returns comes from illiquid assets and smoothed returns. Smoothing significantly differs from one strategy to another.
Harri and Brorsen (2004)	LaPorte, 1977-1998	Hedge fund performance strongly decreases in market capitalization, thereby confirming the hypothesis of market inefficiencies exploitation.
Jaeger and Wagner (2005)	TASS, 1998-2004	Hedge fund returns mainly stem from beta exposure rather than alpha. The underlying factors are more diverse than in mutual funds and require some skill to extract. The worldwide available alpha to hedge funds is limited by the fact that market investments are a zero-sum game.
Kat and Palaro (2005)	Methodological, simulation, and archival, TASS, 1984-2004	Hedge fund-like returns can be replicated with a copula-based technique. Assuming that investors' preferences depend on the probability distribution of terminal wealth, they should prefer replicates to real funds.
Malkiel and Saha (2005)	TASS, 1994-2003	Hedge fund return correlation with equity indices is low, but within hedge funds, variations are far bigger than in other investment classes.
Fung and Hsieh (2006)	Theoretical model, literature review, and TASS, HFR, CISDM, 1994-2004	Hedge fund returns have low correlation with standard asset classes. The Fung and Hsieh (2004b) model explains a large part of these returns. Hedge fund managers diversify to maximize the value of their fund according to the proposed model.

Kat and Palaro (2006a)	TASS, 1984-2004	It is possible to replicate the distribution of most individual hedge funds and funds of funds using simple traded instruments and the dynamic trading technique introduced in Kat and Palaro (2005).
Kat and Palaro (2006b)	TASS, 1984-2004	Less than 20 percent of the hedge funds beat their replicated clone. Good performance worsens through time (decreasing returns to scale).
Adrian (2007)	Tremont, 1994-2006	Covariance, rather than correlation (which is scaled by volatility), is a better measure of increased concentration of risk in hedge funds.
Aragon (2007)	TASS, 1994-2001	Hedge funds with lockups have higher returns. The relationship between returns and redemption, notice period, and minimum investment, is concave. Alpha can be seen as a risk premium for illiquidity, and shares are held by investors with a longer horizon.
Bali, Gokcan, and Liang (2007)	HFR, TASS, 1995-2003	High VaR hedge funds outperform low VaR funds, even after controlling for fund-level characteristics. The relation does not hold for dead funds. Small and young funds perform better.
Darolles and Mero (2007)	Methodological and archival, 1997-2005	A four-step dynamic approach allows replicating equity hedge funds' returns. It allows for dynamically selecting the number of factors. For EH funds, 2 factors are sufficient. Replicates can be built.
Eling and Schuhmacher (2007)	Rothschild, 1985-2004	Ranking hedge funds on 12 different risk measures leads to almost identical results as the Sharpe ratio.
Hasanhodzic and Lo (2007)	TASS, 1986-2005	Hedge fund returns can be partially replicated using linear factor exposures. The clones do not perform as well but are feasible at a lower cost.
Kosowski et al. (2007)	TASS, HFR, CISDM, MSCI, 1990-2002	Even after controlling for systematic risk exposures, hedge managers' skill remains significant in explaining performance and cannot be explained solely by luck.
Liang and Park (2007)	TASS, 1995-2004	Hedge fund returns are positively explained by expected shortfall and tail risk, two left tail risk measures. Other risk measures are not explicative.
Xiong, Idzorek, Chen, and Ibbotson (2007)	TASS, Morningstar, 1995-2006	The relationship between hedge fund size and performance is concave, and the relationship between size and standard deviation is decreasing.
Ammann and Moerth (2008)	TASS, CISDM, 1994-2005	In larger hedge funds, contrasted against smaller funds, performance (returns, alphas, Sharpe ratios) is smaller and risk is higher.
Bacmann, Held, Jeanneret, and Scholz (2008)	HFR, 1994-2007	Although a large part of hedge fund returns comes from systematic exposure, cloning them is not straightforward. Without solving the issues of missing factors, misspecified factors, and dynamic asset allocation, clones will underperform funds.
Brown, Goetzmann, Liang, and Schwarz (2008b)	TASS, SEC ADV Form, 1998-2006	Voluntarily transparent hedge funds perform better. Operational risk increases with conflicts of interest between investors and managers. Due diligence is a source of alpha: large funds of funds perform better than their too-small-to-do-good-due-diligence peers.
Kuenzi (2008)	HFR, 2003-2008	Hedge funds have option-like exposures, which can have many sources and are depending on the strategy. Due to the complexity of these exposures, knowledge of what the manager actually does is often necessary.
Liang and Park (2008)	TASS, 1994-2005	Offshore funds outperform onshore funds due to a bigger link between share restrictions and asset illiquidity. Lockups and other restrictions increase performance, but more so for offshore funds.
Agarwal, Bakshi, and Huij (2009a)	TASS, 1994-2004	Hedge fund returns are exposed to volatility, skewness, and kurtosis risk. When included in the Fung and Hsieh (2004b) model, these risk factors have explicative power and alter the alpha rankings.

Billio, Getmansky, and Pelizzon (2009)	TASS, 1994-2008	Hedge funds have economy dependent systematic risk exposures. They tend to be less exposed when the markets are down than when they are normal or up, suggesting that managers are market-timers. When markets are down, credit and liquidity are significant risk factors for hedge funds. Contagion seems to be limited to the LTCM event.
Bollen and Whaley (2009)	CISDM, 1994-2005	An optimal change point regression model permits a better measure of dynamic risk exposures. 40 percent of the hedge funds experience a significant shift. Shifts are associated with higher Sharpe ratios.
Brown, Goetzmann, Liang, and Schwarz (2009)	Quantitative model and archival, TASS, SEC ADV Form, 1998-2006	Operational risk and financial risk are positively related. Operational risk is more significant in explaining failures than financial risk. It can be detected with the use of a scoring model.
Darolles, Gouriéroux, and Jasiak (2009)	Quantitative model and archival, HFR, 2004-2007	The Sharpe ratio is sensitive to large tails. The L-Performance measure is able to handle such peculiarities of hedge fund returns.
Griffin and Xu (2009)	SEC 13F, 1980-2004	Hedge funds are only marginally better at stock picking than mutual funds and show no skill in market timing and style picking. Hedge fund holdings do not have forecasting power about stock returns.
Klaus and Rzepkowski (2009)	TASS, 2004-2008	Hedge funds have a negative exposure to liquidity risk, both from counterparts and investors. The risk can be partially mitigated by diversifying funding sources.
Teo (2009)	TASS, HFR, 1994-2008	Hedge funds with low share restrictions who load on market-wide liquidity risk outperform those who do not. Funds with low incentive fees tend to load more on this risk.
Agarwal, Fung, Loon, and Naik (2010b)	Albourne, CISDM, TASS, HFR, 1993-2003	Convertible arbitrage hedge funds' returns are well explained by a strategy combining long convertible bonds delta-hedged by short shares of the bond issuer along with buy-and-hold positions in these markets.
Aggarwal and Jorion (2010b)	TASS, 1996-2006	Hedge fund managers perform better during the first two to three years after inception. There is no relationship with size, although large funds from multi-fund fund families perform better.
Boyson (2010)	TASS, 1994-2004	Hedge fund managers herd more as they become more experienced. Deviating from herding increases the probability of being terminated. Experienced managers underperform newcomers, but herding is not the cause.
Boyson, Stahel, and Stulz (2010)	HFR, 1990-2008	There is contagion among hedge funds' worst returns. This contagion is triggered by large liquidity shocks, but liquidity itself is not captured by standard liquidity factors.
Gibson and Wang (2010)	TASS, 1994-2006	For a large number of hedge funds, alpha is a compensation for systematic liquidity risk exposure. It is particularly pronounced for Convertible Arbitrage, Long/Short Equity, Global Macro, and Funds of Funds.
Kang, In, Kim, and Kim (2010)	Quantitative model and archival, TASS, 1994-2007	Hedge fund returns have an asymmetric dependence with equity markets. They are more correlated in down markets. The relation is stable through time, but the magnitude decreases strongly with investment horizon.
Liang and Park (2010)	TASS, 1995-2004	Expected shortfall, tail risk, and performance are good predictors of hedge fund failure. Funds with high watermarks are less likely to fail. Size, age, and lockups reduce the probability to liquidate but not to fail.

Patton and Ramadorai (2010)	Quantitative model and archival, CISDM, HFR, TASS, Morningstar, BarclayHedge, 1994-2009	Hedge fund risk exposures not only vary between months but also within. A new method using daily along with monthly information has a better detection power of time-varying risk exposures. Cost of leverage, return from carry-trade, and market indices are important explanatory variables.
Sadka (2010)	TASS, 1994-2008	Hedge fund returns are affected by market-wide liquidity risk. Funds that load highly on this risk subsequently outperform, so their returns are explained mostly by beta rather than alpha.
Aggarwal and Jorion (2011)	TASS, 1994-2009	Managed accounts make hedge fund investment transparent to at least some investors. This transparency does not reduce hedge fund returns.
Avramov, Kosowski, Naik, and Teo (2011)	TASS, HFR, CISDM, MSCI, 1990-2008	Macro-economic variables, such as default spread and VIX, help predict hedge fund returns when implemented in a model that allows for predictability in alpha. In and out of sample predictability are related.
Bae, Baik, and Kim (2011)	SEC 13F, Bloomberg, CRSP, Compustat, 2000-2009	Hedge fund equity holdings and holdings variations predict stock returns. This is consistent with hedge funds exploiting private information. Stocks held by hedge funds have higher abnormal returns at earnings announcements.
Dudley and Nimalendran (2011)	CS/Tremont, 1994-2008	Hedge fund return dependence is much higher in the left tail and has two sources, funding liquidity and trading of assets with low collateral value.
Feng, Getmansky, and Kapadia (2011)	TASS, 1994-2010	Large hedge funds perform the best, collect the most fees, and rely less on management fees.
Ibbotson, Chen, and Zhu (2011)	TASS, 1995-2009	Hedge fund alphas over a traditional stock, bond, and cash investment are positive every year except in 1998, and they represent 1/4 of the returns. An equivalent proportion of returns is captured by costs, while betas capture the remaining part. Bigger funds outperform smaller ones.
Li, Zhao, and Zhang (2011)	TASS, 1994-2003	Hedge fund managers educated in better institutions tend to perform better and take less risk. Work experience has much weaker effects.
Pareek and Zuckerman (2011)	Experimental and archival, TASS, Google Image, 2000-2009	Hedge fund managers that are rated the most trustworthy, based on photographs, have a higher probability of survival than their peers but lower risk-adjusted returns than them, perhaps because of overinvestment.
Sun, Wang, and Zheng (2011)	TASS, 1994-2009	A measure of the distinctiveness between a hedge fund and its strategy peers is positively associated with future risk-adjusted returns and therefore indicative of managerial skill. The measure persists through time, thus the correlation with the strategy index too.
Titman and Tiu (2011)	Altvest, HFR, TASS, HedgeFund.net, mHedge, 1994-2005	Hedge funds that have low systematic factor risk exposures tend to perform better in terms of Sharpe ratio. Although, a large part of the volatility of their returns is unexplained by those factors.
Agarwal, Jiang, Tang, and Yang (2012)	SEC 13F, CISDM, HFR, MSCI, TASS, Eureka, 1999-2007	Private information and fear of price impact of trade appear to be the reasons some hedge funds make confidentiality requests to the SEC. Confidential holdings have higher performance than standard holdings, indicating managerial skill.
Aragon, Hertzel, and Shi (2012)	SEC 13F, TASS, 1999-2006	Hedge fund confidential positions outperform during the period they are undisclosed. Managers used confidentiality to protect private information and to avoid price impact of trade.
Aragon and Martin (2012)	TASS, Bloomberg, SEC 13F, 1999-2006	Hedge fund managers have good option selectivity and volatility timing skills. Also, a portfolio of stocks based on lagged hedge fund call option holdings gives abnormally positive returns.

Avramov, Barras, and Kosowski (2012)	TASS, HFR, CISDM, MSCI, BarclayHedge, 1994-2008	A simple trading rule, along with a strategy that combines fund return forecasts from macro-economic variables—such as default spread and VIX—delivers outperformance even during the 2008 crisis. In and out of sample performance are related. Not all funds outperform, but some do.
Brown, Goetzmann, Liang, and Schwarz (2012)	HedgeFund-DueDiligence.com, 2003-2008	The probability of hedge fund failure and poor performance increases with operational risk as measured by a correlation-based measure using information in third-party due diligence reports.
Getmansky (2012)	TASS, 1977-2003	Hedge fund performance and assets under management follow a concave relationship, more so for funds holding illiquid assets that have high trading price impact.
Shi (2012)	SEC 13F, TASS, 1980-2009	Portfolio holdings disclosures negatively impact subsequent hedge fund performance, increase correlation with other funds, and result in an increased incentive fee level.

Agarwal and Naik (2000a) go in the same direction and have similar findings. They show that hedge funds are exposed to currencies, bonds, and equities by performing a generalized style analysis on hedge fund indices. They underline that there are differences in exposures from one investment strategy to another; see also Kazemi et al. (2003). Agarwal and Naik (2000c) complement this study by observing that, due to their relatively singular exposures, hedge funds are a good diversification to traditional portfolios. Similarly, Fung and Hsieh (2001, 2002a, 2004b) create, propose, and test a relatively complex set of trend-following option-based factors that explains up to 80 percent of hedge fund returns. Although the power of the model is strategy dependent, the factors quickly became the standard for hedge fund performance studies. Additionally, even though the authors call these factors *primitive*, they do not in any case reflect a passive investment strategy; see Fung and Hsieh (2001). Using a more traditional set of factors mainly borrowed from the mutual fund literature, Capocci and Hübner (2004) are able to explain a significant proportion of equity hedge fund returns, confirming that sources of performance depend on the investment strategy considered and that in some strategies, even simple models have a significant explanatory power. Subsequent studies further confirm that an important part of hedge fund returns can be explained by exposure to factors, and that the difficulty is in identifying the appropriate factors for the various hedge funds and investment strategies; see, for instance, Brown and Goetzmann (2003), Jaeger and Wagner

(2005), Malkiel and Saha (2005), Chen and Ibbotson (2006), Fung and Hsieh (2006), Bacmann et al. (2008), Kuenzi (2008), Agarwal et al. (2010b), Avramov et al. (2012), or Avramov et al. (2011). Some studies propose to replicate hedge fund returns, exploiting their beta exposures. Complex factors, such as the ones of Fung and Hsieh (2004b), are not all tradable. Therefore, they cannot directly and have to be modified to be used for replication purposes.[7] Nevertheless, Kat and Palaro (2006a), (2006b) show that most hedge fund returns are replicable with simple instruments and that, most of the time, the original hedge funds fail to beat their clones. Darolles and Mero (2007) propose a four-step dynamic approach which optimally selects the number of factors necessary to replicate hedge fund returns. They show that for equity hedge funds, only two factors are sufficient. Hasanhodzic and Lo (2007) follow a similar route but find less extreme results. They are able to create clones that partially mimic hedge fund returns at a lower cost, but they underperform the hedge fund. Bacmann et al. (2008) develop this view by underlining the difficulties inherent in hedge fund replication. They argue that, because of missing factors, misspecified factors, or dynamic asset allocations, clones are due to underperform original hedge funds. Titman and Tiu (2011) further confirm this fact and show that a large part of hedge fund returns remains unexplained by systematic market factors and that they might be exposed to more advanced sources of returns. These papers underline both the advantages and drawbacks of clones. On the one hand, clones cannot, by definition, provide alpha to the investor since they are only partial hedge fund copies based on easily identifiable factors. On the other hand, they require lower fees and transaction costs, which sometimes allow them to produce returns that are similar to the ones of the funds they copy. All-in-all, this suggests that while hedge fund returns can, up to some extent, be explained (and replicated), a significant proportion remains unexplained, and other tools, such as advanced risk sources or

[7] See Sadka (2010) for a modified investable version of the Fung and Hsieh (2004) model.

time-variation in exposures, might play an important role and give hedge funds an edge over replicates.

1.3.2 Advanced Market Risk Exposures

Due to their specific investment strategies, hedge funds' non-normal returns might be influenced by risks that cannot be captured by standard factors and risk measures. These exposures might be non-linear and might also vary through time. Following these ideas, Mitchell and Pulvino (2001) study the changes in beta exposures of risk-arbitrage strategies. They find a zero beta along with positive returns in good market periods but underline a tendency for the betas to increase in poor market periods, thereby sometimes leading to large negative returns. Kat and Miffre (2003) confirm that static models are misspecified for hedge funds and that there is a necessity to allow for time-variation in their beta exposures to correctly measure their performance. They find hedge funds to be better performers in down markets. Fung and Hsieh (2004b) confirm these dynamics by applying a Kalman filter backwards and identify several break points in hedge funds' factor loadings. Using an optimal change point regression model which allows for shifts in exposures, Bollen and Whaley (2009) show that 40 percent of the funds experience significant shifts in their risk exposures. These shifts are associated with higher Sharpe ratios. Kang et al. (2010) document an asymmetric dependence between hedge funds and equity markets with higher correlations in down than in up markets. Finally, Patton and Ramadorai (2010) go deeper and underline the dynamic nature of hedge funds by identifying risk exposure shifts within months.

Some authors identify higher order risk exposures. Bacmann and Scholz (2003) show that two risk measures, the Omega[8] and the Stutzer[9] measure, can take into account the non-normality of hedge fund returns by better ranking the funds based on their riskiness. Agarwal

[8] This measure uses the entire information contained in a fund's returns. It can be understood as the ratio between above-the-threshold returns and under-the-threshold returns; see Keating and Shadwick (2002).

[9] This measure can be seen as a Sharpe ratio for non-normal distributions. With normal distributions, it is equal to the Sharpe ratio; see Stutzer (2000).

and Naik (2004) follow the same path and document that hedge funds' left tail is underestimated by standard methodologies and that their exposures to common factors are non-linear. Kat and Palaro (2005) successfully use a copula approach to replicate the distribution of hedge fund returns instead of the returns themselves. Adrian (2007) argues that with respect to covariance, correlation is not a good measure for risk concentration in hedge funds since it is scaled by individual volatilities. Bali et al. (2007) identify Value-at-Risk to be positively related to returns, therefore underlining that performance is at least partially linked to an exposure to tail risks. Eling and Schuhmacher (2007) rank hedge funds based on twelve different risk measures and point out that they lead to virtually the same ranking as the Sharpe ratio. Liang and Park (2007) study different risk measures and report that expected shortfall and tail risk are positively and significantly related to returns, whereas other risk measures are only marginally or insignificantly explicative. Agarwal et al. (2009a) document an exposure of hedge fund returns to volatility, skewness, and kurtosis. When added to the Fung and Hsieh (2004b) model, these risk measures have a significant explanatory power and are remunerated in terms of returns. Billio et al. (2009) underline a market dependent systematic risk exposure. Darolles et al. (2009) underline the sensitivity of the Sharpe ratio to fat tails, which are common in hedge funds, and propose a performance measure (L-measure) which is able to handle such peculiarities. Indeed, since hedge fund returns tend to depart from normality, the tools necessary to explain them extend far beyond the mean-variance framework and linear market exposures.

Along with the above-mentioned advanced return drivers, an important risk that is often overlooked is illiquidity, or how an exposure to illiquid investments or financing translates in terms of returns. Consistent with Amihud (2002), assets' returns are partially explained by an illiquidity premium, which should appear in hedge funds' returns. Getmansky et al. (2004) first recognize that hedge funds can be invested in assets with limited liquidity and show that serial correlation in their returns partially comes from an exposure to these assets. Billio et al. (2009) document a significant exposure to liquidity and credit risk when markets are down, but not when they are up. They also point out that contagion is limited to the L.T.C.M. event and does not seem to be a standard source of liquidity and risk exposure. Klaus and Rzepkowski (2009) study the financing side and show that a shock on funding liquidity, whether it stems from counterparts or internal investors, negatively affects hedge fund returns. The effect can be reduced by diversifying the counterparties. Sadka (2010) finds that hedge fund returns are importantly exposed to market-wide liquidity risk and that this risk is positively rewarded. Teo (2009) concentrates on funds with lower share restrictions and corroborates these findings. He shows that funds loaded on market-wide liquidity risk outperform those which are not. In the same vein, Gibson and Wang (2010) observe that, for a significant number of hedge funds, alpha is actually only a compensation for systemic, or market-wide, liquidity risk exposure. Boyson et al. (2010) document contagion among hedge funds' worst returns and explain that it is triggered by large shocks to funding and assets liquidity, but this shock-liquidity risk cannot be captured by the usual liquidity proxies used in factor models. Finally, Dudley and Nimalendran (2011) show that returns dependence is larger in the left tail because of two sources, exposure to funding liquidity and trading of assets with low collateral value. As shown above, the sources of illiquidity are various. Markets, funding, or investments can all play a role, and their exact identification is an ongoing work. While it seems that, when identified, exposure to illiquidity sources is rewarded, extreme shocks can trigger negative returns. Thus, as with other exposures, there is here also a risk-return trade-off not to be neglected. In the following, I extend the explicative set further and document whether non-market related factors play a role in explaining returns.

1.3.3 Size, Liquidity, Secrecy, and Operational Risk

Beyond market related factors, there is a large set of variables which are often closely related to each other. Nevertheless, the literature has tried to pinpoint the ones that are key in explaining returns. Early on, Liang (1999) tries to link hedge fund returns to measurable characteristics and identifies a positive relation between hedge fund size and returns. Koh et al. (2003), Brown, Fraser, and Liang (2008a), Ibbotson et al. (2011), and Feng et al. (2011) reach similar conclusions. On the contrary, Kazemi et al. (2003) find that larger funds tend to underperform smaller ones, although they have a lower risk. Harri and Brorsen (2004), Kat and Palaro (2006b), Bali et al. (2007), and Ammann and Moerth (2008) also document a negative size-return relationship. Getmansky (2012) tries to reconciliate these apparently opposite findings about the size-return relationship by showing that the relation is actually concave, suggesting that there exists an optimal size. The concavity is more pronounced for funds that are exposed to illiquidity. Xiong et al. (2007) confirm return is a concave function of size but also corroborate the findings (decreasing relation) of Kazemi et al. (2003) with respect to risk. Aggarwal and Jorion (2010b) take a different stance and identify a more complex relationship. They document that hedge funds perform the best right after launch and that there is no apparent relationship with respect to size; also see Gregoriou and Rouah (2002). Nevertheless, funds from large multi-fund investment firms appear to perform better. As we see, the evidence is mixed. While some discrepancies could be attributable to differences of period under study or database, even studies over a similar period and database sometimes give opposite results. Therefore, when put together, it appears that the only possibility to explain these seemingly opposing results is a concave-like relationship between hedge fund size and returns.

Another characteristic which has been especially focused on is the liquidity of investors' funds, which depends on the level of share restrictions and translates how long it takes for an investor to enter a fund and to withdraw her money from the fund. These restrictions take the form of lockup periods, redemption frequency, advance notice, or minimum investment amounts. We have seen that liquidity is priced at the fund level. The question is then whether it is also the case at the investor level. In this vein, Liang (1999) shows that the length of lockup and fund returns are positively linked. Koh et al. (2003) confirm these results. Kazemi et al. (2003) also argue in this direction and show that returns are higher for funds with a lockup period of one quarter than for funds with a lockup period of one month. However, the difference vanishes when risk-adjusted, instead of simple, returns are considered. Aragon (2007) exclusively concentrates on share restrictions and shows that funds which use lockups outperform the ones that do not. Moreover, he finds a concave relationship between performance and other share restrictions, namely redemption period, advance notice, and minimum investment. He therefore argues that the outperformance generated by high-share-restriction funds is actually a liquidity premium paid to the investor choosing to invest over longer horizons. This is directly linked to the market wide illiquidity premia since it allows these high-share-restriction funds to specifically invest in high-premia illiquid assets. Liang and Park (2008) contrast onshore and offshore hedge funds and find that offshore funds outperform their onshore counterparts mainly because of a stronger link between the share restrictions they employ and the illiquidity of the assets they hold. This translates into the fact that share restrictions are positively related to performance for both types of funds, but more for offshore funds. Finally, Liang and Park (2010) differentiate between hedge fund failure (bankruptcy) and liquidation (other reasons than bankruptcy) and show that funds using lockups have a lower probability to liquidate but not to fail. In regard of these studies, it appears that share restrictions represent an exposure of investors to illiquidity risk and that this risk is rewarded in terms of higher average returns. Nevertheless, while they might give more latitude to managers in their everyday operations, they apparently do not change the outcome in cases of extreme events, and bankruptcy is as likely with share restrictions as without.

One peculiarity of the hedge fund industry is its rather limited obligations of disclosure in terms of holdings, strategy, and returns. It could therefore be argued that hedge funds enjoy superior performance because, contrarily to mutual funds, when they have an investment strategy or decisive information, they do not have to share it with everyone. Nevertheless, in the US, all investment management firms that have more than USD 100 million of assets under management are required to report their large and long holdings to the SEC on a quarterly basis. They can, however, request a temporary secrecy, or delayed reporting about their holdings. The literature recently became interested in this topic. Agarwal et al. (2012) concentrate on these (temporary) confidentiality requests addressed to the SEC and study the performance of confidential hedge fund holdings. They find that these undisclosed positions outperform the funds' public positions. Aragon et al. (2012) go in the same direction and confirm that hedge funds' undisclosed positions outperform *during* the period they are undisclosed but not after. Consistently, Shi (2012) finds that after they start to report their holdings to the SEC, hedge funds produce significantly reduced returns. Therefore, private information and fear of a price impact of trades appear to be reasons some hedge funds request privacy about their holdings. On the other hand, Aggarwal and Jorion (2011) are interested in managed accounts, which are essentially private hedge funds dedicated solely to a specific client but which mimic the fund available to the other clients of the firm. They find that, although these investments are generally fully transparent to the managed account investor, this transparency does not impact the returns of the fund. Considering the limited number of studies involved, it would be hard to reach a definitive conclusion about secrecy. What seems to emerge is that hedge funds which request confidentiality to the SEC have good reasons to do so. It does not mean, however, that all hedge funds need it or take advantage of it, but it allows some of them to enjoy returns they would not have been able to generate if they were subject to full disclosure. Clearly, further research is needed to identify whether, when, and why secrecy can be an advantage.

Finally, there are a few other explications that relate returns to the inner workings of hedge funds and to the people working within. Brown et al. (2008b, 2009, 2012) document operational risk. They show how operational risk increases with conflicts of interest between investors and managers and how it is directly related to financial risk. They further show that operational risk is a better predictor of fund failures than financial risk and that it can be detected with the help of a scoring model. Additionally, they find that operational risk is not only related to the extreme event of fund failure but that it more simply translates into poor fund performance. On another level, Li et al. (2011) find a direct relation between the quality of managers' education and their propensity to take risk. Managers from better institutions tend to have less risky positions. On the other hand, work experience has a much weaker explanatory power. At last, Pareek and Zuckerman (2011) stay at the manager level and take an innovative view. They document the fact that managers who are judged the most trustworthy, based on photographs, have a higher probability of survival but lower risk-adjusted returns than their peers. This fact may be partially explained by overinvestment with these managers. As they seem more reliable, they attract more money than what they are able to manage successfully. As we can see from the few papers cited above, as any other organization, a hedge fund is not a perfect machine; the inner mechanics and the people composing it greatly influence the output produced.

1.3.4 Performance beyond Risks

After having gone through a long list of variables that explain hedge fund returns, we can finally turn towards the part of returns that remains unexplained and is usually referred to as alpha or manager skill. The numerous studies about performance persistence seem to indicate that skill is indeed present, up to some extent, in hedge funds. The question that we did not address so far is what this skill is. Cerrahoglu et al. (2003) employ various parametric and non-parametric methods to partially answer the question. Allowing for time-varying betas, they identify that skill is indeed present, but there are only a very few managers for which this skill comes from market-timing ability. Jaeger and Wagner (2005) document that most hedge fund returns come from risk premiums but acknowledge that managers' skill comes from their ability to extract these premiums from advanced sources of risk. In a sense, they have some sort of risk-picking ability. They also underline the fact that there is only a limited quantity of alpha available to hedge fund managers because worldwide financial markets are a zero-sum game, so not all managers can have alpha. Griffin and Xu (2009) add to this finding by identifying no market-timing or style picking ability in hedge funds, and only marginally better stock picking ability than in mutual funds. On a specific time-period, the technology bubble, Brunnermeier and Nagel (2004) contradict these findings and show that hedge funds were good at timing the market since they were heavily loaded on technology stocks but managed to reduce their positions before the collapse. Kosowski et al. (2007) find that, even after controlling for risk exposures, hedge fund managers' skill remains significant. They rule out the possibility that alpha of top hedge funds could be explained by luck only. Billio et al. (2009) confirm a tendency for hedge funds to be less exposed when markets are down than when they are normal or up, thereby rejoining the market-timing ability. In the same vein, Aragon and Martin (2012) identify option selectivity and volatility-timing skills. A strategy of holding stocks based on lagged hedge fund option holdings gives abnormal returns. Bae et al. (2011) consistently report that hedge fund equity holdings variations predict stock returns and that stocks held by hedge funds have higher returns at earnings announcement. Ibbotson et al. (2011) confirm the presence of alpha and detail that it is equally shared between investors and managers (through fees). At last, Sun et al. (2011) associate manager skill to the ability to deviate from the pack. They document that distinctiveness from peers in the same investment strategy is predictive of future returns. From the above, it seems clear that hedge fund managers possess some sort of skill. Yet, it is not clear whether this skill comes from a superior ability to access the information or from a superior ability to process the information. In the same sense, it is also not clear whether managers are good at choosing stocks that are under- (or over-) valued or rather at changing their holdings in due time. There is clearly a need for further research in this area, but with the wide availability of SEC 13F filings that detail hedge fund holdings, it is only a matter of time before further evidence appears.

As we have seen, explanatory sources of hedge fund returns are numerous. Although some of them are common to other investment vehicles and are easily identifiable, many are very specific and need a fair amount of digging to be uncovered. It further appears that not only are hedge fund investments and strategies important in explaining returns, but fund-level characteristics greatly influence them too. While these concerns have been covered extensively, two closely related domains need further research: secrecy and sources of skill. Indeed, until recently, hedge funds have been considered as, and have actually been, black boxes. The rules are now evolving. On the one front, investors are more and more involved and sophisticated and tend to request higher levels of transparency. On the other front, while regulators partially agreed to accommodate specific regimes for hedge funds in the past, they are less and less willing to do so and are continuously tightening the rules. Indeed, the European Union devotes an entire chapter (IV) to transparency in its directive on Alternative Investment Fund Managers to come into force in July 2013. It introduces a previously non-required set of pre-investment disclosures to prospect investors as well as on-going liquidity, risk, and leverage disclosures to current investors. These will be accompanied by annual financial statements, to be provided to all investors and to the regulator. In the United States, the Title IV of the Dodd-Frank Act, which is expected to impact hedge funds by the end of fiscal year 2012, goes in the same direction and imposes tight reporting requirements on hedge funds that were previously exempted.[10] These tighter regulations could, however, be counterproductive—as underlined by Kaal (2011)—and result in regulatory arbitrage behaviors. Whether these behaviors will materialize and whether increased transparency will affect hedge fund returns over the long term is still to be determined, but since there are some hints that hedge fund skills might rely, at least partially, on their superior information, it might well be the case.

1.4 Relation between Investors' Flows, Performance, and Risk

So far, we have reviewed hedge fund performance and the various risk exposures and characteristics that might affect it, disregarding the sources of funding necessary to achieve this performance. In the following, I turn towards the investors, who are in fact the sufficient and necessary element that allows investment funds to exist. Hence, these funds cannot be seen on their own since their interaction with investors and other parties is continuous. Because of the legal structure of hedge funds, investors have to vote with their feet, and their reactions are thus strictly limited to two possibilities: investing or withdrawing money. Therefore, the question I address is whether and how investors react to and affect hedge fund performance and risk taking. The corresponding literature is summarized in Table 1.3.

Table 1.3: Relation between Investors' Flows and Funds' Performance

This table summarizes the articles that establish a link between investors' flows and funds' performance. It describes the methods and the samples used, along with a summary of the key results. When not precised, the method is archival. The papers are order by year of publication and author.

Reference	Method / Sample	Key result
Ippolito (1992)	Theoretical model and archival, Wiesenberger, 1965-1984	Mutual fund investor flows follow good performance, but investors also consider investment costs and augment their investment share in the funds they have rather than going to other funds.
Chevalier and Ellison (1997)	Morningstar, CRSP, 1982-1992	Mutual fund flows follow good and poor performance. They are more sensitive to extreme values, but they are insensitive to small losses. Managers react by modifying the risk of their portfolio towards year-end, depending on their incentives to attract new investor flows.

[10] See Title IV of the Dodd-Frank Act (http://www.sec.gov/about/laws/wallstreetreform-cpa.pdf) and Chapter IV of the Directive on AIFM (http://register.consilium.europa.eu/pdf/en/10/pe00/pe00060-re01.en10.pdf).

Sirri and Tufano (1998)	ICDI, 1972-1990	Mutual fund flows follow performance (asymmetrically), size, and media coverage. High marketing funds, proxied by fees, attract flows. Investors care about risk and limit managers' incentive to increase it.
Goetzmann, Ingersoll, and Ross (2003)	U.S. Offshore Funds Directory, 1989-1995	Large and superior funds experience net outflows, but this is because they do not accept more money. Money flows out of the poorest performers, but this varies through time. Larger funds tend to have outflows, while the opposite is true for smaller ones.
Agarwal, Daniel, and Naik (2004)	HFR, TASS, MAR, 1994-2000	Hedge fund investors provide money to managers with good recent performance, higher incentives, and lower withdrawal limitations. Flows subsequently decrease future performance.
Berk and Green (2004)	Theoretical model	The performance chasing behavior of mutual fund investors combined with increasing investment costs and decreasing returns to scale imply that money inflows decrease performance up to the point when it is competitive.
Berk and Tonks (2007)	CRSP, 1962-2004	There is persistence in the returns of the worst mutual funds because of investors' unwillingness to withdraw their funds.
Huang, Wei, and Yan (2007)	Theoretical model and archival, CRSP, 1981-2001	A learning model that also includes participation costs explains the asymmetric behavior of mutual fund investor flows with respect to performance.
Xiong et al. (2007)	TASS, Morningstar, 1995-2006	Hedge funds have an almost linear relation between net flows and performance.
Ammann and Moerth (2008)	TASS, CISDM, 1994-2005	Hedge funds with higher inflows outperform their peers in the next 12 months.
Fung, Hsieh, Naik, and Ramadorai (2008)	HFR, TASS, CISDM, 1995-2004	Funds of hedge funds that have alpha see a reduction in it after inflows (which follow good performance). In aggregate, investor flows to the hedge fund industry have contributed to a reduced cross-sectional alpha.
Zhong (2008)	CISDM, 1994-2005	Hedge fund investor flows to small funds increase performance, and the opposite effect is observed for large funds. Strategy-level flows always negatively impact future performance (capacity limits), but the strength of the effect depends on strategy and on fund characteristics.
Aragon and Qian (2009)	Theoretical model and archival, TASS, 1994-2007	Hedge fund investor flows are more sensitive to past performance in the presence of high watermarks, especially following good performance.
Baquero and Verbeek (2009)	TASS, 1994-2004	At the quarterly horizon, hedge fund investor flows are more sensitive to poor than to good performance. At the annual horizon, the pattern is the opposite. Moreover, performance is more persistent where flows are less responsive.
Ding, Getmansky, Liang, and Wermers (2009)	TASS, 1994-2005	Hedge funds have a convex relation between performance and investor flows when there are no share restrictions, but the relation is concave when there are. Moreover, fund flows are followed by good performance, but this is not the case in funds with the greatest share restrictions.
Teo (2009)	TASS, HFR, 1994-2008	Hedge funds that receive high inflows outperform those with high outflows; the flows affect performance at the monthly horizon. The effect is higher for funds which are highly exposed to market liquidity risk.
Boyson (2010)	TASS, 1994-2004	For hedge fund managers, deviating from the herd does not trigger more inflows from investors.
Chen, Goldstein, and Jiang (2010)	Theoretical model and archival, CRSP 1995-2005	Flows are more sensitive to poor performance in mutual funds that are less liquid because investors fear that withdrawal by other investors will negatively impact returns. The effect is not there for large investors.

Ozik and Sadka (2010)	TASS, 1994-2008	Hedge fund investor flows predict performance (smart money). Rather than coming from investors being skilled manager pickers, it comes from their skill at understanding flows. The effect is more important for high-flow-impact funds. The evidence only exists for inflows, not outflows.
Ahoniemi and Jylha (2011)	TASS, 1994-2008	Hedge funds receiving large inflows outperform during the flow month and one to two months after (smart-money). The effect is stronger for high-flow-impact funds and is only present if funds continue to flow in. Therefore, flows imply returns—not the other way around. There is no effect for low-flow-impact funds.
Bae et al. (2011)	SEC 13F, Bloomberg, CRSP, Compustat, 2000-2009	The difference of money flows between well and poorly performing hedge funds is limited.
Ben-David, Franzoni, and Moussawi (2011)	SEC 13F, TASS, 2007-2009	During the recent crisis, hedge fund investors were three times faster than mutual fund investors at withdrawing their funds after poor performance. The usual share restrictions acted oppositely to their purpose and triggered withdrawals.
Bolliger, Guidotti, and Pochon (2011)	HFR, 2009-2010	After the 2008 crisis, hedge fund investors kept chasing best performers, but liquidity, domicile, and fee structure also influenced their decision.
Li et al. (2011)	TASS, 1994-2003	Hedge fund managers educated in better institutions tend to attract more investor flows. The relation between flows and lagged returns is positive and symmetric, and negative with respect to size and age.
Ozik and Sadka (2011)	TASS, 1998-2008	Investor flows predict performance (smart money) in share-restricted hedge funds. Since managers have insider information about flows, the effect is more pronounced in funds where the manager is invested.
Pareek and Zuckerman (2011)	Experimental and archival, TASS, Google Image, 2000-2009	Hedge fund investors give relatively more funds to managers that are rated the most trustworthy, based on photographs, as compared to their peers.
Titman and Tiu (2011)	Altvest, HFR, TASS, HedgeFund.net, mHedge, 1994-2005	Hedge fund investors value low systematic risk exposure. Inflows to otherwise identical funds are higher by about one percent for each ten percent decrease in R2.
Brown et al. (2012)	HedgeFund-DueDiligence.com, 2003-2008	Hedge fund investor flows are not affected by the level of operational risk of the funds in which they invest; they keep chasing returns.
Shi (2012)	SEC 13F, TASS, 1980-2009	Hedge fund investor flows diminish in holdings disclosure periods, indicating that investors negatively value 13F disclosures.
Getmansky (2012)	TASS, 1977-2003	Hedge fund investor flows follow current returns, but the relationship with past returns is concave. Also, flows decrease in age, AUM, return standard deviation.

The first empirical attempts to gauge whether investors react to performance come from the literature on mutual funds. Ippolito (1992) proposes a theoretical model and tests it on twenty years of mutual fund data. He observes that mutual fund investors chase good performers and flee poor performers. Investors also consider investment costs and prefer to augment their share in the funds they are already invested in rather than going to other marginally better funds. Chevalier and Ellison (1997) confirm and underline that investors are more sensitive to extreme values and virtually insensitive to small negative performances. They also document an adaptation of managers as a result of investors' behavior and show that they might modify their risk exposures towards year-end depending on their incentives to attract new investors. Sirri and Tufano (1998) complement these findings and demonstrate that not only do investors chase performance, they do so asymmetrically by over-investing in good performers and failing to disinvest from poor performers. In addition, it appears that fund-family size and media coverage are directly linked to inflows. They also argue that high marketing expenses, as proxied by larger fees, contribute to augment the reaction of flows towards performance. Finally, they suggest that investors take into account risk, thereby limiting the managers' incentive to be too exposed. Interestingly, in one of the first studies to tackle the topic in the hedge fund literature, Goetzmann et al. (2003) find conflicting results. While there seems to be a tendency, although unstable through time, for the worst funds to experience outflows, top performers also experience net outflows. The authors suggest that these results come from top hedge fund managers being unwilling to accept new inflows because of capacity concerns. Agarwal et al. (2004) partially challenge these findings and show that investor flows go towards hedge funds with recent good performance, higher incentive fees, and lower share restrictions. They also show that after-inflows performance is significantly deteriorated. This latter fact receives an explanation in Berk and Green (2004), who propose a model in the mutual fund context that explains why inflows deteriorate performance. They prove that, in a world where funds encounter increasing investment costs and decreasing returns to scale, investors' chase of good performance reduces any outperformance to zero. Getmansky (2012) further details the performance-flow relationship in hedge funds. She finds a positive relation between investor flows and current returns but identifies a concave relation towards past returns, so the best funds do not attract as much inflow as their performance suggests. Also, older and larger funds, as well as riskier ones, experience lower inflows. This seems to, at least partially, confirm the findings of Goetzmann et al. (2003) and further underlines that the flow-performance relationship is anything but straightforward. Berk and Tonks (2007) explain the asymmetry in the flow-performance relationship in mutual funds by the unwillingness of investors to withdraw their funds from the worst performing funds. Huang et al. (2007) propose a learning model to explain the same pattern. Xiong et al. (2007) study funds of hedge funds, and in the vein of Agarwal et al. (2004), identify an almost linear relationship between flows and returns. Fung et al. (2008) go in the same direction and document that well performing funds attract inflows, although their subsequent performance is then reduced. Ammann and Moerth (2008) go against this latter finding and show that funds with higher inflows outperform their peers in the next twelve months. As we see, a consensus is hard to extract, and there appear to be various factors that influence the bidirectional relation between flows and performance.

Zhong (2008) tries to reconciliate the above studies by observing that inflows to small funds increase performance while the opposite is true for large funds. Moreover, inflows at the strategy level appear to negatively impact performance because of capacity constraints, but the effect is not the same, depending on the strategy. His work suggests that some strategies consist in exploiting very small niches while other leave more room to expand. Aragon and Qian (2009) find that investors react more positively to flows in hedge funds which use high watermarks, since they will not need to pay incentive fees unless the performance is positive after their investment. Baquero and Verbeek (2009) supplement our knowledge by adding a time dimension. They show that, at the quarterly horizon, investors are much more concerned about poor performance, so poor funds experience outflows while good funds only see limited inflows. On the contrary, at the yearly horizon, the pattern is opposite, and investor flows react more strongly to good rather than to poor performance. Moreover, investors seem to be able to identify subsequently poor performers by leaving, but the funds they join do not outperform thereafter. Ding et al. (2009) attempt to reconcile previous studies and identify an effect of share restrictions, which modify the reaction of investors towards performance. With limited share restrictions, the flow-performance relationship appears as convex, while in the presence of high share restrictions, it is concave. They argue first that the restrictions limit investors' willingness to invest in less-than-stellar performers because it might be hard for them to leave. And second, once they are in, the limited flow reaction might stem from the impossibility of leaving. Finally, in the funds with limited share restrictions, inflows are followed by good performance, whereas this is not the case in funds with high restrictions. Teo (2009) further documents the effect on performance and finds that funds with high inflows outperform the ones with high outflows at the one-month horizon. Exposure to liquidity risk exacerbates the performance spread between high inflow and high outflow funds. Chen et al. (2010) investigate the twin effect of liquidity in mutual funds and show that small investor flows are more sensitive to the poor performance of less liquid funds because they fear that the withdrawals from other investors will deteriorate future performance. Large investors do not care. Ozik and Sadka (2010, 2011) confirm this awareness towards other investors' behavior and show that flows are followed by good performance because of their understanding of other investors rather than because of an ability to identify good funds. Since managers have an information advantage, the effect is more present in the funds where the manager is invested. Though, they only identify an effect for inflows, not for outflows, and the effect is more pronounced for funds whose performance reacts stronger to flows; see also Ahoniemi and Jylha (2011). Coming back to the effect of performance on flows, Bae et al. (2011) find limited flow differences between good and poor hedge funds, whereas in other investment funds, the relation towards performance is positive and strong. Ben-David et al. (2011) challenge this view, at least during the recent crisis, and find that hedge fund investors were more reactive in withdrawing their money after poor performance than mutual fund investors. They conclude that the usual share restrictions acted oppositely to their supposed use and triggered fears, which triggered withdrawals. Bolliger et al. (2011) complement this view with the fact that investors kept chasing the best performers after the 2008 crisis, but they also considered liquidity, domicile, and fee structure in their allocation decision. This return chasing behavior is confirmed by Brown et al. (2012), regardless of operational risk. On the contrary, Titman and Tiu (2011) find that investors take into account systematic risk and prefer to allocate to, otherwise equal, funds with low systematic risk exposures. Apparently, though, it does not mean they want very innovative strategies, since Boyson (2010) shows that managers who deviate from the herd (in terms of investment strategy) do not receive higher inflows. Shi (2012) complements these findings by showing that investors also value secrecy, since their flows diminish in holdings disclosure periods. Here again, Li et al. (2011) and Pareek and Zuckerman (2011) investigate miscellaneous characteristics and show that managers educated in better institutions and the ones who look the most trustworthy, based on photographs, tend to attract more flows.

From the above, it is clear that the relation between hedge funds and their investors is not clear-cut. While it seems that investors try to pick the best performing funds, they also have a tendency to stay in poorly performing funds longer than would be expected because they refuse to cash in negative returns. This is a well-known behavioral bias called disposition effect and has been documented in multiple financial situations; see, for instance, Odean (1998) or Grinblatt and Keloharju (2001). Also, the effect of inflows on subsequent performance can be different, depending on the size of the fund, the investment horizon, or the strategy considered. Therefore, the effect of size is consistent with the capacity constraint hypothesis since inflows to small funds positively affect performance, but the contrary is true for large funds. Variations with respect to the horizon considered also go in this direction since it seems that funds which receive inflows outperform for some time but then not anymore, again indicating that inflows eventually make the fund too large to be able to outperform, consistent with Berk and Green (2004). Additionally, investors take into account other parameters in their investment decisions—risk, for instance. They have, however, a different approach than one might expect since they actually value low systematic risk exposures and apparently do not take into account operational risk. They also appear to be good at predicting the behavior of their investor peers and thus manage to receive outperformance from the funds they invest in. Share restrictions can affect both the funds' performance and their decision to invest or disinvest. Finally, we see that this industry is based on investors' confidence in the ability and the honesty of the managers they delegate their money management to since they value education and trustworthiness. It would therefore be interesting to see how the value of these managers' personal characteristics did evolve and will evolve in the future, considering the various scandals that stained the hedge fund industry and the follow up regulation that is being put in place. One would indeed expect that both the scandals and tighter regulation would motivate investors to move away from apparent ability and honesty, since both appeared to be falsified in the past, and that regulation should allow for easier quantitative monitoring of both financial and operational risk.

1.5 Hedge Funds' Performance versus Mutual Funds' Performance

We have seen in the previous sections that, contrarily to mutual funds, there is a significant proportion of hedge fund managers who are able to outperform and that they do so with some degree of persistence. In reality, most of this outperformance is explained by various fund-level and risk exposure factors. Nevertheless, an unexplained proportion remains and it is attributed to manager skill and possibly to secrecy. While secrecy is specific to hedge funds, there is no *a priori* reason for skill to be less widespread among mutual fund managers than hedge fund managers. In the following, I therefore review the papers explaining some potential reasons behind this apparent lack, or more limited use of skill. The literature can be found in Table 1.4.

Table 1.4: Literature about the Differences between Hedge Funds and Mutual Funds

This table summarizes the articles that pinpoint hedge funds' specificities with respect to mutual funds. It describes the methods and the samples used, along with a summary of the key results. When not precised, the method is archival. The papers are order by year of publication and author.

Reference	Method / Sample	Key result
Fung and Hsieh (1997)	Morningstar, Paradigm, TASS, ~1990-1995	Hedge funds' investment strategies are more dynamic than mutual funds'.
Ackermann et al. (1999)	HFR, MAR, 1988-1995	Incentive fees are positively related to risk-adjusted performance of hedge funds.
Liang (1999)	HFR, 1992-1996	Trading is more dynamic and systematic risk is lower than in mutual funds. Incentive fees, high watermarks, size, and lockups are positively related to hedge fund performance.
Edwards and Caglayan (2001)	MAR, 1990-1998	Higher incentive fee levels are associated with higher excess returns.
Das and Sundaram (2002)	Theoretical model	Asymmetric fee structures (hedge fund type) are better for investor welfare than the symmetric structure (mutual fund type).
Goetzmann et al. (2003)	Theoretical model	Hedge fund fee contracts have option-like features due to high watermark contracts, which give incentives to managers to increase risk. The higher the probability for the investor to leave, the more value these contracts have for the manager.
Hodder and Jackwerth (2007)	Theoretical model	Hedge fund incentive contracts have option-like features. When under high watermark by a limited amount, the shortsighted manager will increase the risk level. Similarly, risk is drastically reduced when a little above the high watermark.
Christoffersen and Musto (2008)	Theoretical model	High watermarks affect expected returns, and they depend on public confidence about managers' ability, which influences initial fund size.
Foster and Young (2008)	Theoretical model	Hedge fund incentive contracts are good for rewarding performance but fail to align investors' and mangers' interest because they motivate risk-taking from managers, and moreover, they can be tricked by "fake" alpha.
Kostovetsky (2008)	CRSP, Morningstar, Thomson, 1993-2005	Mutual funds are less attractive to young managers than hedge funds. This translates, in the Northeast, into young mutual fund managers underperforming old ones and into a higher exit rate from mutual funds.
Agarwal, Daniel, and Naik (2009b)	CISDM, HFR, MSCI, TASS, 1992-2002	Greater managerial incentives lead to greater performance in hedge funds. The delta measure of the manager's wealth sensitivity to performance better measures incentives than incentive fees. Also, higher share restrictions improve on performance.
Aragon and Qian (2009)	Theoretical model and archival, TASS, 1994-2007	High watermarks are suboptimal under information symmetry between investors and managers but are valuable to investors when there is asymmetry. They are also important for funds with illiquidity exposures.
Panageas and Westerfield (2009)	Theoretical model	Hedge fund managers subject to high watermark contracts will not take very high risks because of the indefinite time horizon of the contract.
Teo (2009)	TASS, HFR, 1994-2008	Funds with low incentive fees tend to load more on market-wide liquidity risk.
Amvella (2010)	Theoretical model	The time horizon of the hedge fund manager limits his incentives to take risk. Moreover, to maximize the fees perceived, the manager will have to choose an optimal level of risk.
Aragon and Nanda (2010)	TASS, 1995-2007	Hedge funds with high watermarks are less likely to increase their risk when losing money. Risk-shifting is nevertheless present, more pronounced for young funds and negatively related to mid-year performance.

Chakraborty and Ray (2010)	Theoretical model calibrated on CISDM	The Pareto optimum between hedge fund managers and investors could, when the manager's option is too much out of the money (under high watermark), be improved by lowering incentive fees and increasing management fees.
Deuskar, Pollet, Wang, and Zheng (2010, 2011a)	TASS, HFR, CRSP, 1993-2006	The best mutual fund managers do not leave the industry but are rather proposed to start an in-house hedge fund. Poor performing managers leave and join the hedge fund industry, where they perform better. High expense-ratio mutual fund managers subsequently underperform in hedge funds.
Fairchild and Puri (2011)	Theoretical model	Hedge fund managers prefer asymmetric remuneration contracts, and investors prefer symmetric ones. Symmetric contracts are better at creating hedge fund value but might deter managers' willingness to start a fund and prevent them from performing due to fear of downside risk.
Glode and Green (2011)	Theoretical model	Investors learn about a hedge fund manager's investment strategy by investing with her. In the fear that investors could leave and open a fund with a similar strategy, managers share the profits with them and do not extract the entire rent for themselves, contrary to mutual funds.
Ramadorai and Streatfield (2011)	TASS, HFR, CISDM, Morningstar, BarclayHedge, 1994-2009	Management fees have been rising through time, but they are not related to hedge fund outperformance, while higher incentive fees are (weakly).
Ray (2011)	TASS, 1986-2010	Hedge funds have a higher risk, lower Sharpe ratio, and a higher probability of failure when they are under their high watermark. The magnitude of the increase in risk is positively linked with incentive fees and negatively with management fees.

When evoking the lack of skill in mutual funds as compared to hedge funds, the first explanation that comes to mind is a lower number of skilled managers in the former type of funds. To the best of my knowledge, only two recent papers tackle the issue. Kostovetsky (2008) corroborates this theory and proposes a case study in the Northeast region of the U.S. He documents that young managers are more attracted towards hedge funds than towards mutual funds. This translates into a lower performance of young mutual fund managers as compared to older ones, even after controlling for various fund characteristics. The exit rate of well performing mutual managers is increasing through time, and their average education level is declining. Deuskar et al. (2011a) shed a different light on the matter, however. According to them, the best mutual fund managers do not actually leave the industry but are rather proposed to start an in-house hedge fund. Nevertheless, the ones who used to have a high expense ratio in their mutual fund days do not manage to deliver a better performance once they are in hedge funds. Hence, there is some tendency for managers to go towards hedge funds rather than mutual funds. More interestingly, though, the mutual fund industry needs to propose hedge fund positions to its best performing managers to be able to retain them. Therefore, there must be something inherent to this industry that attracts talent and explains the better performances observed. Liang (1999) gives a hint by showing that trading is more dynamic and systemic risk is lower in hedge funds as compared to mutual funds. It means hedge fund managers actually manage their portfolio dynamically and try to perform regardless of market conditions. The reason behind this behavior can be summarized as follows: they have incentives to do so. As the author observes, hedge fund performance is positively related to incentive fees and high watermarks.

Hence, the answer apparently lies in the remuneration scheme inherent to hedge funds. A series of papers corroborate this proposition about incentive fees; see Ackermann et al. (1999), Edwards and Caglayan (2001), Goetzmann et al. (2003), among others. Das and Sundaram (2002) further show that this type of asymmetric fee structure is better for investors' welfare than the standard symmetric scheme. Hodder and Jackwerth (2007) develop on high watermarks and show that they encourage managers who are below their high watermark to take more risk, and they limit their risk-taking behavior when above. Christoffersen and Musto (2008) theoretically confirm an effect on fund performance. Panageas and Westerfield (2009) augment these findings and show that because of indefinite horizon, the manager subject to high watermarks will limit risk. Amvella (2010) confirms the limiting effect of the time horizon and further comments that, because of the incentive structure, the hedge fund manager will have to choose an optimal level of risk to maximize the fees perceived. Aragon and Nanda (2010) add that, because of high watermarks, managers are less likely to increase their risk when they are too far below the high watermark. Nevertheless, they do so when their performance is negative but not too bad (more pronounced for younger funds with shorter reputation history). Agarwal et al. (2009b) compute the sensitivity of managers' wealth to underlying performance by taking into account the different components of the remuneration schemes. They show that managers with more incentives perform better. Ramadorai and Streatfield (2011) document a significant positive relation of incentive fees towards performance but no relation with management fees. Additionally, Teo (2009) pinpoints that funds with low incentives tend to take on more liquidity risk to profit from the high premium that goes with this exposure. Only Ray (2011) documents a negative conflicting view about high watermarks and finds that they are related to lower Sharpe ratios and higher probabilities of failure. Furthermore, he argues that this risk increases with the level of incentive fees and reduces with management fees.

Some authors discuss the optimality of this type of remunerations. Foster and Young (2008) agree on the fact that incentive contracts are good for rewarding performance. However, they argue that they are bad for investors because they motivate managers to take too much risk and can be tricked by what "fake alphas" (relatively simple, very risky strategies, where the returns do not come from managerial skill but from the high risk to which investors are exposed). Aragon and Qian (2009) interestingly show that high watermarks are suboptimal for investors under information symmetry between them and the managers (as in mutual funds) but are optimal in the case of information asymmetry (as in hedge funds), thus justifying their application in hedge funds. Chakraborty and Ray (2010) theoretically show that when the fund is too far under the high watermark, the Pareto optimum, in terms of welfare, between managers and investors could be improved by raising management fee and decreasing incentive fee levels. Fairchild and Puri (2011) take a mixed position and argue that investors would prefer symmetric remuneration schemes because they are better at creating hedge fund value, but they acknowledge the fact that they might demotivate hedge fund managers from starting a fund and performing afterwards because of the downside risk they would be exposed to.

Finally, Glode and Green (2011) propose that the outperformance might simply stem from managers' fear. They argue that informed investors could leave the fund and replicate the strategy if the manager did not reward their investments enough. Instead of extracting all the alpha for herself, as expected under the Berk and Green (2004) framework, the scared manager will leave a proportion of it for the investors. Their proposition, however, relies on the single assumption that investors of hedge funds know enough to replicate the strategy on their own. This assumption is idealist, at best. While some investors in some hedge funds might have some information about the strategy, the general situation is far from the one described by the authors, who cite Yale University's Endowment CIO: *"We require complete transparency. We either know every position, or we don't invest."* To give one simple example, how exactly would somebody know all the positions of the millisecond trades undertaken by a 100,000 lines program in an algorithmic trading fund?

It appears from above that skill is present in the investment industry in general, but there are more incentives to use it under the typical hedge fund remuneration scheme. Therefore, while it is clear that these incentives play a role in explaining hedge fund returns, it is yet to be understood why and how managers change them from time to time. Indeed, Agarwal and Ray (2011), along with Deuskar, Wang, Wu, and Nguyen (2011b), acknowledge that hedge funds change their fees from time to time. They propose various fund-level and performance-related factors explaining the changes. But they lack a theoretical framework and do not pinpoint what is the real underlying motivation for the managers to implement these changes. Clearly, at a time when hedge funds' remuneration schemes are under pressure, it would be of foremost importance to explore the underlying mechanics.

1.6 Reliability of Current Research

In the previous section, we have reviewed the literature about hedge fund performance. As we have seen, results are sometimes conflicting. The methodologies and periods under study are, of course, partially explicative of these conflicts, but some differences might come from the data itself. Errors in financial data are nothing new and there have always been some mistakes in companies' financial statements or reported stock prices. But the last few decades have witnessed an exponential development of secondary data providers, which all contribute to the potential sources of errors. The amount of data is growing at a fast pace, along with the necessary IT requirements to maintain it properly. Mergers and consolidation between databases are common, and so are separations of databases into sub-categories, as well as creations of new products based on unexploited historical data. Researchers and practitioners rely more and more on this data, often without questioning its validity. The quality of the data is therefore of foremost importance. I focus on hedge fund databases and closely review the potential sources of errors in an industry where financial reporting is still mostly[11] done on a voluntary basis (see Appendix A for an analysis of the reliability of financial databases in general).

Unlike many other research fields, finance relies on historical data and, most of the time, experiments cannot be replicated. While in the early days of finance, researchers used to gather the data themselves, virtually all recent empirical studies rely on the data provided by a handful of vendors. Whether this data contains errors is not questioned here. Errors happen even in the most well maintained systems. Moreover, as with any information disclosed by private organizations, this data can be subject to manipulation from the managers. Therefore, the presence of errors in widely available commercial products is doubtless. The important

[11] Hedge funds can decide whether and to whom to report their returns and characteristics. Some of them do, nevertheless, have partial mandatory reporting obligations to the SEC. Indeed, the SEC requires institutional investment managers with at least USD 100 million under management to quarterly report their long positions (over 200000 USD or 10000 shares) with a maximum delay of 45 days.

question, though, is whether these errors are important enough to potentially impact research results and whether something can be done to mitigate them.

Hedge funds are particularly concerned with the issues mentioned above but additional potential problems arise from the loose regulation of the industry. Indeed, even though European and American regulators have recently been pushing towards greater transparency,[12] hedge fund managers are still reporting their returns on a voluntary basis. This is an important difference with respect to other financial data. As a matter of fact, the data contained in financial databases is generally publicly available, and the value added by the data vendors is to collect it and create an easily accessible version. For hedge funds, it is different. The data is not publicly available, so data vendors are actually in charge of collecting and organizing the data that hedge fund managers are *willing* to publish. For instance, hedge funds that close to new investors might decide to stop reporting to databases while other funds might not start to report at all. This gives rise to some errors that are specific to this industry. Thus, I first concentrate on the representativity of the databases. Then I review the literature about data biases that stem from the way hedge fund reporting is organized. These biases are well-known and often succinctly discussed in performance-related papers, but I here concentrate on the studies which cover the subject more specifically or which treat it in an innovative way. I finally switch to the quality of the data itself. The corresponding literature is summarized in Table 1.5.

Table 1.5: Literature about the Reliability of Hedge Fund Data

This table summarizes the articles that document the reliability of hedge fund data. It describes the methods and the samples used, along with a summary of the key results. When not precised, the method is archival. The papers are order by year of publication and author.

Reference	Method / Sample	Key result
Brown, Goetzmann, Ibbotson, and Ross (1992)	Mathematical model and simulation	Survivorship biases samples and creates artificial persistence in returns. Moreover, it will create fake relations between volatility and returns.
Ackermann et al. (1999)	HFR, MAR, 1988-1995	Six biases are studied: survivor, termination, self-selection, liquidation, backfilling, and multi-sampling.
Brown et al. (1999)	U.S. Offshore Funds, 1989-1995	Hedge fund returns data is prone to a significant survivorship bias, which might influence research results.

[12] See Section 1.2.2 of the present paper.

Fung and Hsieh (2000)	TASS, 1989-1999	Separation between biases due to hedge fund data nature and biases arising from the techniques and statistical procedures used.
Liang (2000)	HFR 1993-1997, TASS 1993-1998	Two hedge fund databases have significantly different returns, inception dates, NAVs, fee levels, and investment styles for funds covered by both databases. Survivorship bias is more than two percent per year. Hedge funds mainly disappear because of poor performance.
Liang (2003)	TASS, U.S. Offshore Funds Directory, up to 2000	Auditing improves on the reliability of hedge fund reported returns, and larger funds tend to be more audited than small ones. Data quality is also dependent on the fund category.
Getmansky et al. (2004)	Theoretical model and archival, TASS, 1977-2001	Hedge fund returns suffer from smoothing and serial correlation because of the illiquidity and subsequent difficulty to price the underlying assets the manager is invested in.
Malkiel and Saha (2005)	TASS, 1994-2003	Hedge fund data is biased upwards because of voluntary reporting and backfilling bias. Moreover, survivorship bias accentuates this effect.
Chen and Ibbotson (2006)	TASS, 1994-2004	Backfilling and survivorship bias are important in hedge fund data.
Fung and Hsieh (2006)	Theoretical model, literature review, and archival, TASS, HFR, CISDM, 1994-2004	Self-selection, survivorship, backfill, and liquidation biases, as well as illiquidity-induced serial-correlation, are important in hedge fund data. Therefore, the indexes created from this data might not correctly represent investors' actual experience.
Hodder, Jackwerth, and Kolokolova (2008)	Quantitative model and archival, Altvest, 1994-2006	Hedge funds that delist without clear reasons have a little lower mean than the average hedge fund. Even if average delisting returns are not dramatically low, some funds exhibit large negative returns.
Bollen and Pool (2009)	CISDM, 1994-2005	Hedge fund managers misreport returns. The number of small gain is greater than the number of small losses. It does not depend on database.
Fung and Hsieh (2009)	Barclays, CISDM, HFR, TASS, up to 2007	Data biases arise from hedge fund migrations between databases or from database mergers. It is hard to know if funds ceased reporting because of liquidation or because of a database migration. Also, some good performing funds do not report, mitigating the studies about self-selection.
Agarwal, Fos, and Jiang (2010a)	CISDM, HFR, Eureka, MSCI, TASS, SEC 13F, 1980-2008	Young hedge funds from high-frequency strategies are more likely to self-report than others. The non-reporting funds only slightly outperform the reporting ones. This indicates that self-reporting bias might not be too big of an issue. Performance deteriorates after the start and end of reporting.
Aggarwal and Jorion (2010a)	TASS, 1994-2001	There is an important survivorship bias in the TASS database because of the way is has been merged with another database. The performance impact is of more than five percent. A sorting algorithm is proposed.
Aiken, Clifford, and Ellis (2010)	SEC NSAR-A/B Forms, 2004-2008	Hedge funds that choose to report outperform those who do not, on average. Funds that delist have a much lower return than those who stay in. Non-reporting funds have fatter left tails.
Bollen and Pool (2010)	CISDM, TASS, 1994-2008	Fraud in hedge fund returns can be detected ex-ante by the use of the appropriate performance flag.
Cumming and Dai (2010)	CISDM, 1994-2008	Jurisdiction has an influence on the propensity for hedge funds to misreport returns. The propensity is the highest in jurisdictions which allow wrappers and in funds without lockups.
Liang and Park (2010)	TASS, 1995-2004	There are good reasons to liquidate hedge funds other than failure. Liquidation reasons in databases are less informative than performance and size variations.

Agarwal, Daniel, and Naik (2011)	CISDM, HFR, Eureka, MSCI, TASS, 1994-2006	Hedge fund managers with the greatest incentives and the biggest latitude to manage returns tend to misreport their returns. There is strong evidence that funds underreport during the year to make reserves they can use in case of poor return months or to increase December returns. There is weak evidence that they buy securities in December to artificially increase their prices and thus their returns.
Schneeweis, Kazemi, and Szado (2011)	CSFB, CISDM, 1998-2010	The comparison of two hedge fund databases shows differences of means and standard deviation between strategy portfolios and overall database portfolios. The differences are small but suggest that, on aggregate, these two databases do not contain the same data.
Patton, Ramadorai, and Streatfield (2012)	TASS, CISDM, HFR, Morningstar, BarclayHedge, 1994-2011	Database revisions are not random, and they are partially predictable by fund level characteristics. Revising funds have lower returns and higher tail risk than non-revising ones. Hedge fund managers mostly revise their fees downwards.

1.6.1 Representativity of the Database

Not only can hedge funds decide to report their returns or not; they can also decide to whom to report, and the options are relatively wide. Table 1.6 gives an overview of the existing databases along with the number of funds they cover.

Table 1.6: Major Private Hedge Fund Databases Overview

This table describes the major hedge fund databases. Because of mergers and acquisitions, most of them have several names; the most recent name is in bold. The numbers are provided by the database vendors as of 1st March 2012.

Database (and aliases)	Description	Number of funds covered
Morningstar Altvest Investorforce MSCI	The database developed by Altvest was acquired by Investorforce, later acquired by Morningstar, which also acquired MSCI hedge fund indices. It is now completely integrated under the Morningstar name.	Over 8,000
BarclayHedge Barclay Group	Formerly known as the Barclay Group, this database was established in 1985 and is not affiliated to the Barclays Bank.	Over 4,900
CISDM MAR Zurich	This oldest hedge fund database was created in 1979 by Managed Account Reports (MAR). It was sold to Zurich, which later donated it to the Center for International Securities and Derivatives Markets (CISDM) of the University of Massachusetts.	Over 4,500 live Over 9,000 dead
EurekaHedge	Founded in 2001, EurekaHedge is an independent alternative investment data provider based in Singapore.	Over 6,000
HedgeFund Intelligence AsiaHedge EuroHedge InvestHedge	Established in 1998, HedgeFund Intelligence is an online provider of alternative investment news and performance data.	Over 800 in Asia Over 1,300 in Europe Over 1,300 funds of funds

HFR	Hedge Fund Research (HFR) was founded in 1993 and is a provider of hedge fund research and data. It is part of the HFR Group, which also provides investment management via HFR Asset Management.	Over 6,800 live Over 10,000 dead
TASS Lipper Thomson Reuters	The Trading Advisors Selection System (TASS) database, propriety of Tremont, was acquired by Lipper, later acquired by Reuters, which was taken over by Thomson. Along with HFR, it is the most used database in hedge fund research.	Over 6,800 live Over 10,000 dead

From Table 1.6, we can see that data vendors are numerous and their coverage greatly varies. While HFR and TASS contain the largest number of funds, the other databases are also relatively important, and it is impossible to tell which one is the most representative of the hedge fund market. In fact, Agarwal et al. (2010a) document that there is no single database that contains more than a quarter of all reporting funds and that more than 70 percent of the hedge funds only report to a single database. These funds are *de facto* unobservable (and virtually inexistent) for the users of another database. This is an important issue for at least two reasons. First, in order to have a representative view of reporting hedge funds, it is necessary to collect the data from most, if not all, data vendors. This is a costly and difficult process because in the absence of a common identifier, there is no straightforward methodology that allows deleting duplicate funds across databases. As a matter of fact, and to the best of my knowledge, only one academic institution has been able to create such a representative database, aggregating the data from five of the largest data vendors.[13]

The second reason is that even by collecting all available data, an important part of existing hedge funds will not be covered because they do not report to any database, and there is nothing to do about this. In this situation, the observable sample is not necessarily representative of the population, which may create biases if there are specific reasons not to report. Therefore, as long as reporting will be done on a voluntary basis, a true picture of the hedge fund industry will remain out of reach. In the following, I review the biases that appear because of these reporting behaviors.

[13] The Oxford-Man Institute of Quantitative Finance. Saïd Business School, University of Oxford, UK.

1.6.2 Hedge Fund Data Biases

Managers can have multiple reasons both to report and not to report. Since they are forbidden to advertise, they may report their returns as an alternative source of advertising. They can also decide not to report because they want to be as secret as possible or because they have enough assets under management. A multitude of other motivations could be argued both for and against reporting. As compared to other fields in finance, this is already a source of two closely-related biases, self-selection and backfilling. The first makes the group of reporting *observable* funds a non-random sample of the actual *unobservable* group of existing funds. The second creates upward biased time-series of returns since funds can decide if and when they want to report their returns, and they will most often do so after good performance. So, it is expected that the returns before the date of entry into a database are higher than the returns afterwards.[14] Both biases have been analyzed extensively, and studies are mostly unanimous about the fact that both biases significantly push the returns upwards; see, for instance, Ackermann et al. (1999), Fung and Hsieh (2000), Malkiel and Saha (2005), Chen and Ibbotson (2006), or Fung and Hsieh (2006). In an innovative analysis, Hodder et al. (2008) study the returns of hedge funds which stopped reporting (self-selected not to report anymore) and show that their returns are on average slightly, but significantly, lower than the returns of the ones still reporting, further confirming the upward push. In a more recent study, Aiken et al. (2010) use holdings data from a set of registered funds of funds to recreate a quarterly returns time-series of the hedge funds they are invested in. This allows them to have return time-series for some hedge funds that do not report to any commercial database. They compare the returns of reporting funds with returns of funds that do not report and identify a significant positive performance bias towards reporting funds. Self-selection bias, although impossible to

[14] The combination of these two biases creates what is often referred to as *incubation bias.* That is, a bias arising from the fact that before disclosing their returns to the public, young funds have a period of incubation in which they test their strategy (often with the funders money). They will only consider reporting if this strategy is successful (so that they did not go bankrupt), and even in that case, they may still decide whether and to whom to report.

eliminate, can be limited by using several data providers as underlined in Agarwal et al. (2010a), so the bias is reduced to the funds not reporting to any commercial vendor. These authors, however, find no significant difference in performance between reporting and non-reporting funds, even though they document that performance starts to deteriorate when funds start reporting. As for the backfilling bias, various techniques have been proposed to control for it. The most generally used technique is to remove the first 24 to 36 months of each return time-series, but the drawback is that this may also remove non-backfilled data. Aggarwal and Jorion (2010b) control more strictly for backfilling bias by using a backfilling indicator provided by the TASS database to effectively remove all bias due to returns that are concerned. This technique has the advantage of only keeping the non-backfilled data but relies on the assumption that the backfilling indicator is correct, which might not always be the case.

Another important source of bias that also exists in other investment funds, though, is survivorship. It stems from the fact that failed funds tend to be excluded from performance studies, thus pushing average returns upwards. In hedge funds, though, it is augmented by the so-called termination and liquidation biases, which arise because funds can decide to stop reporting or to liquidate without actually going bankrupt. Among the first, Brown et al. (1992) analyze the extent of this bias on investment funds and show that it tends to significantly push returns upwards. Brown et al. (1999) analyze the issue in hedge funds and arrive at similar conclusions. On the other hand, Ackermann et al. (1999) argue that positive and negative survivorship biases are weak and offset each other. That is, on average, the poor performance of funds that disappeared because they died is compensated by the good performance of funds that ceased reporting voluntarily. They nevertheless underline that dead funds were more volatile than their live counterparts. Liang (2000) contradicts them and goes back to the consensus by identifying a survivorship bias of approximately plus two percent per year in hedge fund returns. According to him, hedge funds mainly disappear from databases because of poor performance and not because of voluntary end of reporting. Malkiel and Saha (2005), Chen and Ibbotson (2006), and Fung and Hsieh (2006) arrive at the same conclusions. Fung and Hsieh (2009) underline the fact that it is hard to know whether funds stop reporting because of self-selection, liquidation, or migration to another database. Consequently, while they acknowledge the existence of self-selection and survivorship bias, they argue that it might be less extreme than previously documented. Liang and Park (2010) also confirm that there are multiple reasons, other than failure, to delist from hedge fund databases and that liquidation reasons given in databases are only limitedly informative. Aggarwal and Jorion (2010a) identify a novel and hidden source of survivorship bias due to the way the TASS database was augmented after a merger with another data provider. They find this bias to affect hedge fund returns by a significant five percent per year on average. They propose a sorting algorithm to mitigate the issue.

From above, we see that the fact that hedge funds can choose if, when, and to whom to report can have significant effects on the returns. Since the corresponding biases directly stem from the lack of regulation, they will continue to exist as long as hedge funds are not obliged to report. From a perspective purely oriented towards data quality, regulations pushing towards more transparency would be welcome. Nevertheless, it appears that most of these biases are relatively easily identifiable and can, at least partially, be mitigated by various techniques. As a matter of fact, they have been so much documented that virtually all hedge fund studies mention at least some of them, yet not all studies take the necessary steps to ensure a bias-free sample. Considering the recent developments, biases are often (not always) removable. Therefore, no study using hedge fund data should be undertaken without properly accounting for these biases and making the appropriate corrections.

1.6.3 Hedge Fund Data Quality

The above-mentioned biases can be categorized as database-related biases. Although problematic, these biases are known and can, up to some extent, be mitigated. More worrying, the presence of strategic misreporting, reporting errors, and revisions in the databases are hard to identify unless they have a systematic pattern or stem from a specific and identifiable event. Because of the prevalence of a number of obvious biases discussed above, the literature has not concentrated much on these deeper problems until the last decade, when a limited number of studies have started to tackle the related issues.

Among the first, Liang (2000, 2003) evaluates the reliability of reported returns by comparing two databases and also two different snapshots from the same database. He identifies significant and sometimes large differences in both comparisons. He further shows that auditing clearly improves on the quality of the data since the discrepancies are significantly lower for audited hedge funds. He therefore underlines that the errors mostly come from the fund side and not the data vendor side. Getmansky et al. (2004) identify another problem coming directly from hedge fund reported returns—the illiquidity bias. This bias stems from the ambiguous situation hedge fund managers face. On the one hand, they sometimes hold illiquid assets that are difficult to price before sale. On the other hand, they have to provide monthly return figures to clients and data vendors. Managers therefore end up *estimating* a value, thereby providing smoothed and serially correlated returns. This is often referred to as the *mark-to-model* problem. The reported returns are inaccurate, but it is because of an inaccurate valuation of the underlying assets and not because of voluntary manipulations by the managers. Bollen and Pool (2009), on the other hand, identify a tendency to voluntarily misreport. They analyze pooled hedge fund returns and find a significant discontinuity. The number of small gains is much larger than the number of small losses, thus suggesting voluntary performance overstating by hedge fund managers. Bollen and Pool (2010) propose some performance flags which can be used to identify misreporting funds *ex ante*. Cumming and Dai (2010) test some misreporting drivers and identify that jurisdiction and share restrictions play an important role in misreporting. Agarwal et al. (2011) identify evidence of strategic misreporting by finding a December return pick, which cannot be explained by standard factor exposures. They interpret it as an upward management of hedge fund December returns. They show that fund managers with the greatest remuneration incentives and the biggest latitude to hide misreporting (volatile returns, illiquid investments) are the most likely to manage their returns. In fact, there is strong evidence of under-reporting during the year to make reserves, which can be used in case of poor-return months or to increase the December returns in order to cash in as much fees as possible and because of annual end-of-year auditing. Managers do, however, only weakly tend to borrow from the next year's return by massively buying securities to artificially inflate their prices along with their end-year returns. Schneeweis et al. (2011) compare two hedge fund databases (CSFB and CISDM) at the aggregate level. They find differences of means and standard deviation between strategy portfolios and overall database portfolios. The differences are small, but they suggest that, on aggregate, these two databases do not contain exactly the same data. Finally, Patton et al. (2012) follow Liang (2003) and Ljungqvist, Malloy, and Marston (2009) and study database revisions to find that they are not random and that they are partially predictable by fund level characteristics. They also document that most fee revisions are mostly downwards, thereby suggesting dishonest behavior by hedge fund managers. They conclude that revising funds have lower returns and higher tail risk than non-revising ones.

A number of questions remain open, however. It is yet unclear whether revisions are done because the fund strategically misreported its returns or because of simple errors from the hedge fund or data vendor side. Multiple snapshots of multiple databases should allow answering this question. Also, although the presence of errors and misreporting is clear, it would be interesting to see whether they have a significant impact on typical performance studies. Finally, it would certainly be interesting to combine research about the December returns spike with research about returns revisions. This could allow seeing whether the funds with a December return spike are subsequently more likely to revise their December returns downward rather than returns from other months, or whether they are more likely to revise other months' returns upward rather than the ones of December.

1.6.4 Implications on Empirical Results

All things considered, hedge fund data suffers from important issues and should be treated with caution. First, there are obvious biases stemming from voluntary and largely unregulated reporting. Second, the relative lack of control leads some hedge fund managers to misreport their returns, for various reasons and to various extents. Third, funds covered by multiple databases show differences in terms of reported returns between databases. Fourth, different versions of the same database do not contain the same figures, and the revisions have a non-random pattern.

In this context, the reliability of many empirical results cannot be taken for granted and certainly not be considered as representative of an entire industry. The situation is, however, not desperate, and in a period of regulatory changes, there are some actions that could, at a limited cost, be undertaken to improve on the situation. First, auditing significantly improves on the quality of the reported data (see Section 3.2.3) and should therefore be rendered mandatory. Second, since many funds do not report at all or only when it is in their favor, a detailed reporting, such as the one existing for mutual funds, should be introduced. Since secrecy is a potential issue for some funds (see Section 2.2.4), this reporting could be limited to regulatory agencies and investors, as suggested by Shi (2012) and Patton et al. (2012). These agencies could then make an anonymous version available to researchers. The information so revealed should be divided into two datasets, one containing the holdings, the other containing the performances, with no common identifier. This way, it would be possible to paint an accurate picture of the performance and risks involved in this industry without revealing fund-specific trading secrets. The general public and investors, who are interested in specific funds and not the entire industry, would keep relying on commercial databases. Third, in order to ease the aggregation of multiple databases, a mandatory common identification number (such as the ISIN) could be introduced. Since reporting to databases remains voluntary (only reporting to regulatory agencies needs to be mandatory), the data vendors would still be able to co-exist and compete against each other since none of them would contain the entire universe of funds. Considering the importance of this industry in the financial markets, it seems important to enable measures that would allow regulators to have a clear view. Taken together, the measures proposed above would certainly allow a better monitoring of hedge funds and hopefully help avoid inconvenient surprises, such as the L.T.C.M. debacle or the Madoff fraud mentioned in the introduction of this paper.

1.7 Conclusion

In this paper, I review the literature about hedge fund performance and data reliability. I confirm some myths while I dismiss some others. The outperformance of hedge funds is confirmed. Nevertheless, the length of the outperformance remains debated, and both very short and very long persistence horizons are mentioned in the literature. I review the numerous drivers of performance that have been documented. From this analysis, it appears that most of hedge funds' performance stems from beta, rather than alpha, exposures. However, manager skill still plays a role in explaining returns. I confirm the return chasing behavior of investors, but it appears that other factors also influence their allocation decisions since they tend to stay in underperforming funds for longer than expected. The literature confirms the capacity constraints of hedge fund strategies since, over the long term, performance decreases with flows. I identify a new potential explanation about performance differences between mutual funds and hedge funds, which does not rely on the lack of skill but on the lack of incentive. Hedge funds remuneration schemes seem indeed able to be motivating enough to attract the best mutual fund managers. All these results must, however, be treated with caution. Indeed, financial data is confirmed to be affected by several unreliability sources. Problems of coverage, reporting, definition, and classification all contribute to the issue. For hedge funds, the situation is even more severe because of the limited reporting obligations to which they are constrained. Therefore, the data has many biases that should be considered and controlled appropriately. Moreover, misreporting is also present since different databases do not contain the same data, and figures are revised in a non-random manner. In this context, I propose some recommendations for regulatory changes that might help to obtain a better picture of the hedge fund industry.

I finally ask some questions for further research, namely: What exactly does a hedge fund manager's skill consist of? Why and how do hedge fund managers modify their incentive schemes? To what extent is misreporting voluntary, and does it materially affect research results?

Appendix 1.A: Errors in Financial Databases

In this appendix, I review the literature about the sources of errors in financial databases in general. Although the sources of errors sometimes co-exist, I nevertheless categorize the related literature here below into four categories. Table 1.A.1 summarizes the corresponding papers.

Table 1.A.1: Literature about the Sources of Errors in Financial Databases

This table summarizes the articles that document the sources of errors in financial data. It describes the methods and the samples used, along with a summary of the key results. When not precised, the method is archival. The papers are order by year of publication and author.

Reference	Method / Sample	Key result
Rosenberg and Houglet (1974)	CRSP, Compustat, 1963-1968	CRSP and Compustat diverge. Rare, large, independent errors appear in both databases, and they significantly impact the nature of the data.
Miguel (1977)	Compustat, SEC 10K, 1972	There is a 30 percent error rate in R&D expenditures in Compustat as compared to the original SEC filings. When available, multiple matched databases should be used. It is better to use the original data, if possible.
Bennin (1980)	CRSP, Compustat, 1962-1978	CRSP and Compustat (PDE) diverge, but the error-rate is lower than previously documented. CRSP remains the most reliable.
Vasarhelyi and Yang (1986)	Value Line, Compustat, 1971-1981	Data definitions are different between databases and can lead to more variations in reported values than actual reporting errors.
Sarig and Warga (1989)	CRSP, Lehman, 1981-1985	Price discrepancies between two bond databases grow larger with the illiquidity of the bond because the likelihood that the price is not updated increases. The mean of differences is zero, so they only affect higher moments. Noise can be reduced by filtering of certain characteristics.
Schwert (1990)	Multiple Databases, 1802-1987	The practice of time-averaging returns induces autocorrelation and reduces volatility. Also, not including dividends misestimates mean returns.
Philbrick and Ricks (1991)	Value Line, I/B/E/S, Compustat, 1984-1986	Data received from analysts is treated differently from one database to another. The EPS forecast errors can be more significantly impacted by the data selection rather than by the data source.
Venkatesh (1992)	CRSP, 1988	CRSP uses closing trade price rather than the average between closing bid and ask price. CRSP prices induce more volatility than quoted prices, but the magnitude decreases with stock price. Studies remain mostly unaffected, but it is better to use quoted price for illiquid securities.
Kinney and Swanson (1993)	Compustat, 1985-1988	Two sources of error affect Compustat tax data: construction error and reporting (coding) error. The error rate increases with the specificity of the industry and is higher for the less visible items (footnotes).
Courtenay and Keller (1994)	CRSP, Moody's Dividend Record, 1989-1990	Stock dividends and splits data in CRSP are highly accurate for 1989. The probability of having an error is three percent, and the effect on researches should be relatively limited.
Guenther and Rosman (1994)	Compustat, CRSP, 1982-1990	There are important differences in industry classification codes between the CRSP and Compustat databases. 11 financial ratios out of 14 have a lower variance in Compustat. This can affect researches materially.

Kern and Morris (1994)	Value Line, Compustat, 1971-1990	Compustat and Value Line do not cover exactly the same firms. Moreover, total assets and sales figures reported in both databases often do not match with actual financial statements.
Ball, Kothari, and Wasley (1995)	CRSP, 1962-1988	Contrarian strategies profits implemented on CRSP closing prices are upward biased since there are twice as many last trades established at the bid than at the ask price. Without the bias, most contrarian profits vanish.
Mutchler and Shane (1995)	CRSP, Compustat, NAARS, 1985 and 1990	The coverage of the NAARS database appears to be lower for firms that are small, have a higher probability of bankruptcy, and which receive qualified opinions from auditors who are more likely to be small too. There are also coverage discrepancies between industries.
Davis (1996)	CRSP, Compustat, 1963-1978	Survivorship bias is significant in Compustat but is not severe enough to entirely explain the return predicting power of commonly used ratios.
Kahle and Walkling (1996)	CRSP, Compustat, 1974-1993	There are significant differences in industry classification between CRSP and Compustat. Respectively, 79, 50, 36, and 21 percent for the 4-, 3-, 2-, and 1-digit SIC codes. Compustat does not keep a track record of industry classification, which explains part of the differences. Financial tests return significantly different results, depending on the database used.
Anderson and Lee (1997)	Compact Disclosure, S&P Corp. Text, Value Line, CDA Spectrum, 1992	There is a clear reliability ranking between four ownership databases. Regression results obtained from the two best ones are not significantly different from using the actual base data, but using the two worst ones leads to significant differences.
Pierce and Skantz (1997)	Value Line, I/B/E/S, 1983-1993	Non-recurring gains or losses can significantly impact earnings but are not always included in earnings figures reported in the databases. Moreover, inclusion in actual earnings does not mean inclusion in forecasts.
Shumway (1997)	CRSP, 1962-1993	There is a delisting bias in CRSP NYSE-AMEX stocks. When stocks are delisted unexpectedly, delisting returns are missing for many of them. CRSP only reports full monthly returns, so first and last trading months are often also missing.
Canina, Michaely, Thaler, and Womack (1998)	CRSP, 1964-1993	The CRSP equally-weighted monthly returns compounded from daily data are significantly biased. The bias can be avoided by using the index levels on the first and last day instead of returns.
Shumway and Warther (1999)	CRSP, 1972-1995	There is a delisting upward bias in CRSP Nasdaq stocks that is significantly larger than the bias reported by Shumway (1997). Once corrected for this bias, size effect on returns vanishes.
Elton, Gruber, and Blake (2001)	Morningstar, CRSP, 1979-1998	There are significant differences in returns between two mutual fund databases. CRSP has omission bias for old data and small funds. CRSP mutual fund returns are biased upwards because of how they are adjusted. In CRSP, mergers are not always reported at the right date.
Bhojraj, Lee, and Oler (2003)	CRSP, Compustat, 1994-2001	The comparison of four industry-wide classifications finds that the GICS classification creates more homogenous groups of stocks but disagrees with other classifications frequently.
Krishnan and Press (2003)	Compustat, 2000	The comparison of SIC and NAICS industrial classifications shows that NAICS results in lower variance in financial ratios and thus better groupings.
Mills, Newberry, and Novack (2003)	Compustat, Confidential US Tax Data, 1981-1995	Compustat's net operating loss carryforward item is used as a proxy for firms' U.S. tax-loss carryovers, but they are not always the same because of the methodology used by Compustat and because of coding errors.
Payne and Thomas (2003)	I/B/E/S, 1984-1999	The use of adjusted or unadjusted versions of I/B/E/S can lead to significantly different conclusions because of rounding errors in the adjusted data.

Yang, Vasarhelyi, and Liu (2003)	Value Line, Compustat, 1971-1981	Most variation between databases can be explained by definition differences, while another part is due to reporting errors.
Ulbricht and Weiner (2005)	Compustat, Worldscope, 1985-2003	Compustat and Worldscope do not cover all the same firms, which leads to differences in the cross-section across years (not within). The coverage of Worldscope is larger than Compustat after 1997 and inversely before.
Ince and Porter (2006)	Datastream, CRSP, 1975-2002	Datastream and CRSP do not have exactly the same coverage, and the data is not always reliable. Moreover, one must be careful to apply adequate filters when working with Datastream data. Only after thorough cleaning are the results obtained from the two datasets similar.
Lara, Osma, and Noguer (2006)	Seven databases, 1990-1999	Replicating a simple study using different databases leads to different results, mainly attributable to differences in coverage. Once matched, differences are much more limited.
Alves, Beekes, and Young (2007)	Six databases, 1970-2004	Coverage of UK firms varies from one data vendor to another. Variables are not all computed the same way. Results from replicated studies give different results, depending on the database used.
Acker and Duck (2009)	I/B/E/S, Worldscope,1999-2006	Many year-end earnings announcements are wrong in I/B/E/S. I/B/E/S and Worldscope do not report the same announcement date (for UK firms). In I/B/E/S, forecasts are sometimes dated after announcement dates.
Ljungqvist et al. (2009)	I/B/E/S, 2000-2007	The I/B/E/S database suffers from substantial changes from one update to another. Changes consist of alterations, additions, and deletions, and they are not random.

1.A.1 Data Definition and Construction

Vasarhelyi and Yang (1986) and Yang et al. (2003) compare accounting figures between two databases and report that differences in data definitions can lead to more variation in reported figures than actual reporting errors. Kinney and Swanson (1993) corroborate these results and point out that the errors are greater for some very specific industries and for data contained in financial statement footnotes. Therefore, data that is harder to understand and to categorize is more often wrong in the databases. Philbrick and Ricks (1991) confirm the definition problem and document differences in how data received from analysts is treated from one database to another. They underline that EPS forecasts can be more impacted by the data selection process than by the data source itself. Sarig and Warga (1989) focus on bond price data and identify differences between two databases that are increasing with the illiquidity of the bond considered because the price is less likely to be updated in the database. They nevertheless show that these differences have zero mean and only higher moments are affected. Moreover, it is possible to reduce these problems by filtering certain bond characteristics. Schwert (1990) reviews almost two hundred years of data and in particular analyzes pre-CRSP data. He shows that the ancient practice of time-averaging returns artificially induces autocorrelation and reduces the volatility of the underlying true returns. Additionally, the exclusion of dividends misestimates mean returns, thereby confirming the appropriateness of CRSP's adjusted prices and returns. Keeping the focus on CRSP, Venkatesh (1992) identifies a caveat in the way closing prices are recorded. CRSP keeps the closing price of the last trade of the day rather than the mid-point between bid and ask prices. This practice increases the volatility of reported prices as compared to the quoted prices. However, the magnitude decreases with stock price and stock liquidity, and the authors affirm that most studies are not likely to be affected. Ball et al. (1995) show that contrarian strategies implemented on CRSP data are upward biased because there are twice as many last trades executed at the bid price as compared to the ones executed at the ask price. This bias is severe since once removed, most profits documented about contrarian strategies disappear. On the other hand, Courtenay and Keller (1994) praise CRSP and its accuracy in implementing stock splits and dividends and show that the probability of encountering an error is less than three percent, which the authors suggest should have a very limited influence on most studies and researches. Pierce and Skantz (1997) are interested in earnings figures and forecasts reported in Value Line and I/B/E/S. They report some inconsistencies in how the variables are coded in the databases. Namely, they document that non-recurring gains and losses are not always included in earnings reported in the databases, although they materially impact them. Moreover, the inclusion of these non-recurring items in the actual earnings figure is not synonymous with inclusion in the earnings forecasts, thereby further adding to the inconsistency. Shumway (1997) and Shumway and Warther (1999) study CRSP and document a bias arising when firms are unexpectedly delisted.

Indeed, many delisting returns are missing, thus biasing the available returns upwards. This bias is most pronounced for Nasdaq firms. Once corrected for this bias, there remains no evidence of the previously documented outperformance of smaller stocks. Additionally, since CRSP only reports full month returns, first and last partial trading months' observations are often missing. Also working on CRSP, Canina et al. (1998) document another issue. Compounded over monthly horizons, the *daily* returns of the CRSP equally weighted portfolio significantly differ from the *monthly* returns available in the database. This problem has been previously documented, but the magnitude was uncertain. The authors find a significant difference of six percent per year. However, it is relatively easy to circumvent this problem by using index levels to compute holding period returns. Elton et al. (2001) are interested in mutual fund data from CRSP. They document a systematic upward bias in mutual fund returns because of the adjustments for payments, such as dividends and capital distributions. They show that if two distributions occur the same day, which is not uncommon for mutual funds, the formula used to compute the adjusted returns significantly biases them upwards. The methodology to rectify this problem is nevertheless straightforward. Mills et al. (2003) obtain confidential U.S. tax data and use it to test the quality of the Compustat database. They specifically focus on U.S. tax-loss carryovers and document that Compustat's net operating loss carryforward item appears to be a good proxy to identify companies with tax-loss carryovers when it is complemented by other Compustat variables, although special care must be taken when companies have foreign operations or in case of acquisitions. Payne and Thomas (2003) compare the adjusted version of the I/B/E/S database to the unadjusted one. They document important errors in the adjusted version, which are due to rounding to only two digits. They show that the problem is relatively severe and could sometimes impact the conclusion of research studies. All in all, it appears that empiricists must be very careful when using commercial databases. The way the variables are defined and constructed can have a significant impact on the results. It is therefore important that researchers obtain a thorough understanding of the database they are working with, or they could be at risk of finding falsifiable results. I now switch to a closely related problem which relates to the classification of entities.

1.A.2 Classification Issues

Many authors differentiate their research based on industrial classification. The conclusions they draw are then often industry-specific and could therefore be significantly impacted by how the companies are classified. Guenther and Rosman (1994) tackle the issue by comparing the CRSP's and Compustat's industrial classifications. They compare the intra-industry variance of 14 financial ratios. The idea is that a lower cross-sectional variance is synonymous with greater homogeneity in the grouping and a more accurate classification. They find that eleven out of the fourteen ratios show lower variance under the Compustat classification than under the one of CRSP. They replicate a study and show that the classification difference significantly impacts results, thus underlining the significant differences between the two classification schemes. Kahle and Walkling (1996) analyze the same databases and reach similar conclusions. They document a classification difference between the two sources that is increasing in classification detail. Concretely, over the 10,000 firms analyzed, they find a difference of classification of 21, 36, 50, and 79 percent when comparing the 1-, 2-, 3-, and 4-digit SIC codes, respectively. This important classification gap is partially explained by the fact that Compustat does not keep a track record of industrial classification but only the last available information, contrarily to CRSP. They also show that these differences materially impact research results and conclusions. In the view of these results, Bhojraj et al. (2003) use Compustat SIC codes and compare the classification quality with three other widely used classification schemes, namely: The North American Industry Classification System (NAICS), the Global Industry Classifications Standard (GICS), and the Fama and French (1997) classification algorithm. They show that the GICS results in more homogenous groupings in terms of cross-sectional variations of various financial ratios and stock returns co-movements. However, this grouping is also the most divergent from the three other ones, which appear to be relatively close to each other in their classification. In the same vein, Krishnan and Press (2003) compare SIC codes with NAICS using a similar methodology as Guenther and Rosman (1994) and show that NAICS results in more homogenous groupings. Though, they only find very limited differences when replicating a study under one grouping or the other, even though regression coefficients show lower intra-industry variation under NAICS. They underline that the materiality of the classification impact will vary from one study to another. Taken together, these studies confirm the importance of understanding how databases are constructed because the impact on results can be substantial.

1.A.3 Coverage Issues

As we have seen, there are a number of substantial differences between databases, and it is arguably better to use multiple sources. Nevertheless, for budget or accessibility reasons, researchers often rely on a single database. Therefore, the question to answer is whether the entities covered by different databases are the same, and if not, to find the sources of the differences. Kern and Morris (1994) compare Value Line and Compustat and show that they do not cover the same firms. They identify a tendency of Compustat to better cover large firms. Moreover, replicating a study, they find significantly different results depending on the database that is used, and they link most of this difference to the sample of firms covered. Mutchler and Shane (1995) confirm the findings about firm size and further show, by analyzing the National Automated Accounting Research System (NAARS) database, that the coverage is also lower for firms that have a high probability of bankruptcy and for the ones receiving qualified audit reports. These firms are also more likely to be audited by non-big-eight audit firms. Davis (1996) works on Compustat and identifies a significant survivorship bias. Companies that were dead at the creation of the database have a high chance of never being added. Therefore, the problem is especially present for old data. Correcting the bias somewhat reduces the returns predictive power of commonly used financial ratios. Elton et al. (2001) analyze the CRSP Mutual Fund database along with the one of Morningstar and underlines that CRSP is sometimes missing old data and data for smaller funds. Concentrating on Compustat and Worldscope, Ulbricht and Weiner (2005) document differences in the firms covered. They do not identify a significant impact on research results. However, after 1997, the number of firms covered by Worldscope, over the U.S. and Canadian markets, is approximately one fourth greater than the number covered by Compustat. Comparing the U.S. equity coverage of Datastream with respect to CRSP, Ince and Porter (2006) document an improving coverage of Datastream through time. Indeed, while for the year 1975, only 20 percent of the firms contained in CRSP are also covered by Datastream, this percentage climbs to more than 90 percent in 2002. This further underlines the fact that the age of the data is importantly related to its quality. To gauge the extent and the materiality of the differences between databases, Lara et al. (2006) replicate a research study over seven databases (Datastream, Global Vantage, Company Analysis, Worldscope, Thomson Financial, Financials, and BvD Osiris). They find differences in results, which are mostly attributable to differences in coverage. Once matched with each other so that only the firms present in all databases are kept, the differences in results are much more limited. In a similar vein, Alves et al. (2007) analyze UK firms over six databases (Datastream Company Accounts Historical Archive, Worldscope, Extel, Company Analysis, and Thomson Research). They identify significant variations in the firms covered, as well as in the data items covered. All of these studies further confirm the importance of the choice of the data source in financial research and that multiple sources should be used whenever possible.

1.A.4 Reporting Errors

The three sources of errors we have reviewed so far have in common that they can be traced back to specific reasons, which can often be controlled for. There is one source which is harder to point out because it can either come from a technical difficulty or even from a simple human error. Indeed, up to nowadays, many numbers that are entered into a database are entered via human intervention. Additionally, the original data can also be corrupted due to errors in financial statements, for instance. No data is thus error-prone. Most of the above-mentioned studies have their results partially explained by reporting errors, but there are a few papers, summarized here, which put a specific emphasis on this issue. Kinney and Swanson (1993) document that the figures found in Compustat are at least partially wrong because of reporting errors. Kern and Morris (1994) compare Value Line and Compustat with original balance sheets and find that many figures reported in both databases do not match the original firms' statements. They relate part of this error to reporting and part to variable construction. Elton et al. (2001) study the CRSP and Morningstar mutual fund databases and identify that mergers between mutual funds are not always reported at the right date in CRSP. This further adds to the difference between the two bases. Mills et al. (2003), in their study of U.S. tax-loss carryovers, also underline that some of the errors in Compustat come from problems in coding. Yang et al. (2003) confirm the issue for both Value Line and Compustat. Ince and Porter (2006) report similar problems in individual equity returns as reported in CRSP and Datastream. Acker and Duck (2009) study U.K. firms and compare I/B/E/S earnings announcements dates with the ones in Worldscope. They identify that the dates are often different between the two databases. Moreover, I/B/E/S forecasts are sometimes even dated after the announcement dates, therefore representing a substantial and misleading source of error for the typical event studies. They, however, state that I/B/E/S seems to be aware of the issue and that there is an ongoing process for correcting these errors. Finally, Ljungqvist et al. (2009) are difficult to categorize under *reporting* errors since they have a dynamic approach towards reliability and document changes from one version of the I/B/E/S database to the other. They specifically focus on three types of changes: alteration, additions, and deletions. They underline the fact that database historical entries are revised. In fact, the same data obtained from different updates of the database does not match. This is an important source of problems since not only is the data not always reliable, it is also time-varying, making errors even more difficult to identify and to account for. Moreover, the differences are not random, so they cannot be considered as pure noise and could potentially impact study results. Indeed, the fact that data is revised is no news; it is the normal process when an error is discovered. The problem really comes from the fact that the revisions are not random.

Chapter 2: The Role of Remuneration Structures in Hedge Fund Performance

(A collaboration with Ivan Guidotti)

2.1 Introduction

Despite a slower growth and a relative cutback in performance in the recent years, hedge funds have been outperforming mutual funds for most of the past decades. Prior literature abounds with possible explanations for this lasting performance. Most of them are linked to the advanced risk exposures taken by hedge fund managers, while a smaller proportion finds an explanation in funds' characteristics and managerial skill. Interestingly, though, the mutual funds industry is able to retain its most skilled managers; see Deuskar et al. (2011a). Therefore, skill alone does not explain why hedge fund managers outperform their mutual fund peers. So, there must be some inherent differences between these two industries that play a role in the performance differential.

Berk and Green (2004) explain the lack of performance persistence in mutual funds. Mutual fund managers, because of their remuneration structure, have an incentive to let their fund grow as much as possible. Contrarily, in the hedge fund industry, we observe a tendency to limit the size of the funds by refusing new investments and even forcing investors to redeem. Hedge fund managers' incentives must be different from the ones of mutual fund managers. Moreover, hedge fund performance persists for relatively long periods.

In this context, this paper proposes and tests a model that explains hedge fund outperformance. The model connects performance, fund size, and managers' remuneration within a global framework. We show how the income-maximizing behavior of hedge fund managers, their specific remuneration schemes, and the absence of costless investable benchmarks are sufficient to explain hedge fund managers' outperformance. We first illustrate that the model of Berk and Green (2004) is not consistent with the empirical evidence observed in the hedge fund industry. For this reason, we adapt it by assuming that hedge fund managers cannot invest in a costless passive benchmark. This hypothesis is supported by the absolute return objective of hedge funds, by the monitoring exerted by investors, and by the managers' efforts of limiting the size of the funds. Using this modified model, we show how the specific structure of hedge fund remuneration schemes gives incentives to the managers to limit the size of their fund to maximize their remuneration. The implications of our model are consistent with what is observed in hedge fund data, namely investment restrictions, important investor flows, performance persistence, and highly rewarded managers, along with a limited abnormal performance. We further argue that managers can employ their discretion over remuneration schemes to set the fees at a level that allows them to maximize their income. Importantly, managers do not engage in rent-extracting practices, but they control the size of their fund by manipulating their management fees. As a consequence, the size of the fund converges toward the size that optimizes the performance and, indirectly, the remuneration of the manager.

We verify the validity of our model by testing its implication on a unique sample of hedge fund management fee increases. The empirical findings support our model. We find that managers who revise their management fees successfully affect the performance for new investors and flows in the optimal direction. Moreover, we show that fee revisions effectively protect the performance for the existing investors, leading to outperformance and persistent returns. Furthermore, we find that fee revisions are not intended to align the remuneration terms with the ones of the competitors. Altogether, we illustrate that, within the hedge fund industry, the remuneration structure plays a central role in explaining the persistence of returns.

This paper contributes to two strands of research. First, by pinpointing the mechanisms behind the persistent outperformance of hedge funds, we add to the literature on the determinants of hedge fund performance. Contrarily to the majority of the existing studies, we do not focus on risk exposures or manager skills, but on fund characteristics. We provide support to the idea that hedge fund outperformance and persistence are possible because of the limited size of these funds.

Second, we complement the literature on remuneration in the money management industry. The peculiar remuneration schemes of hedge funds have been the subject of many studies, and consistently with financial theory, these papers generally conclude that performance-related remunerations are associated with higher returns; see Ackermann et al. (1999), Edwards and Caglayan (2001), Goetzmann et al. (2003), and Agarwal et al. (2009b). Furthermore, several recent studies underline the formerly unnoticed dynamic nature of hedge fund remuneration contracts; see Agarwal and Ray (2011), Deuskar et al. (2011b), and Ramadorai and Streatfield (2011). On the one hand, our paper helps in understanding the mechanisms that transform incentive fees into persistence and outperformance. On the other hand, we provide a theoretical framework to rationalize the recent advances on fee dynamics. With respect to that, we show that the behavior of managers, even if self-interested, has positive consequences for investors.

Our paper also contributes to the current regulatory debate. After the 2008 turmoil, the perception of the remuneration schemes of hedge funds changed drastically. Politicians and public opinion blamed the performance fees to be a source of excessive risk taking. As a consequence, regulators put a specific emphasis on remuneration schemes in the recent revisions of financial regulations. The Dodd Frank Act, for instance, states: "*Federal regulators shall jointly prescribe regulations or guidelines that prohibit any types of incentive-based payment arrangement, or any feature of any such arrangement, that the regulators determine encourages inappropriate risks (...).*"[15] We provide evidence that the remuneration structure commonly used by hedge funds effectively aligns the interests of investors and managers. The revised regulation thus threatens the outperformance of hedge funds and investors' returns.

[15] See the title IX, sec. 956 (b) of the Dodd-Frank Wall Street Reform and Consumer Protection Act, http://www.sec.gov/about/laws/wallstreetreform-cpa.pdf. Also see chapter III of the Directive on Alternative Investment Fund Managers (AIFM), http://register.consilium.europa.eu/pdf/en/10/pe00/pe00060-re01.en10.pdf.

Our work contrasts with that of Agarwal and Ray (2011) and Deuskar et al. (2011b) in that these authors focus on fund level determinants of fee changes. On the contrary, we propose a theoretical framework which explains management fee changes with the single assumption that managers try to maximize their remuneration. We show that investors have a rational reaction towards these changes in that they vote with their feet and allocate their money to the managers who fulfill their investment constraint. Similarly to these studies, our results are consistent with the self-interested behavior of both managers and investors. But, on the opposite, we show that this has a positive impact on the hedge fund industry. Our work is also closely related to the paper of Glode and Green (2011). This paper proposes a model which explains hedge fund performance persistence with potential information spillovers. We provide an alternative explanation based on the characteristics of hedge funds.

The remainder of the chapter is organized as follows. In Section 2.2, we develop our theoretical framework. Section 2.3 introduces our testable propositions. Section 2.4 discusses the data. Section 2.5 details our computations and findings. Section 2.6 concludes.

2.2 Link between Performance, Size, Flows, and Remuneration

2.2.1 Evidence in the Mutual Fund and Hedge Fund Industry

Berk and Green (2004) propose a model of active management that explains why investors keep investing into mutual funds, allowing fund managers to pocket consequent fees, even if these funds deliver no abnormal performance; see e.g. Grinblatt and Titman (1989) or Malkiel (1995). Under a limited set of assumptions,[16] the model predicts that managers will let their funds grow as much as possible. This results in a lack of performance persistence and, in equilibrium, zero net outperformance.

[16] The model assumes an income maximizing behavior of managers, a competitive supply of capital, and returns subject to diseconomies of scale.

The model is widely accepted in the mutual funds literature, even if challenged by empirical evidence; see e.g. Fama and French (2010). Its predictions are, however, inconsistent with empirical findings on hedge funds. While it has been documented that outperforming hedge funds attract flows and that these flows subsequently deteriorate performance, hedge funds keep outperforming persistently; see e.g. Fung et al. (2008). Indeed, in the hedge fund industry, there is evidence of performance persistence over relatively long periods; see e.g. Edwards and Caglayan (2001), Kosowski et al. (2007), or Jagannathan et al. (2010). Moreover, contrarily to the mutual fund industry, hedge fund managers refuse to let their funds grow beyond given thresholds by closing them to new investments or by redeeming investors' money.[17] Thus, the model of Berk and Green (2004) does not fully capture the specificities of the hedge fund industry. An intuitive reason might be the difference in fee structures between hedge funds and mutual funds. The model can, however, be extended to accommodate incentive fees, and its predictions remain unchanged. Thus, the difference in fee structures alone cannot explain the peculiarities of the hedge fund industry underlined above. Glode and Green (2011) propose an explanation of hedge funds' persistent outperformance based on information spillovers. They assume that insider investors become informed of the proprietary strategy of the hedge fund in which they invest. Managers fear that investors could divulgate or replicate the strategy, thereby hurting the fund's profitability. For this reason, managers reward investors at a higher than minimal rate, so investors have no incentive to disclose the proprietary strategy. While this proposition might be true for some funds in some investment strategies, we think it is a rather ambitious assumption in an industry where secrecy, or at least opacity, is the rule. Moreover, this theory does not explain why hedge fund managers restrain the size of their funds. In the present paper, we provide a straightforward explanation to persistent outperformance that directly derives from the combination of two specificities of hedge funds with respect to mutual

[17] See, for instance, Jones, S., *Brevan Howard to return $2bn to investors*., The Financial Times, 09/20/2011. http://www.ft.com/intl/cms/s/0/c8f7f736-e373-11e0-8f47-00144feabdc0.html#axzz1Z8NyNDbM

funds: the performance-related remuneration scheme and the absence of a passive costless benchmark investment. While the first specificity is well known, the second deserves some rationalization.

Mutual funds are generally benchmarked against a market index. The managers' objective is to beat the benchmark, regardless of the sign or level of its return. Hedge fund managers face a different challenge: the typical objective of a hedge fund is to deliver an absolute return, regardless of the market conditions; see Fung and Hsieh (1997) and Harri and Brorsen (2004). This means being uncorrelated with the market indexes, and a passive investment in a benchmark is thus inconsistent with the objective of hedge funds; see Brown et al. (1999), Agarwal and Naik (2004), or Lhabitant (2006, p. 25). This does not mean that hedge funds do not invest *at all* in market indices, but when they do, they do it *actively*. Also, given the high fees they pay and the low limitations fund managers face in their investment strategy, investors have an incentive to continuously monitor the funds they are invested in. If managers use some kind of passive benchmark or if they deviate too importantly from their contractually agreed investment style, investors tend to terminate the contract; see Baquero and Verbeek (2009) or Lhabitant (2006, p. 576). The monitoring of the investors also prevents managers from keeping the assets of the fund in cash, which may be considered as a benchmark. Moreover, liquidity restrictions such as lockups, redemption frequency, and notice periods precisely exist because hedge funds are invested in illiquid strategies that cannot be unloaded instantaneously. Investments in a passive benchmark would make such restrictions superfluous; see Agarwal et al. (2004). Additionally, as underlined in Berk and Green (2004, p. 1276): *"if managers can expand the fund by investing a portion of it in the passive benchmark (...) efficient outcomes can be achieved with a proportional fee that does not change over time."* Therefore, in the presence of a passive benchmark, changes of fees would be unnecessary, but they are actually numerous among hedge funds, thereby further consolidating our assumption; see Deuskar et al.

(2011b). Finally, if hedge fund managers would use a passive benchmark, they could simply invest any additional inflows into it to avoid hurting the return of their strategy.[18] Instead, we observe that managers close their funds to new investment or even force investors to redeem; see Goetzmann et al. (2003).

2.2.2 Mutual Fund-Like Remuneration in the Absence of a Costless Investable Benchmark

The literature shows that hedge funds are facing decreasing return to scale, so the performance-size relation is concave; see e.g. Getmansky (2012). Managers exploit investment opportunities that are finite. The more assets they have under management, the more they have to spread their skills among these assets, and the higher the investment costs they face. Managers differ in their ability to generate returns and in the strategy they implement. As such, the funds are imperfect substitutes to each other, and they compete monopolistically. In this context, we first consider a hedge fund manager who is solely remunerated with a percentage of the assets under management (mutual fund-like remuneration). Formally, the remuneration of this manager is:

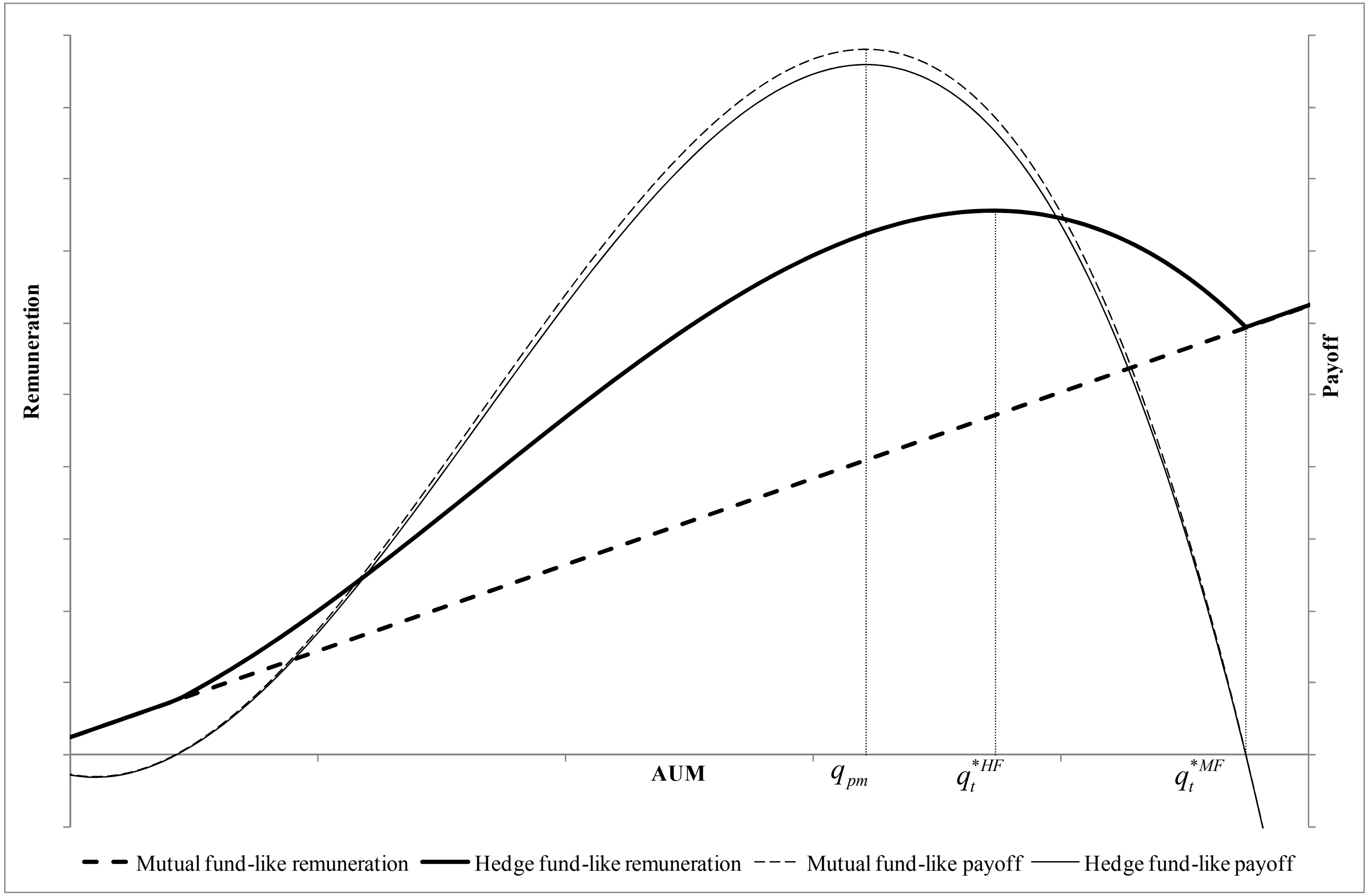
(1) $Remun_t^{MF} = q_t mf$,

where q_t stands for the Assets Under Management (hereafter AUM) of the fund, mf the management fee, and the superscript " MF " indicates that the remuneration comes solely from the management fee. Figure 2.1 illustrates. The dashed thin line represents the concave relation between performance and AUM as pinpointed by Getmansky (2012). The performance is represented by the monetary payoff for investors, i.e. the product of return and AUM. The shape of the curve is consistent with the fact that the entire portfolio is invested in the costly investment strategy.

[18] These passive benchmarks do not only encompass traditional indices but also the liquid hedge fund trackers offered by several investment banks.

Figure 2.1: Optimal Size under Different Fee Structures

This plot displays the relation between size, performance, and remuneration when there is no costless investable benchmark. The plot shows both the case in which the remuneration solely comes from a management fee and the case in which the fund also charges an incentive fee. The three quantities represent the size that maximizes the payoff to investors q_{pm}, the size that maximizes the manager's remuneration q_t^{*HF}, and the size for which the total payoff is null q_t^{*MF}.



If a costless passive benchmark was at disposal, the curve would be to the right. As illustrated by the negative returns on the left hand side of the graph, funds are facing fixed costs that prevent them from realizing positive returns before a break-even size is reached. The strategy exploited has increasing investment costs, but the performance increases at first because the fixed costs are spread among more assets. A maximum is eventually reached, and the performance starts decreasing until it reaches zero, after fees and costs.

As illustrated by the dashed bold line, the remuneration of the managers is directly proportional to the level of AUM, so they have an incentive to increase the size of their fund as much as possible, regardless of the performance generated. Investors, who provide their money competitively among existing funds, invest into funds as long as their net performance is positive. If we express this condition in monetary, rather than relative terms, this means that investors provide funds to the managers as long as the net expected payoff is positive. Formally:

(2) $TP_{t+1}^{MF} = q_t R_{t+1} - C\left(q_t\right) - q_t mf > 0$,

where TP_{t+1}^{MF} is the total payoff, R_{t+1} the gross return of the strategy, and $C\left(q_t\right)$ the investment costs faced by the manager.

Thus, in equilibrium, managers maximize their remuneration and the funds do not provide investors with any outperformance. The equilibrium is reached when:[19]

(3) $\dfrac{C\left(q_t^{*MF}\right)}{q_t^{*MF}} = \phi_t - mf$,

where q_t^{*MF} is the optimal AUM of the fund, and ϕ_t is the expected gross return. At the optimum, the average cost of the strategy is equal to the gross return of the strategy netted of management fees.

[19] For a formal proof of the model, please refer to Appendix A.

2.2.3 Hedge Fund-Like Remuneration in the Absence of a Costless Investable Benchmark

Let us now consider the typical hedge fund which applies a management fee and a performance fee. Then, the remuneration of the manager is:

(4) $Remun_t^{HF} = \left(q_t\phi_t - C\left(q_t\right) - q_t mf\right) pf + q_t mf$,

where pf is the performance fee and the superscript " HF " indicates that the remuneration has both a fixed and a variable component (hedge fund-like). The continuous lines in Figure 2.1 illustrate this situation.

The relation between net performance and size is similar. However, a slight kink appears when the line goes above zero because incentive fees kick in. The main change concerns the relation between remuneration and size. The relation is no longer linear, and remuneration now increases along a bell-shaped curve since it is dependent on both the AUM *and* on the performance. The remuneration reaches a maximum when:

(5) $C'\left(q_t^{*HF}\right) = \phi_t - mf + \dfrac{mf}{pf}$,

where q_t^{*HF} indicates the optimal AUM for a fund whose remuneration scheme includes a performance-based fee. At this point, the payoff of the fund is still positive:

(6) $E\left(TP_{t+1}^{*HF}\right) = \left(q_t^{*HF}\phi_t - C\left(q_t^{*HF}\right) - q_t^{*HF} mf\right)\left(1 - pf\right) > 0$.

This means that, in equilibrium, the demand for the fund is positive and that the manager has an incentive to limit inflows to the fund. Importantly, the manager does not control the size of the fund to avoid hurting the performance but to preserve her own remuneration. If the expected equilibrium payoff is positive, the equilibrium expected return is also positive, and the outperformance is thus persistent. In fact, since managers limit the size of their fund, the flows that would drive away performance do not occur.

Furthermore, the manager's remuneration is not maximized at the same size that maximizes the total payoff to investors. The total payoff is maximized with an AUM, q_{pm}, that satisfies:

(7) $C'\left(q_{pm}\right)=\phi_t - mf$.

The payoff to investors reaches its maximum at an AUM that is *smaller* than the one that maximizes the manager's remuneration. The difference between the two quantities depends on the ratio between the incentive fee and the management fee (mf/pf). *Ceteris paribus*, the higher the incentive fee with respect to the management fee, the smaller the difference between the two quantities, the smaller the size of the fund, and the more aligned are the interest of the manager and of the existing investors. If the manager is remunerated only with a performance fee, the remuneration and the payoff are maximized simultaneously. This is consistent with the findings of Agarwal et al. (2004), who document that funds with greater incentives, as measured by the sensitivity of remuneration to performance, perform better.

Altogether, in the absence of an investable costless passive benchmark, the incentive-based fee is an efficient mean for aligning the interest of investors and managers. It makes the remuneration of the manager concave, and it gives her an incentive to limit the size of the fund. Even if managers behave in a self-interested way, i.e. to preserve their own remuneration, this prevents inflows that would result in performance deterioration. Thus, the performance of hedge funds persists, and the industry outperforms. This is consistent with what is observed in the industry, i.e. performance persistence over long horizons and restrictions of the funds' size.

2.3 Testable Hypotheses

The ideal test for the model introduced above would consist in verifying whether the AUMs of the funds converge toward their optimal levels. However, as the cost functions of the funds are unknown, we cannot conduct this test. Nevertheless, the model implies that rational hedge fund managers who want to maximize their remuneration undertake actions that push the AUM of the fund closer to the optimal size. For instance, funds below the optimal AUM level must increase their size, while funds at or above their optimal AUM must stabilize or decrease their size. We analyze the actions of the managers and verify whether the consequences of those actions are consistent with the model.

As discussed in the previous section, investors enter the funds as long as the expected net performance is positive. If managers want to converge toward the optimal size, they have to adjust the net performance for the investors, presented in Equation (6). As $0 < pf < 1$, the management fee is the only term which can modify the sign of the expected payoff; see Appendix A. Indeed, the incentive fee consists of a fraction of the total payoff that is due only when the performance is positive. The model thus implies that managers modify the management fee to approach the optimal size.[20] Alternatively, to control the size of the fund managers may close the fund to new investments. This behavior is not considered in the present work for several reasons. First of all, the process of closing the fund to new investors is exogenous to our model, whereas the fee structure plays a central role. In addition, funds discretionarily refuse new investments, even if in the databases they appear as open to investments. In fact, managers may avoid to notify the funds' closures to the databases to enter the screening process run by investors; see Baquero and Verbeek (2009). Moreover, a majority of managers, when closing their funds, also stop reporting to the databases, making the subsequent performance and flows unobservable.

We first consider a fund whose AUM is at q_t^{*HF} —a fund that has reached its optimal size. The manager has the incentive to prevent additional investments, which would deteriorate her remuneration, by increasing the management fee. Importantly, these fee increases only apply to the new investments in the fund; see Appendix B. As illustrated in Figure 2.2, the manager has to set the management fee applicable to new investments (denoted mf') at a level that neutralizes the marginal abnormal performance, i.e. the net performance remunerating the

[20] As a matter of fact, in unreported results, we find that variations of incentive fees are not an efficient means to control size.

capital freshly invested in the fund.[21] In this way, the new investor, who would invest an amount q' in the fund, receives an amount:

$$(8) \quad E\left(TP'_{t+1}\right)=\left(q'_t\phi_t-q'_t\bar{C}-q'_t mf'\right)\left(1-pf\right)\leq 0,$$

where $\bar{C}=C\left(q_t^{*HF}+q'_t\right)\Big/\left(q_t^{*HF}+q'_t\right)$ is the average investment cost. As the expected net performance of the new investments is not positive, investors do not enter the fund, and thus the AUM of the fund stabilizes. Importantly, the revision of the management fee level has no short term impact on the remuneration of the manager. In fact, the new fees only apply to the new inflows, which actually do not occur. As such, the remuneration of the manager is protected.

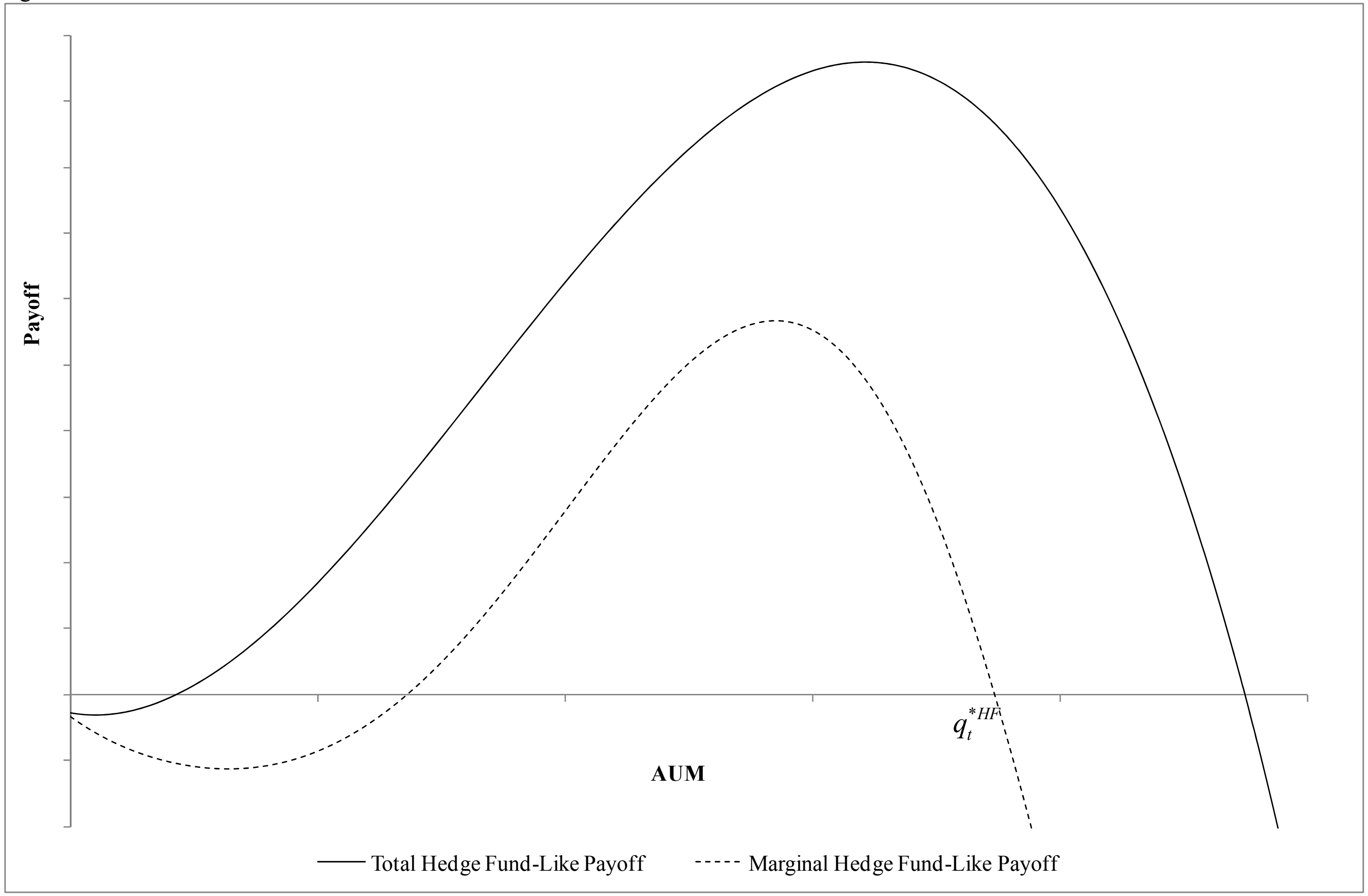
The same behavior can be adopted by managers of funds that passed the optimal size to prevent further increases of size. On the contrary, funds that are below the optimal size may decrease their management fee, so investors are incited to enter the fund. However, we do not expect any significant short term effect on the inflows. As a matter of fact, investors are in demand of funds that are due to raise their fees. For that reason, they immediately perceive the change in marginal performance after the fee change, and they stop allocating. On the contrary, investors are not willing to invest in the funds that are due to lower fees. Indeed, before investing, investors need the time to notice the increase in marginal performance and conduct a throughout due diligence on the fund; see Baquero and Verbeek (2009). As such, there is an information gap between investors already interested in a fund and those who have yet to become interested. For these reasons, in the current study, we focus exclusively on *increases* of management fees.[22]

[21] In the rest of the paper, we distinguish marginal performance, the return received on additional investments, from the total performance, the return received by existing investors.

[22] Consistently with our model, unreported results confirm that decreases of management fees affect the marginal performance but not the flows to the fund.

Figure 2.2: Impact of Management Fee Increases on Marginal Investors' Payoff

The plot displays the impact that an increase of management fee has on the payoff for the marginal investor. The total payoff is illustrated by the continuous line (equivalent to the standard situation in Figure 2.1) while the marginal payoff after the increase is illustrated by the dashed line. q_t^{*HF} is the size that maximizes the manager's remuneration from Figure 2.1.



The model predicts that managers of funds with an AUM that reached or passed the optimal point control their size to protect their remuneration. To reach their goal, managers have to stop inflows by increasing the management fee to a level which makes the marginal abnormal performance insignificant, at least. In fact, a decrease of performance that does not neutralize the abnormal marginal return, even if significant, does not effectively stop the inflows. This leads us to the first proposition:

Proposition 1: Increases of management fees decrease the likelihood of realizing significantly positive marginal net performance and of experiencing significant flows.

Importantly, this proposition is not a mere mechanical consequence of the increase in fees. Undoubtedly, fee increases are likely to depress performance, but they do not necessarily make the marginal abnormal performance *significantly negative*. We interpret this marginal performance control as a signal of the managers' willingness to control the size of the fund. The second part of the proposition related to flows intends to verify that management fee increases are an efficient way to control flows.

According to our model, managers control the size of the funds to protect their remuneration, which is equivalent to protecting performance for existing investors. In fact, the remuneration of the manager is maximized when returns for existing investors are positive. We thus expect that the net total performance for the existing investors remains stable or even improves when managers raise their management fees. For this reason, we test the following proposition on the total performance of the fund:

Proposition 2: Increases of management fees increase the likelihood of realizing persistent net performance.

If the two propositions are simultaneously verified, it means that the remuneration of the manager, which is unobservable,[23] remains stable. Indeed, since the remuneration is a

[23] The remuneration of the manager can only be estimated by imposing strong assumptions (timing of flows, order of outflows, frequency of fee payment, …); see Feng et al. (2011).

function of the AUM and the total performance, if these two variables remain unchanged, remuneration does not change either.

2.4 Data

2.4.1 Construction of the Database

We obtain our dataset from the Hedge Fund Research (HFR) database. The database contains information on more than 6,800 living funds and, in a "graveyard" module, over 10,000 dead funds. Each month, HFR releases three updates of the database. At each update, the previous version of the database is overwritten. The subscribers, who only have access to the database from the HFR website, can only download the latest update. Each update of the database contains a snapshot of the characteristics of each fund (compensation terms, liquidity details, service providers, etc.), as well as other practical information (contact person, address, etc.). The database contains, among others, tables with the entire time-series of returns, NAV, and AUM of the funds.

To obtain a time-series of fund characteristics, we combine 83 different HFR updates released between January 2005 and November 2011. We follow a procedure that is similar to the one used by Aragon and Nanda (2011) and Patton et al. (2012). Contrary to these authors, who focus on the different versions of the returns time-series, we collect the snapshots of funds' characteristics.[24] Among the 14,240 funds contained in our raw sample, we select the ones reporting in USD, net of fees, and that report their terms at least once (management fee, incentive fee, high watermark, hurdle rate, redemption frequency, and notice period). This results in a sample of 10,028 funds. For these funds, we compute gross returns, flows, and amounts of fees collected, as well as the variables required for our empirical analysis, which

[24] Since April 2008, hedge fund terms are available on a daily basis from TASS as documented in Agarwal and Ray (2011). Nevertheless, as changes in terms do not occur at a daily frequency and returns are generally provided at a monthly frequency, more frequent observations would not improve the quality of our dataset.

are defined in Appendix C. The algorithm used to compute gross returns is similar to the one employed by Feng et al. (2011). Because of missing AUMs, we cannot compute the flows and the total remuneration for 1,519 funds, which are dropped from the sample. We end up with a sample of 8,509 funds, out of which 3,842 are alive as of November 2011, while 4,667 stopped reporting during our sample period. These figures are in line with the attrition rates documented in the literature; see Liang and Park (2010). For these 8,509 funds, we reconstruct the time-series of hurdle rates using data obtained from Morningstar. 37% of the funds are equity long/short funds. The second most frequent strategy is fund of funds (25%), followed by macro (16%), relative value (15%), and event-driven (9%).

Note that, even if we do not rely on any "graveyard" database, our approach is not subject to survivorship bias. Since we construct our dataset by merging several monthly updates of HFR, all the funds that reported at least once to HFR are retained in our sample, independently from their eventual disappearance from the database. Our results could, however, potentially be prone to backfilling bias. Nevertheless, since funds tend to change their fees when they reach a certain degree of seniority and since we focus on the performance around the fee change, the probability that we base our calculations on backfilled track records is low.

2.4.2 Fee Changes

Even though we are solely interested in management fee changes, we first collect some statistics about all possible modifications of the compensation terms. To identify these changes (management fee, incentive fee, high watermark, and hurdle rate), we analyze the time-series of fund characteristics. For each change, we verify whether it is due to misreporting. We consider two types of reporting errors. The first consists of a change of terms that is changed back to the original value in the following release of the database. The second type of misreporting occurs when the fund changes its terms several times in a row. In this case, we only retain the latest change. Among the 8,509 funds retained, this analysis identifies 798 changes. Sometimes, the same fund modifies several terms at the same time. In these cases, we consider this as a single *change event*. [25] We identify 639 different change events implemented by 573 funds.

Table 2.1: Number of Changes by Fee Component and Direction of Revision

This table reports the number of changes and the number of funds that revised their fees. *Incentive fees* accounts for the changes in performance fee, high watermark, and hurdle rate. In Panel A, we only distinguish between the components of the compensation scheme. In Panel B and C, we also classify them according to the direction of the change.

	All Fees	Management Fee	Incentive Fees	Several Fees
Panel A: All Changes				
N Changes	639	334	174	131
N Funds	573	312	167	124
Panel B: Increases of Fees				
N Changes	399	235	97	67
N Funds	386	233	94	66
Panel C: Decreases of Fees				
N Changes	240	99	77	64
N Funds	235	98	77	64

Table 2.1 contains stylized facts on fee changes. From Panel A, we see that the management fee is the term changed the most often (more than 50% of the changes). In 20% of the changes, several terms are changed simultaneously. As illustrated in Panel B and C, we find more increases than decreases of fees. This has already been pointed out by Deuskar et al. (2011b) and Agarwal and Ray (2011), who use a different dataset. This is true especially for management fee revisions. Increases of management fee revisions represent more than 70% of all the management fee revisions. Thus, by focusing on increases of management fees, we analyze the most recurrent type of fee revision, which account for more than 35% of all the changes. The fact that fund managers mainly change the management fee is consistent with our model. However, we also observe changes of incentive fees, as well as of high

[25] In the rest of the present document we refer to "change events" as changes.

watermarks and hurdle rates. This suggests that fund managers also modify fees for other reasons than size management. The analysis of these changes is left for future research.

2.4.3 Fund-level Variables

Table 2.2 contains descriptive statistics about the fund-level variables. For each fund, the last available observation is used. Thus, the observations have different dates, but each fund is considered only once.

The median fund included in our sample has a monthly return of 0.5%, is 5.25 years old, has USD 30 million under management, and it takes about four months to redeem from it. It charges a management fee of 1.5% and an incentive fee of 20%. The vast majority of the funds (89%) have a high watermark provision. Hurdle rates are only applied by 12% of the funds.

Table 2.2: Descriptive Statistics of the Sample

This table shows summary statistics about the variables of the sample. For all the funds, we use the latest observation. As such, the dates considered vary across funds, but each fund is considered only once. This also implies that, for funds that revised their management fee, the fee level considered is computed after the changes. The last columns report the differences between the means and the medians. The equality of means is tested with two-tailed t-tests. The t-statistics are reported in brackets. The equality of medians is tested with Wilcoxon rank sum tests. The z-statistics are reported in brackets. Statistical significance of 10%, 5%, and 1% are indicated by *, **, and *** respectively.

	Funds without Management Fee Increases N=8509			Funds with Management Fee Increases N=233			Difference of Means		Difference of Medians	
	Mean	StDev	Med	Mean	StDev	Med	Mean(change) – Mean(no change)		Median(change) – Median(no change)	
Avg Monthly Net Return (%)	0.60	1.15	0.54	0.87	0.49	0.82	0.26***	(7.63)	0.28***	(8.14)
StDev Net Return (%)	3.63	3.05	2.78	4.05	2.53	3.36	0.42***	(2.48)	0.58***	(4.33)
Age (Years)	6.32	4.76	5.08	10.78	4.62	10.33	4.45***	(14.44)	5.25***	(14.37)
Size (mio USD)	74.54	112.93	28.54	151.85	228.56	59.85	77.32***	(5.12)	31.31***	(7.19)
Redemption Period (Days)	114.40	91.50	120.00	131.90	94.82	120.00	17.50***	(2.77)	0.00***	(3.84)
Management Fee (%)	1.59	1.43	1.50	1.92	2.47	1.50	0.33***	(2.05)	0.00***	(5.06)
Incentive Fee (%)	16.73	6.81	20.00	17.27	5.46	20.00	0.54	(1.48)	0	(0.28)
HWM (1/0)	0.89	-	-	0.94	-	-	0.05		-	
Hurdle Rate (1/0)	0.12	-	-	0.11	-	-	-0.01		-	

These figures are in line with the global HFR sample, indicating that our selection procedure does not bias the sample. The table also reveals that the funds raising their management fees have significantly higher and more volatile returns; see also Agarwal and Ray (2011). The difference with the funds that do not raise their management fee is significant at all conventional levels. Moreover, management fee-changing funds also have longer redemption periods and are better established (bigger and older) than the other funds. Finally, funds that raise their management fee have higher management fee levels, even if their incentive fee is not significantly different from the other funds.

2.5 Estimations and Results

2.5.1 Management Fee Increases as a Means to Control Flows

We use a difference-in-differences analysis (DID) to test our propositions. For any change date, the *treatment* group is composed of the funds that experienced a management fee increase at date t, while the *control* group consists of all the funds that are alive at that date, which never experienced any fee change and which follow the same investment style as the treated fund. Since Cai and Liang (2011) and Gibson and Gyger (2007) find evidence of strategy misreporting and opportunism, instead of using self-reported strategies, we identify investment styles using a clustering algorithm. At any change date, the funds reporting their returns over the preceding twelve months are clustered into five categories using a PAM algorithm with a dissimilarity measure based on rank correlation of returns.[26] The *before* and *after* periods are defined with respect to the dates of the treatments, i.e. the change dates.

We first focus on the impact of management fee revisions on marginal performance by estimating the following logit model:

[26] The optimal number of categories has been selected by maximizing the silhouette width; see Kaufman and Rousseeuw (2008). Gibson and Gyger (2007) show that the PAM—Partitioning Around Medoids—algorithm, when dealing with hedge funds, has several advantages over the more common k-mean algorithm.

$$(9)\quad \begin{aligned} DMargAlpha_{t,j} &= a_0 + a_1 DTreat_j + a_2 DAfter_t + a_3\left(DTreat_j \times DAfter_t\right) \\ &+ a_4 Control_{t,j} + a_5 Quarter_t + a_6 Strategy_j + \varepsilon_{t,j} \end{aligned},$$

where $DMargAlpha_{t,j}$ is a dummy variable equals of one if the marginal abnormal performance of fund *j* is significantly negative at time *t* and zero otherwise. $DTreat$ equals to one if the fund is in the treatment group (fee revision) and zero otherwise. $DAfter$ is a dummy variable equals one if *t* is after the fee revision and zero otherwise. $Quarter$ and $Strategy$ control for quarterly time effects and strategy fixed effects.[27] Following Agarwal et al. (2009b), Ding et al. (2009), and Getmansky (2012), we introduce. $Control$, a set of control variables based on funds' characteristics as well as on lagged performance and flows. A detailed definition of these variables is given in Appendix C.

To test the impact of management fee increases on flows, we replace $DMargAlpha$ with $DFlow$, a variable that equals one if the flows are not significantly different from zero, and zero otherwise. The set of control variables is also changed consequently. The model thus writes:

$$(10)\quad \begin{aligned} DFlow_{t,j} &= a_0 + a_1 DTreat_j + a_2 DAfter_t + a_3\left(DTreat_j \times DAfter_t\right) \\ &+ a_4 Control_{t,j} + a_5 Quarter_t + a_6 Strategy_j + \varepsilon_{t,j} \end{aligned}.$$

The interaction between $DTreat$ and $DAfter$ is the parameter of interest, and we expect its coefficient, a_3, to be significantly positive for both models.

We estimate Equations (9) and (10) considering two semesters around the fee changes.[28] Table 2.3 displays the results. As expected, the coefficients of the interaction terms are significantly positive for both equations. As stated in our first proposition, when funds increase the management fee, they decrease the likelihood of generating positive alpha for the

[27] Results remain unchanged when we reduce the frequency of time control variables to yearly.

[28] Results are robust to different lengths of the period around the fee change (6, 18 and 24 months). Moreover, the outcome is not affected by the interdependence that exists between performance and flows; see e.g. Agarwal et al. (2004) or Fung et al. (2008). The confidence level of the coefficients only changes marginally when the two regressions are estimated simultaneously using a three-stage least squares methodology.

marginal investor. Thereby, management fee revisions decrease the funds' attractiveness toward incumbent investors. This relation is not only statistically significant, but also economically: the odds of generating insignificant abnormal marginal return almost triples when there is an increase in management fee.[29] Interestingly, when controlling for the effect of management fee changes, the size of the fund is not significantly related to performance. This fact is at odds with several studies that find a strong size-performance relation; see Agarwal et al. (2004), among others. With respect to the other control variables, we obtain several coefficients that are consistent with the ones of existing studies. For instance, consistently with Agarwal et al. (2004), the level of the incentive fees and the length of the redemption period are significantly negatively related to the likelihood of generating negative abnormal performance, even if the impact of the redemption period is not economically significant. Moreover, there is a momentum effect also in marginal performances: the lagged marginal performance in fact decreases the probability of posting negative future abnormal performances.

As a consequence of the change in attractiveness driven by the management fee increase, the flows of the funds evolve accordingly to our prediction; see the right column of Table 2.3. The coefficient of the interaction term is indeed strongly and significantly positive. By raising their management fee, the managers increase the likelihood of having insignificant flows. This relation is also economically significant. An increase in management fee more than doubles the odds of experiencing insignificant flows. Given the construction of the dependent variable, the coefficients of the control variables cannot be compared with the ones of the existing studies. However, since several of them are significant, we can conclude that investors are influenced by a number of variables beside the one we are interested in.

[29] The change in odd ratio is calculated as *exp(1.05)-1*, where *1.05* is the coefficient of interest from Table 2.3.

Table 2.3: Consequences of Management Fee Revisions on Marginal Alpha and Flows

This table reports the results of a DID regression describing the relation between fee revisions and marginal alpha, as well as fee revisions and flows in the two semesters around the fee change. Dependent variables are expressed as dummy variables; detailed definitions are given in Appendix C. Standard errors (in brackets) are clustered by strategy. Statistical significance of 10%, 5%, and 1% are indicated by *, **, and *** respectively.

	DMargAlpha	*DFlow*
$DTreat_t$	-0.93**	-0.56*
	[0.370]	[0.328]
Dafter	-0.08	0.26***
	[0.152]	[0.082]
$DTreat_t$ x *Dafter*	1.05***	0.78***
	[0.268]	[0.241]
$Size_t$	0.00	-0.21***
	[0.013]	[0.013]
$Management\ Fee_t$	-0.12	-1.36
	[1.596]	[1.223]
$Incentive\ Fee_t$	-3.26***	0.88
	[0.464]	[0.579]
$Redemption\ Period_t$	-0.08*	0.10***
	[0.046]	[0.028]
$MAlpha_{t-1}$	-0.13***	-0.07***
	[0.028]	[0.011]
$Flow_{t-1}$	0.00	-0.04***
	[0.001]	[0.012]
Age_t	-0.01	0.05**
	[0.006]	[0.019]
$Volatility_{t-1}$	-	11.12***
	-	[2.321]
Intercept	-1.97***	2.90***
	[0.191]	[0.263]
Strategy	YES	YES
Quarter	YES	YES
Observations	377,086	377,086
R-squared	5.85%	4.61%

Altogether, with both regressions, we find empirical support for our first proposition. Fee changes have significant impacts on marginal abnormal performance and on flows. Management fee increases emerge as an effective means to control the size of fund, and managers exploit this property to manage the AUM of their funds in the direction predicted by our model. Our results are robust to backfilling bias. In fact, the inclusion of a dummy variable to control for backfilled data leaves our results unchanged. Tests run on a sample considering only the information after the funds' entry into the database lead to unchanged conclusions. Considering the minimal impact of backfilling on our results, we prefer not to lose observations, and we present the results of the entire sample.

2.5.2 Impact of Management Fee Increases on Total Performance

We now turn to the second proposition by analyzing the consequences of management fee increases on total performance, i.e. the performance for the existing investors. Our model assumes that the ultimate goal of fee changes is to protect, or even improve, the performance for these investors. To investigate this, we estimate whether the likelihood of improving the total performance is affected by management fee increases. Formally, we estimate the following equation:

$$(11)\ DTotAlpha_{t,j} = a_0 + a_1 DTreat_j + a_2 Control_{t,j} + a_3 Quarter_t + a_4 Strategy_j + \varepsilon_{t,j}\ ,$$

where $DTotAlpha$ equals to one if the total abnormal performance remains constant or improves after the fee change and zero otherwise (see Appendix C). This variable is defined according to the value of the *total* abnormal performance, not the *marginal* one. Table 2.4 reports the results.

As predicted in our second proposition, the coefficient of the treatment variable is significantly positive. Hedge funds, by raising their management fee, protect performance for existing investors. The effect is economically significant. The odds of generating a persistent total performance increases by more than 50% when a fund raises its management fee, even after controlling for variables that are known to affect the performance of hedge funds. With respect to these control variables, we find several coefficients that are consistent with the findings of Agarwal et al. (2004). As a matter of fact, incentive fee is significantly positively related to abnormal performance, whereas the level of lagged flows is negatively related to performance. Though, even if the latter coefficient displays a strong statistical significance, its economical relevance is weak.

Table 2.4: Impact of Fee Revisions on Average Abnormal Return

This table reports the results of a logistic regression describing the relation between fee revisions and total alpha. The dependent variable is expressed as a dummy variable; detailed definitions are given in Appendix C. Standard errors (in brackets) are clustered by strategy. Statistical significance of 10%, 5%, and 1% are indicated by *, **, and *** respectively.

	DTotAlpha
$DTreat_t$	0.46**
	[0. 196]
$Size_t$	0.01
	[0.017]
$Management\ Fee_t$	-0.12
	[1.408]
$Incentive\ Fee_t$	2.56***
	[0.480]
$Redemption\ Period_t$	0.05
	[0.061]
$Alpha_{t-1}$	-0.09***
	[0.032]
$Flow_{t-1}$	-0.01**
	[0.001]
Age_t	0.01***
	[0.002]
Intercept	2.51***
	[0.113]
Strategy	YES
Quarter	YES
Observations	185,543
R-squared	3.86%

Since both the size of the fund and the total performance for the existing investors remain constant, the remuneration of the manager, which is a function of these two variables, should remain unchanged. This fact is consistent with our model, which states that managers behave in self-interest, intending to optimize their performance. However, thanks to the incentive fee, this behavior results in the protection of the performance generated for existing investors.

2.5.3 Do Funds Align their Fees with Competitors?

One alternative explanation to our size management hypothesis could be that fund managers change their fees in order to align them with competitors. For instance, Agarwal and Ray (2011) and Deuskar et al. (2011b) find that the fees before the change are lower than the average of the industry. They conclude that funds modify their fees to bring them in line with the industry average. This is inconsistent with our model, which predicts that fees are changed strategically. To further investigate the alignment hypothesis, each time that a management fee increase occurs, we record the old and the new fee, as well as the average fee for the funds in the same style-cluster. In addition, we record the level and the style-cluster average of the incentive fee. Then, we compare i) the old and the new management fees to the average management fee of the control funds and ii) the incentive fee, which remains unchanged, to the average incentive fee of the control funds.

Table 2.5: Differences in Fee Levels before and after Fee Revisions

This table contrasts the levels of management and incentive fees of the funds that changed their management fee with the other funds of the same style cluster. Fee levels are expressed in percentage terms. Standard deviations are reported in brackets. Statistical significance of 10%, 5%, and 1% are indicated by *, **, and *** respectively.

	(i)	(ii)	(iii)	(i)-(iii)	(ii)-(iii)
	Before Fee Change	After Fee Change	Peers	Before minus Peers	After Change minus Peers
Panel A: Management Fee					
Mean	1.23	2.25	1.62	-0.39***	0.63***
	[0.969]	[3.169]	[0.131]	[0.064]	[0.207]
Panel B: Incentive Fee					
Mean	18.73	-	18.18	0.55	-
	[4.523]	-	[3.224]	[0.362]	-

Table 2.5 contains the results. Panel A shows the statistics of the management fee, as well as the statistic testing whether the average fee level is equal to the one of strategy. In Panel B, we find the same figures for the incentive fee. We see that funds increasing their management fee have initial fees that are significantly *lower* than the strategy average. However, the revised fee is significantly *higher* than that of competitors. One could then argue that these funds are "cheaper" in terms of incentive fee (i.e. they apply a lower incentive fee) and that

they compensate it with the management fee. From Panel B, we see that this is not the case. The incentive fee of these funds is in fact not statistically different from those of their peers.

As it appears, management fee revisions are not a simple alignment with competitors. Funds that change their management fees, i.e. the majority of fee revisions, go further and set fees at a higher level than the competitors' average. Moreover, these funds do not use the management fee to compensate for an unaligned incentive fee. Consistently with our model, these results show that funds do not change their fees to simply adapt them to industry level.

2.6 Conclusion

In this paper, we propose a simple explanation to the persistent outperformance of hedge funds. Managers control the size of their funds by changing their management fee. In this way, the AUM of the fund remains close to the optimal size and the performance is not diluted by additional flows. With respect to the models already present in the literature, we take into account hedge fund peculiarities, namely the fact that the fees charged to investors depend on the timing of the investment, that managers' remuneration are not linearly related to fund size, and that the use of passive benchmarks is not possible. Our study gives a theoretical framework to appraise the recent developments made in the literature on compensation contracts in the hedge fund industry and the impact of those contracts on performance. In particular, it provides an insight on the relation between fees, performance, and flows. The predictions of our model reproduce empirical facts observed in the literature, i.e. outperformance, persistence, and inflow refusal.

The evidence from our model is relevant for the current regulatory debate. We show that incentive fees are crucial in the alignment of investors' and managers' interests when there is no investable benchmark. The performance fee introduces non-linearity in the size-remuneration relation, which leads to size control and, consequently, outperformance.

Appendix 2.A: Flows, Size, Performance, and Remuneration in the Absence of a Costless Investable Benchmark

In this appendix, we modify the model of Berk and Green (2004) by assuming that the manager is not allowed to invest into a benchmark but only into her proprietary strategy. We first analyze the case in which the manager only receives a management fee, and then we include an incentive fee into the remuneration scheme.

As in the original model, we assume that the proprietary strategy is subject to diseconomies of scale. The return of the strategy, gross of all costs and fees is R_t and does not depend on the size of the fund. However, by implementing the strategy, the manager incurs a variable cost (price impact of trades, execution costs, …) denoted $C(q_t)$, where q_t is the amount invested into the strategy. The authors also assume that $C(0)=0$, $C(q_t)<q_t, \forall q_t$, $C'(q_t)>0, \forall q_t$, and $C''(q_t)>0, \forall q_t$. In words, the strategy is subject to diseconomies of scale, and the gross return after cost decreases with the quantity invested.

2.A.1 Mutual Fund-Like Remuneration

If there is no benchmark and no incentive fee, the manager receives a remuneration that only depends on the quantity of assets managed by the fund, formally:

(A.1) $$Remun_t^{MF} = q_t mf$$

where q_t stands for the AUM of the fund and mf the management fee. The manager runs the fund if her remuneration, at any point in time, is greater than the fixed cost she incurs (denoted $F>0$); otherwise, she shuts the fund down.

The total payoff of the fund, which is paid to investors at the end of each month, is:

(A.2) $$TP_{t+1}^{MF} = q_t R_{t+1} - C(q_t) - q_t mf$$

Investors chase the best performers: they infer managers' skill from past performance and invest into the *supposedly* most-skilled funds. At each period, investors use the new data at their disposal to update their inference. Money flows into funds with infinite elasticity as long as the expected value of the payoff is positive. Therefore, money flows into outperforming funds, and because of decreasing returns to scale, the total payoff gradually decreases until becoming insignificant.

The objective of the manager is to maximize her remuneration, which solely comes from a percentage of the AUM. The manager has an incentive to let the fund grow *ad vitam æternam*. Thus, she solves the following problem:

$$\text{(A.3)} \qquad \begin{aligned} &\max_{q_t} \quad Remun_t^{MF} = q_t mf \\ &s.t. \quad E\left(TP_{t+1}^{MF}\right) = q_t \phi_t - C(q_t) - q_t mf \geq 0 \\ &\qquad\qquad F \leq q_t mf \\ &\qquad\qquad q_t \geq 0 \end{aligned},$$

where $\phi_t = E\left(R_{t+1} \middle| R_1, ..., R_t\right)$ is the expected return gross of all costs and fees.

As the remuneration is strictly increasing with q_t and the payoff is strictly decreasing with q_t, the remuneration is maximized when the expected payoff (to the investors) is nil, i.e. when:

$$\text{(A.4)} \qquad \begin{aligned} &q_t^{*MF} \phi_t - C(q_t^{*MF}) - q_t^{*MF} mf = 0 \\ &\phi_t - mf = \frac{C(q_t^{*MF})}{q_t^{*MF}} \\ &C(q_t^{*MF}) = \left(\phi_t - mf\right) q_t^{*MF} \end{aligned},$$

where q_t^{*MF} indicates the optimal size of a fund invested only in the active strategy and which cannot invest into a benchmark. In equilibrium, the average cost of the strategy is equal to the excess return of the strategy netted by the management fee ($\phi_t - mf$). Thus, even in the absence of an investable benchmark, if the manager is remunerated with a management fee only, funds are not expected to outperform and there is no performance persistence.

2.A.2 Hedge Fund-Like Remuneration

We now consider the case in which there is also an incentive fee. We assume that the incentive fee is accrued monthly but paid when the investors leave the fund (this is equivalent to assume that the manager applies a high watermark provision and that the payment of the incentive fee is deferred to the moment at which the investor leaves the fund). The corresponding remuneration and the total payoff are respectively:

(A.5) $$Remun_t^{HF} = \begin{cases} \left(q_t\phi_t - C(q_t) - q_t mf\right) pf + q_t mf & \text{if } q_t\phi_t - C(q_t) - q_t mf > 0 \\ q_t mf & \text{otherwise} \end{cases},$$

(A.6) $$E\left(TP_{t+1}^{HF}\right) = \begin{cases} \left(q_t\phi_t - C(q_t) - q_t mf\right)(1 - pf) & \text{if } q_t\phi_t - C(q_t) - q_t mf > 0 \\ q_t\phi_t - C(q_t) - q_t mf & \text{otherwise} \end{cases},$$

where pf is the performance fee and the expression $q_t\phi_t - C(q_t) - q_t mf$ is the incremental NAV net of cost and management fees (without considering subscription and redemptions). In words, as soon as there is a positive return, the performance-based remuneration kicks-in, decreasing the total payoff.

Investors participate in the fund only if $E\left(TP_{t+1}^{HF}\right) > 0$. This implies that the expected incremental NAV is positive. The expressions for remuneration and expected payoff can thus be rewritten as follows:

(A.7) $$Remun_t^{HF} = \left(q_t\phi_t - C(q_t) - q_t mf\right) pf + q_t mf$$

(A.8) $$E\left(TP_{t+1}^{HF}\right) = \left(q_t\phi_t - C(q_t) - q_t mf\right)(1 - pf)$$

To maximize her remuneration, the manager solves the following problem:

(A.9) $$\begin{aligned} &\max_{q_t} \ Remun_t^{HF} = \left(q_t\phi_t - C(q_t) - q_t mf\right) pf + q_t mf \\ &s.t. \quad E\left(TP_{t+1}^{HF}\right) = \left(q_t\phi_t - C(q_t) - q_t mf\right)(1 - pf) \\ &\qquad\qquad F \le \left(q_t\phi_t - C(q_t) - q_t mf\right) pf + q_t mf \\ &\qquad\qquad q_t \ge 0 \end{aligned}$$

The first order condition is:

(A.11) $$\left(\phi_t - C'\left(q_t^{*HF}\right) - mf\right)pf + mf = 0$$

And the solution of the problem:

(A.12) $$C'\left(q_t^{*HF}\right) = \phi_t - mf + \frac{mf}{pf}.$$

When the size of the fund is q_t^{*HF}, the expected total payoff is strictly positive. To see that, define $\left\{q_0 \middle| TP^{HF}(q_0) = 0\right\}$ and compute $Remun^{HF}(q_0) = q_0 mf$ and $C\left(q_0\right) = q_0\left(\phi_t - mf\right)$. As the cost function $C\left(q\right)$ is strictly convex, the remuneration of the manager defined in (A.5) is concave. We can write:

(A.13) $$\begin{aligned} Remun^{HF}\left(q_0\right) &\leq Remun^{HF}\left(q_t^{*HF}\right) + \frac{\partial Remun^{HF}\left(q_t^{*HF}\right)}{\partial q_t^{*HF}}\left(q_0 - q_t^{*HF}\right) \\ q_0 mf &\leq Remun^{HF}\left(q_t^{*HF}\right) \end{aligned}.$$

In words, the maximal remuneration is at least equal to the remuneration perceived when the payoff is nil. There are three possible cases:

i) $q_0 < q_t^{*HF}$, which implies that $\overline{C}\left(q_0\right) = C\left(q_0\right)/q_0 = \phi_t - mf < \overline{C}\left(q_t^{*HF}\right)$. The payoff defined in (A.6) can be rewritten as $TP_{t+1}^{HF}\left(q_t^{*HF}\right) = q_t^{*HF}\left(\phi_t - mf - \overline{C}\left(q_t^{*HF}\right)\right)\left(1 - pf\right)$, which is necessarily negative. As the total payoff is negative, investors leave the fund, and thus $q_0 < q_t^{*HF}$ is not a possible equilibrium point.

ii) $q_0 = q_t^{*HF}$, which implies $Remun^{HF}\left(q_t^{*HF}\right) = Remun^{HF}\left(q_0\right) = q_0 mf$. However, this is false because the first derivative of the remuneration valued at q_t^{*HF} is not equal to zero, which is the necessary condition for the quantity that maximizes the remuneration.

iii) $q_0 > q_t^{*HF}$. Equation (A.13) implies that $0 \leq Remun^{HF}\left(q_t^{*HF}\right) - q_0 mf$, or, $0 \leq \left(q_t^{*HF}\phi_t - C\left(q_t^{*HF}\right) - q_t^{*HF} mf\right)pf + \left(q_t^{*HF} - q_0\right)mf$. As the last term of the equation is negative, the first term has to be positive, and it is the case only when the total payoff is positive.

So, when the manager maximizes her remuneration, the total payoff for investors is positive. This means that investors would like to invest more in the fund, the manager has to control the flows to her fund, and the performance of the fund persists (because there are no flows that dilute the performance). Notice that $C\left(q_0\right)=C\left(q_t^{*MF}\right) \Rightarrow q_0=q_t^{*MF}$. This means that the incentive fee alone gives the manager an incentive to limit the AUM of the fund. Consequently, in the absence of a costless benchmark, an incentive fee makes the outperformance persistent.

In conclusion, the incentive fee, when there is no benchmark, has three main consequences: i) performance persistence, ii) the industry outperforms, and iii) the manager has an incentive to refuse inflows.

Moreover, if the manager applies incentive fees, the total payoff is maximized when:

$$\text{(A.14)} \quad \begin{aligned} &\left(\phi_t - C'(q_{pm}) - mf\right)\left(1-pf\right)=0 \\ &C'(q_{pm}) = \phi_t - mf \end{aligned}$$

Thus, mf/pf plays a crucial role. If the remuneration only comes from the incentive fee, then $mf/pf=0$, and the manager limits the size of the fund at a level that maximizes the total payoff. In general, the lower mf/pf, i.e. the higher the variable remuneration with respect to the fixed one, the higher the total payoff of the fund.

Concerning the impact of the different fees on the value of q_0, first remember that we defined $\left\{q_0 \middle| TP^{HF}(q_0)=0\right\}$, second $C\left(q_0\right)=q_0\left(\phi_t-mf\right) \Rightarrow q_0=\dfrac{C\left(q_0\right)}{\phi_t-mf}$. It is thus clear that q_0 is not affected by pf and that it is inversely related to mf.

Appendix 2.B: Description of Hedge Fund Fee Revisions

As documented by Agarwal and Ray (2011) and Deuskar et al. (2011b), fee revisions are numerous in the hedge fund industry. In this section, we detail the various tools available to hedge fund managers to change their remuneration terms.[30] One option is to revise the terms specified in the *prospectus*.[31] In this first case, the new fee conditions, whether they consist in an increase or a decrease of the fees perceived, apply to all existing and future investments so that all investors are treated equally.

A second option managers often use is the creation of a new share class. Concretely, the fund manager can choose between opening a new feeder[32] or launching a new mirror fund.[33] The new investment vehicle is aimed at new investors and at new investments from existing investors. Regardless of the fund structure chosen, the manager usually also modifies the liquidity terms (lookup, redemption frequency, and advance notice), the minimum investment, or other covenants to justify the new fee structure. This variety of characteristics makes share classes significantly divergent from each other, and they can arguably be considered as aimed at different clienteles. In addition, when a mirror fund is launched, it is common practice to slightly modify the fund (implementation of the strategy on additional markets, improvement of the risk management processes of the fund, etc.). This makes the mirror fund hardly comparable to the original fund.

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[30] The fee revision possibilities explained here have been put together after discussions with investment professionals of some multi-billion dollar hedge funds, funds of hedge funds, and family offices, as well as the analyses of several legal documents of hedge funds.

[31] The *prospectus*, also known as *offering memorandum*, is the charter of the hedge fund, and it regulates all the aspects of the company. Generally, the prospectus discusses the strategy of the fund, the major risk factors, the external parties involved in the management, the administration of the fund, the fees charged by the fund, the liquidity restrictions, the valuation procedures, and all rules governing the meetings of the boards of directors and of the investors.

[32] The master/feeder structure is frequently used in the hedge fund industry. Under such structure, the investors invest in the feeder fund, which in turn invests in the master fund (also known as fund for funds). The portfolio of the feeder fund is solely composed by shares of the master fund, while the portfolio of the master fund contains the assets underlying the fund. A master fund can have several feeder funds, and each feeder can have different terms, regulations, etc.

[33] In a mirror fund structure, two separate funds are created and managed with similar investment policies, common investment adviser, custodian, and administrator. The portfolios underlying the two funds are almost identical. Each fund of the structure, being a separate legal entity, can apply its own contractual terms.

In theory, these changes could be subject to investors' vote. In practice, hedge fund managers organize the fund in a way that prevents investors from exercising their voting rights; see Shadab (2009). Thus, existing investors, as well as prospective investors, do not have much bargaining power in the above-mentioned processes. Nevertheless, some investors have *side-letters* which make them subject to specific conditions.[34] A common term in *side-letters* is *grandfathering*, which means that if there is any change in the conditions that would adversely affect the investor (such as a fee increase), this change would not apply to the existing and future investments of the *grandfathered* investor. Side-letters can also contain *secured capacities* (i.e. guaranteed investment-lines), so that even if a new share class is created, the investor can continue to invest in the old class up to the guaranteed amount. Other conditions can give discounts on fees in the case of leveraged investments, different lockup periods, or any other specific term; see Lhabitant (2006, p. 120).

Considering the above, we take a conservative view and assume that increases of fees only apply to new investments from existing and new investors, whereas decreases of fees apply across all investments. Also, because of the substantial differences between share classes, we do not consider new share class creation as a fee change but as a creation of a new fund. Actually, hedge fund databases and academic studies follow the same logic and classify each share class as a fund on its own.[35]

[34] A side-letter is a contract that entitles the investor to specific conditions (reduced fees, improved liquidity, enhanced transparency on the fund holdings) which differ from the ones contained in the prospectus of the fund.

[35] Recently, the academic literature started to consider "fund families." Fund families regroup all the funds managed by the same investment company. As such, a family does not only contain all the share classes of a fund, but it may also contain share classes of other funds pursuing different strategies.

Appendix 2.C: Definition of the Variables

Table 2.C.1: Definition of the Variables

This table details the variables used in the paper. An X indicates whether a variable is used or not in the corresponding set of control variables.

Variable Name	Control Marginal Alpha	Control Flow	Control Total Alpha	Variable Definition
Age_t	X	X	X	Number of years since inception
$Alpha_{t-1}$			X	Return in excess of the corresponding strategy index (funds belonging to the same style cluster) for the average investor.
$Flow_t$				Variation of assets under management that is not explained by performance.
$Flow_{t-1}$	X	X	X	
$Incentive\ Fee_t$	X	X	X	Incentive fee level at time *t*.
$MAlpha_t$				Return in excess of the corresponding strategy index (funds belonging to the same style cluster) for a marginal investor.
$MAlpha_{t-1}$	X	X		
$Management\ Fee_t$	X	X	X	Management fee level at time *t*.
$Redemption\ Period_t$	X	X	X	Sum of redemption frequency and notice period, expressed in years at time *t*.
$Size_t$	X	X	X	Natural logarithm of AUM at time *t*.
$Volatility_{t-1}$		X		Volatility of excess returns.

Table 2.C.2: Definition of Dummy Variables

This table details the dummy variables used as dependent variables. The sign < denotes an inequality significant at a 5% level. Panel A gives the general definition. Panel B details the value of the dummies in each possible scenario.

Panel A: *DMargAlpha*, *DFlow*

$$DMargAlpha \quad \begin{cases} DMargAlpha=1 & \text{if } MAlpha_t<0 \\ DMargAlpha=0 & \text{Otherwise} \end{cases}$$

$$DFlow \quad \begin{cases} DFlow=1 & \text{if } Flow_t<0 \\ DFlow=0 & \text{Otherwise} \end{cases}$$

Panel B: *DTotAlpha*

	Post-Treatment Alpha		
Pre-Treatment Alpha	Significantly positive	Insignificant	Significantly negative
Significantly positive	*DTotAlpha=1*	*DTotAlpha=0*	*DTotAlpha=0*
Insignificant	*DTotAlpha=1*	*DTotAlpha=1*	*DTotAlpha=0*
Significantly negative	*DTotAlpha=1*	*DTotAlpha=1*	*DTotAlpha=0*

Chapter 3: Opening the Black Box: An Analysis of Equity Hedge Funds' Performance

3.1 Introduction

The hedge fund industry has, in the past, largely escaped the regulations that aim to protect individual investors by raising capital via private placement. Not surprisingly, the lack of transparency with regards to their characteristics and strategies is often advocated as the key variable that helps generate a positive risk adjusted return (alpha). Most hedge funds, in particular those specializing in equity, claim that releasing their holdings, even at low frequencies, could hurt their performance by revealing their strategy to the public and to competitors. Despite these concerns, since the 2008 financial turmoil, there has been a constant push toward greater transparency. Regardless of the holdings disclosure obligations already in place, and the strong resistance with which hedge funds have opposed them,[36,37] both the European Community's Directive on Alternative Investment Managers and the SEC's Dodd-Frank Wall Street Reform and Consumer Protection Act are currently being implemented.[38] These rapidly changing regulations underline the need for a better understanding of hedge funds' sources of performance and the information content of their disclosures. Indeed, if the information disclosed allows explaining a large fraction of performance by divulgating their investment strategies, the regulation could end up going against the interest of the investors whom it tries to protect. On the other hand, if these strategies are relatively naïve, investors could be paying fees for strategies they could have easily identified and implemented themselves.

[36] See Agarwal et al. (2010a, p.17).
[37] See, for instance, Sam Jones, *Hedge funds lobby SEC over secrecy rule,* Financial Times, 01/15/2012.
[38] See, for instance, Baptiste Aboulian, *MEP bites back at hedge fund lobby,* Financial Times, 04/22/2012.

In this context, I investigate the role of long equity positions in alternative investment managers' portfolios. I argue that skilled hedge fund managers should be able to go beyond what their holding disclosures tell about their strategies and add value with interim trading and non-disclosed positions. In addition, given the fees they charge, they should be expected to display investment skills, even in their choice of long holdings.

Even though recent researches have established a link between secrecy and hedge fund performance,[39] as well as given an understanding of managers' skill inferred from their portfolio holdings,[40] the literature has yet paid little attention to how long disclosed holdings participate in hedge funds' performance. Hedge fund disclosures may contain information that could allow opportunist followers to replicate a fund's investment strategy at a fraction of the cost, thereby allowing them to make short profits while arbitraging away the extra return of the strategy. Hasanhodzic and Lo (2007) show that the replication of hedge fund returns is feasible at a cost that does not exceed performance fees for some families of hedge funds. In fact, Kat and Palaro (2006a, 2006b) confirm that even voluntary reporting, such as being listed in a database, already facilitates hedge fund replication. Moreover, the fact that some funds require secrecy for part of their holdings[41] seems to indicate that at least some funds are worried about the information content of their disclosures; see, for instance, Agarwal et al. (2012) or Aragon et al. (2012). Though, as documented by Bacmann et al. (2008), among others, there are a number of hurdles to hedge fund replication which prevent the creation of exact clones. Additionally, the information disclosures being non-continuous and limited to certain types of positions, the difficulty in exactly matching hedge fund strategies seems to play in their favor.

On this ground, I assess the performance generating ability of alternative investment firms that are specialized in equity, under the light of their long equity positions. First, with the help

[39] See, for instance, Agarwal et al. (2012) and Aragon et al. (2012).
[40] See Griffin and Xu (2009).
[41] Under specific circumstances, holdings disclosures to the SEC can be delayed up to one year.

of well-established performance models, I contrast the global risk-adjusted performance equity focused hedge funds are able to generate with their *observable* long equity holdings to what they generate in *total* once interim trading activity, other positions, investment costs and all fees have been taken into account. Using a dataset which combines monthly voluntarily disclosed returns with mandatorily[42] reported quarterly holdings for 193 equity oriented alternative investment firms (AIFs, hereafter), I show that the large majority of AIFs do not outperform with their *observable* positions, while there are significantly more who do so in *total*. While approximately one out of three AIFs are able to outperform in terms of *total* performance, only a few outperform with their choice of *observable* long holdings. Somewhat reassuringly, though, the proportion of managers underperforming in terms of *total* returns and the proportion underperforming with *observable* positions stay limited to about 3% and 10%. These results suggest that long equity positions are not used to generate performance *per se* but are part of a global investment strategy. However, it remains that the vast majority of AIFs do not deliver any outperformance.

Second, given the widespread inability to outperform *observable* long positions, I specifically measure the stock picking ability of alternative investment managers in the choice of their long positions by using a conditional weight-based measure previously not employed for hedge funds. In particular, I condition the managers' holding changes on three different sets of public information and measure whether their choices are the result of superior stock picking skills or a mere inference from publicly available information. Analyzing returns and holdings changes obtained from the quarterly holdings of the AIFs, I find that most investment managers, about 80%, do not possess any stock picking skill. Though, there is a roughly similar proportion (about one tenth) of significantly skilled and significantly unskilled stock pickers. Also, consistent with Teo and Chung (2011), who show that hedge funds also influence analysts' recommendations (and not only conversely), I find that

[42] Obtained from the 13F forms required by the SEC.

conditioning AIFs' holdings on analyst data influences the proportion of both skilled and unskilled stock pickers. Third, I also investigate the presence of market timing skills, both in the choices of long holdings and in terms of *total* performance. I find that for both *observable* and *total* performance, there are two to three times as many managers who destroy value via market timing than who create value with it. Still, about four out of five are not displaying either positive or negative market timing skill, which means that they generate performance via other skills. Finally, I try to identify a link between performance generating ability with *observable* holdings and *total* performance and find that they are most likely unrelated, thereby showing that long equity holdings are used as a diversifying performance component rather than as an additive one.

This paper contributes to the existing literature in four ways. First, by identifying an inability of most hedge funds to outperform with their *observable* long positions, I show that the outperformance they generate in *total* is also obtained via other positions and trading activities, at least when it comes to the funds specialized in equity. This rejoins the conclusions of Agarwal et al. (2012) and Aragon et al. (2012) who find that *hidden* positions have a higher performance than *observable* ones. Considering the current regulatory-changing environment, this result seems to be worth considering by regulators when implementing new measures.

Second, I am able to show that hedge funds' long equity choices can most often be explained by public information and are not the result of any stock picking skill whatsoever, though a small proportion of them appear to possess this kind of skill, along with a similar proportion that have negative skill. In this vein, I rejoin Griffin and Xu (2009), who find limited evidence of superior skills as compared to mutual funds. I depart from their results, since I find evidence of differential ability between hedge fund managers. Moreover, my results also contrast with the work of Ferson and Khang (2002), since the average level of stock picking ability I identify in hedge funds appears to be higher than that of mutual funds.

However, this higher stock picking ability disappears when the information set is extended to corporate and analysts related factors.

Third, I show that market timing skills are scarce and mostly poor, when present, both in terms of *observable* and *total* returns. Indeed, about four AIFs out of five do not show any evidence of such a skill.[43] When added to my previous finding, it appears that hedge fund investors should be very careful when deciding with whom to invest since they might well end up paying important fees for no skill at all.

Finally, I document that long equity positions are more of a diversifying performance component than an additive one. Thereby, I confirm that even though equity holdings are at the core of equity hedge funds' strategy, they employ other positions and trading activities that, when combined with their disclosed long and large equity positions, allow some of them to generate performance. Therefore, it appears that at least some hedge funds make good use of their undisclosed positions and that further divulgations might well be harmful for them.

The rest of the chapter is organized as follows. Section 3.2 summarizes the institutional situation faced by hedge funds. I discuss the choice of performance models in Section 3.3. The data and sample creation are detailed in Section 3.4. Section 3.5 describes the estimations and presents my results. Section 3.6 concludes.

3.2 Institutional Setting

In the United States, investment firms have long been constrained by some reporting requirements stated in the Securities Exchange Act of 1934.[44] The basic reporting principle is stated in Section 13(f)(1): *Every institutional investment manager (...) which exercises investment discretion with respect to accounts holding equity securities (...) having an aggregate fair market value on the last trading day in any of the preceding twelve months of*

[43] Aragon and Martin (2012) identify volatility timing skills, though in option choices only.
[44] http://www.sec.gov/about/laws/sea34.pdf

at least $100,000,000 (...) shall file reports with the Commission (...). When considered in its integrality, the implication of Section 13(f) is that the SEC requires all institutional investment managers with at least USD 100 million under management to quarterly report their large long positions (over 200,000 USD or 10,000 shares) with a maximum delay of 45 days in so-called 13F forms. These filings must, among others, contain the CUSIP and the number of shares held in all the positions satisfying the above-mentioned constraints. Given the fact that institutional investors are generally long holders of large positions, the information contained in these forms can, up to some extent, allow linking the institutions' returns with the securities they hold. In a near future, the increased disclosure requirement coming with the implementation of the European Community's Directive on Alternative Investment Managers and the SEC's Dodd-Frank Wall Street Reform and Consumer Protection Act should allow for more understanding of hedge funds' exposures and their sources of returns.[45]

Even though all institutional investors are subject to the 13F rule, in the context of hedge funds, there is one particular family of funds that is more concerned since its members primarily invest in equity: equity hedge funds (EHFs hereafter).[46] Of course, these funds not only buy-and-hold large positions, they also hold smaller or short positions, derivatives, and exercise trading activities. Figure 3.1 gives a stylized snapshot of an EHF's balance sheet.

As illustrated by Figure 3.1, the liabilities side of an equity hedge fund's balance sheet is composed of the assets under management (provided by the investors), by short positions, and by other leverage (including debt and other credit arrangements). On the assets side there is

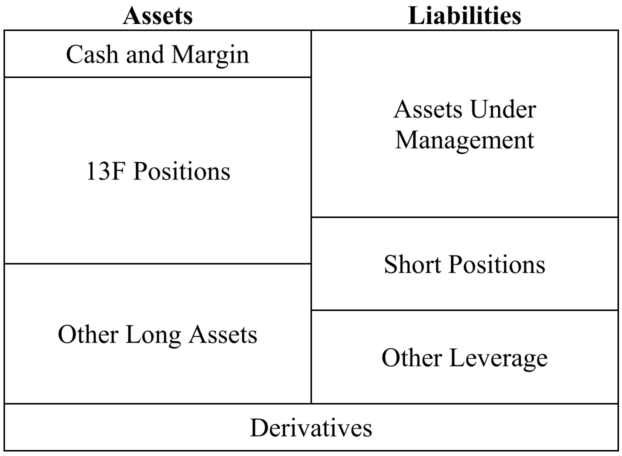
[45] Under the new SEC rules, investment firms with more than USD 150 million under management will have to fill out the PF form. This form requires them to report their AUM, leverage, the fund's five largest investors, gross and net performance for the fiscal year, the percentage of assets invested in certain strategies, the five counterparties to which they have the greatest credit exposures, and the percentage of transactions operated in regulated and OTC markets, among others. These forms shall, however, only be disseminated to governmental agencies and not to the public. The European Directive has similar requirements but applies them to all alternative investment managers marketing their product in the EU, regardless of their size. The US and European rules are available at http://www.sec.gov/rules/final/2011/ia-3308-formpf.pdf and at http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2011:174:0001:0073:EN:PDF

[46] These funds are also called Long/Short Equity.

first the cash position and the margin position typically required as collateral for short and other leverage positions.

Figure 3.1: Stylized EHF Balance Sheet

This figure gives a stylized view of the balance sheet of a typical equity hedge fund. The proportions are only illustrative.



The rest are all the long positions, which can be divided into 13F positions,[47] as described above, and other long assets. The derivatives can be assets or liabilities depending on the positions of the fund. In this situation, the net return to investors is: $R_{NET} = R_{AUM} = R_{13F} + R_{OtherLong} + R_{Short} + R_{Derivatives} - Costs_{Leverage} - Costs_{Investment} - Fees$, if we neglect the return on cash. So, 13F filings can at least describe one part of EHFs' returns. In addition to this information, for the hedge funds which decide to voluntarily report their returns to publicly available databases, it is possible to obtain the net total returns to investors. Combining these returns with the 13F information thus allows assessing the extent to which EHFs rely on their large long positions to generate performance with respect to what comes from their other positions and intra-quarter trading activity minus what is absorbed by fees and costs.

Hedge funds do not, however, directly report in the 13F forms; AIFs do. Concretely, a hedge fund is an investment vehicle detained by an AIF. These AIFs often possess and

[47] In my sample the declared 13F positions typically amount to twice as much as the Assets Under Management. This figure is in line with the leverage generally documented; see for instance: *Assessing the possible sources of systemic risk from hedge funds,* UK Financial Services Authority, February 2012, http://www.fsa.gov.uk/static/pubs/other/hedge-fund-report-feb2012.pdf.

exercise management over several hedge funds. SEC 13F forms are filled at the AIF level so that only the aggregate information about the holdings of all hedge funds managed by the firm is available, without any possibility to trace it back to a particular fund unless the AIF only consists of a single fund. Fortunately, when hedge funds voluntarily report their returns to databases, they also report the information about their parent AIF, thereby allowing the construction of a sample for the realization of the present study as I describe it in Section 3.4.

3.3 Performance Measurement of Equity Hedge Funds

Because of soft regulation, hedge funds are often advocated as very complicated investment vehicles that employ advanced investment strategies not applicable by other types of investment funds, but in fact they are not all that different from mutual funds. Indeed, while it is true that *legally* hedge funds have almost unlimited latitude in their investment choices, *in practice* they do not. There are, in fact, a number of constraints that hedge funds have to comply with in order to be profitable and attract potential investors, and these constraints greatly limit the scope of their investment possibilities. For instance, hedge funds must follow their agreed-upon investment strategy since they are closely monitored by investors; see, for instance, Baquero and Verbeek (2009). Also, they need investment opportunities that are large enough, liquid enough, and predictable enough to allow for a strategy to be implemented. Hence, while some funds invest in art[48] or bet on sport events,[49] and may be successful in doing so, these strategies cannot be implemented on a large scale by a large number of funds.

Given these constraints, most hedge funds end up being invested in both traditional financial assets and *alternative* investments; see, for instance, Agarwal and Naik (2000c) or

[48] See, for instance, Steve Johnson, *Hedge funds: Art fund draws up new model to adorn diversified portfolios,* Financial Times, 06/11/2007.

[49] See, for instance, Nathaniel Popper, *New hedge funds bet on sports, literally,* Los Angeles Times, 04/17/2010.

Fung and Hsieh (2004b). Focusing on EHFs, funds that are specialized in equity, this translates into portfolios that are composed of both an *observable* part that comes from long and large positions in securities that are reported in 13F filings and of a an *unobservable* part that comes from small positions, short positions, and intra-quarter trading activity. The combination of these two parts, along with trading and investment costs, forms the *total* net performance of the fund. EHFs are in this sense, at least partially, mutual funds.

In view of the above, it appears that EHFs rely, up to some extent, on the *observable* part of their portfolio to generate their *total* performance. In this context, my objective is to evaluate whether EHFs solely generate performance with their long equity positions or whether these positions are only part of a global investment strategy. In this vein, I consider a number of performance models to measure the global performance of the *visible* part and of the *total* part. Additionally, I also consider a market-timing measure and stock-picking measure in order identify these particular skills.

I measure the global performance with the help of two typical models from the mutual fund literature. First, since a number of papers in the hedge fund literature document dynamic exposures (see, e.g., Patton and Ramadorai (2010), or Criton and Scaillet (2011)), I follow Ferson and Harvey (1999),[50] The Ferson and Harvey (1999) CAPM writes as follows:

$$(1)\ R_{i,t} = \left(\alpha_{0,i} + \boldsymbol{\alpha}_{1,i}^{'}\mathbf{z}_t\right) + \left(\beta_{0,i} + \boldsymbol{\beta}_{1,i}^{'}\mathbf{z}_t\right)\left(Rm_t - Rf_t\right) + \varepsilon_t,$$

where Rm_t is the market return, Rf_t is the risk free rate, $\mathbf{z}_t = \mathbf{Z}_t - E(\mathbf{Z}_t)$ where $\mathbf{Z_t} = \left\{DY_t, CS_t, TS_t, TB_t\right\}$ is an information set, where *DY* is the dividend yield on the S&P 500, *CS* is the credit spread defined as the month-end-to-month-end change in the difference between Moody's Baa yield and the Federal Reserve's ten-year constant maturity yield, *TS* is

[50] Also see Ferson and Schadt (1996) or Ferson and Warther (1996).

the term spread (difference between the ten-year Treasury bond yield and the three-month Treasury Bill yield), and *TB* is the three-month Treasury bill.[51]

Second, I employ the Fama and French (1992) model accounts for simple strategies based on stock characteristics and writes as follows:

$$(2)\ R_{i,t} = \alpha_i + \beta_{1,i}\left(Rm_t - Rf_t\right) + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \varepsilon_t ,$$

where SMB_t means small minus big and is the return of a portfolio long on a group of small capitalization firms and short on a group of large capitalization firms, and HML_t means high minus low and is the return of a portfolio long on a group of firms with high book-to-market ratio and short on a group of firms with low book-to-market ratio.[52]

Even though these models have sometimes been shown to lack explanatory power in certain contexts, they remain the pillars of the performance measurement literature. They have the advantage of proposing readily replicable and easily interpretable factors. In addition, I also considered the augmented version of the Fama and French (1992) proposed by Carhart (1997), but the additional momentum factor adds little explanatory power. Moreover, Fung and Hsieh (2004a) show that EHFs are mainly exposed to two factors: market and size spread. This model simply being an amputated version of the Fama and French (1992) one, I decided to exclude it too. Finally, based on the same Fung and Hsieh (2004a) paper, I also exclude the Fung and Hsieh (2001, 2002a, 2004b) seven factor model generally used in hedge fund performance measurements since it is better suited to advanced strategies than to EHFs.

In order to assess the market timing skill of EHFs, I follow Goetzmann, Ingersoll, and Ivković (2000), who propose a factor that has option-like features that allow measuring daily

[51] $E\left(\mathbf{Z}_t\right)$ is computed over *t-25 to t-1* on a moving window basis.

[52] See Fama and French (1992).

market timing. The timing factor, TF , simply comes as a supplementary factor in the Fama and French (1992)[53] model presented above. This factor is computed as follows:

$$(3)\ TF_t = \left[\left(\prod_{\tau\in(\text{month } t)}^{t} \max\left\{1+Rm_\tau, 1+Rf_\tau\right\}\right) - 1\right] - Rm_t,$$

where τ is a trading day belonging to month *t*, Rm_τ is the market return for day τ, and Rf_τ is the risk-free rate for day τ. In this context, TF_t is equal to the value added by perfect daily market timing in month *t*, per dollar of funds' assets. The intuition being that a perfect daily timer should be able to provide a protective put to the investors.

Finally, I measure the stock picking. To this goal, a commonly used model is the one of Daniel, Grinblatt, Titman, and Wermers (1997); see also Wermers (2000). This model, however, suffers from biases because the actual holdings are not observable in the months between reporting dates; see, for instance, Grinblatt and Titman (1993). Ferson and Khang (2002) propose an alternative model that conditions the performance measure on publicly available information to circumvent the interim trading bias mentioned above. Concretely, they introduce what they call the conditional weight-based measure (CWM hereafter), which is in fact a measure of the covariance between the portfolio weight changes and the subsequent returns conditioned on publicly available information. The Ferson and Khang (2002) CWM of stock picking ability writes as:

$$(4)\ CWM_{P,t} = E\left[\sum_{j=1}^{N_P}\left(w_{j,t} - w_{b,j,t,k}\right)\left(r_{j,t+1} - E\left(r_{j,t+1}\middle|Z_t\right)\right)\middle|Z_t\right],$$

where $CWM_{P,t}$ is the conditional weight-based measure for fund *P* at time *t*, $N_{P,t}$ is the number of position in portfolio *P* at the time *t*, $w_{j,t}$ is the weight invested in stock *j* at *t*, $r_{j,t+1}$ is

[53] In their work, Goetzmann et al. (2000) also consider adding the market timing factor to the simple CAPM model, but they find the best results with Fama and French (1992). In the same vein, I also considered adding the factor in a conditional CAPM setting, but the explanatory power is lower than with Fama and French (1992). Finally, as above, I also tried this with Carhart (1997), but the additional factor again adds little value.

the observed return for stock j in the month beginning at *t*, $E\left(r_{j,t+1}|Z_t\right)=\mathbf{b_j Z_t}$ is the linear model that explains individual asset returns based on $\mathbf{Z_t}$, the information set, and $w_{b,j,t,k}$ is the benchmark weight for stock *j* at *t*.[54] To check whether stock picking ability (if any) is the result of trading based on public information, I start with the standard information set from the asset pricing literature, $\mathbf{Z_t}=\{DY_t, CS_t, TS_t, TB_t\}$, previously described. In a second step, I sequentially add information that is publicly available and is known to affect stock prices. For a given firm, I first add the following corporate level variables: change in rating (if the firm has issued bonds), stock repurchase, SEO, and M&A (I discriminate between targets and acquirers). Finally, I also add changes in analysts' recommendations (computed over the last month) and earnings surprises. This allows isolating specific contributions of public information to the AIFs' performance. If the manager has no inference beyond what can be inferred from publicly available information, then the CWM is not significantly different from zero

I carry out the above performance estimations on two different returns sets. The first one is based on the *observable* part of the portfolio, while the second one is based on the *total* performance. Given that the CWM requires knowing the actual stock holdings, I can only estimate the stock picking ability on the *observable* part of the portfolio.

3.4 Data

This section gives a detailed view of the data used in my analysis. First, I detail the construction of the two return sets and the factors used to estimate the performance of AIFs, along with the data sources. Second, I propose some descriptive statistics.

[54] For computational details, refer to Appendix A.

3.4.1 Data Construction and Sources

Specifically, I first compute realized AIF monthly returns as the AUM-weighted average of each of their component EHF reported returns. This set of returns represents the *total* net performance of AIFs, including all positions and trading activities along with all costs. Second, I calculate the time-series of monthly returns that an investor could obtain by mimicking the 13F holdings (rebalanced quarterly). Specifically, I assume the quantities reported for each stock (identified by its CUSIP) are held for one quarter, starting from the reporting date,[55] and calculate the portfolio return. I use unadjusted prices, taking into account the eventual splits (or reverse splits) and dividends. For a small subset of stocks which consist of over-the-counter securities, there is no monthly price date available, and I only have the quarterly prices reported in the 13F filings. I gauge the impact of these stocks on AIFs' returns by comparing the returns without these OTC positions to the returns obtained by including a linear interpolation of their quarterly prices and find almost no impact; therefore, I no longer consider these positions in the AIFs' returns computation. This set represents the *observable* returns from long and large equity positions only. To assess the stock picking ability of AIFs, I use the same 13F filings as above. These filings allow combining the monthly returns of a portfolio rebalanced quarterly with the corresponding changes in portfolio weights in order to compute the CWM.

The construction of the factors obtained from the public information sets $\mathbf{Z}_{j,t}$ also deserves some explanations. Corporate events (SEO, repurchases, M&A target, and M&A acquirer) are dummy variables coded as one in the month where one of these events happened to the company under consideration and zero otherwise. Alphabetical credit ratings are

[55] One could argue that the stocks are not held from the reporting date on but from the day after the previous reporting until the current reporting day in order to preserve secrecy. I mitigate this assumption by computing the correlation of returns between TASS and 13F under the two assumptions and testing whether they are significantly different from each other by converting them with Fisher's z-transformation and comparing the transformed values with the standard normal procedure (following Myers and Sirois (2004)). I find that the correlation between returns under the first assumption is significantly higher than under the second, thereby mitigating this issue.

recoded numerically from 1 to 22 (22 being the best, AAA).[56] Analyst recommendations, originally coded from 1 (strong buy) to 5 (strong sell), are recoded inversely to allow for easier interpretation (5=strong buy to 1=strong sell).[57] At last, earnings surprises are coded as 1, 0, or -1, depending on the sign of the difference between actual EPS and average expected EPS for the months in which both actual and expected EPS are disclosed. In months with no disclosures, the variable equals zero.[58]

The data is obtained from a number of sources. Mandatory reported 13F hedge fund equity holdings are gathered from EDGAR. Hedge funds' returns and characteristics are from TASS. Corporate events (SEO, repurchases, and M&A) are from SDC Platinum. Analysts' recommendations and earnings surprises are from I/B/E/S. The S&P 500 returns and dividend yields are obtained from Datastream. Stock returns, prices, and ratings (Standard & Poor's) are from CRSP. The yield on Moody's Baa, on the 10-Treasury, and on the three-month Treasury Bill are from the Federal Reserve's website.[59] The Fama and French (1992) factors are from Kenneth French's website.[60] The Goetzmann et al. (2000) timing factor is calculated with the data presented above.

The sample period goes from January 1994 to June 2011.[61] I start with the AIFs (available from TASS) that are only composed of EHFs, which report in USD,[62] and which provided their returns (net of all fees and costs) at least once in my date range; this represents 1,110 AIFs (1,685 individual EHFs). I downloaded the list of all institutional investment managers that filled a 13F filing at least once during the sample period. These investment managers can be any type of investment manager. I collect their names and hand-match them with my list of

[56] If there is no rating for a given month, the last available information is used and the rating change is computed as rating in *t* minus rating in *t-1*.
[57] If a recommendation is missing, the last available observation is used and the recommendation change is computed as recommendation in *t* minus recommendation in *t-1*.
[58] For summary statistics about the information sets, refer to Appendix B.
[59] http://www.federalreserve.gov/
[60] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/
[61] TASS only came into operation in the mid 1990's, making earlier data bias prone; see, for instance, Fung and Hsieh (2002b). Also, I/B/E/S and SDC Platinum are partially incomplete or imprecise prior to 1994; see, for instance, DellaVigna and Pollet (2009).
[62] This follows most existing literatures and allows eliminating duplicate share classes in foreign currencies.

AIFs to obtain a sample of 268 investment firms. From these, I remove 5 AIFs that are large financial corporations that also manage mutual funds and other investment vehicles. This intermediate sample consists of 263 AIFs.

However, since I need to contrast TASS returns with 13F returns, I further remove the AIFs which manage funds that do not report their AUM (12 AIFs), thereby preventing me from computing their AUM-weighted share in the AIF's return.[63] I also remove the ones that do not have matching observation periods between 13F filings and TASS data (27 AIFs). I further exclude the AIFs whose funds only report quarterly returns to TASS (2 AIFs). Finally, I only keep the AIFs with time-series of returns that are at least 18 months long in order to be able to estimate my models with reasonable precision (minus 29 AIFs). The final sample consists of 193 AIFs managing 452 individual EHFs. On average over the sample period, these 193 jointly represent about USD 330 billion of assets under management, or 57% of the USD 580 billion managed by the 1,110 equity-only AIFs of the original universe.

Table 3.1 reports the distribution of these 193 AIFs across the sample used. As we see, there is on average about 73 AIFs observed by year, while about 10 enter and 8 exit the sample each year. The peak number of AIFs is reached in 2005 (109) but remains high from 2001 to 2008. As one can expect, the highest number of exits happened in 2008 (26, more than three times the average). The average attrition rate of 10.51% is in line with previous studies; see, for instance, Liang (2000).[64] This sample suffers from a clear bias in terms of size, since funds only have to report to the SEC if they have more than USD 100 million under management *on average* during the preceding twelve months. The sample obtained is, however, free of survivorship bias, since all funds that have been active during the sample period are considered in the study.

[63] Some funds do not report their AUM on a monthly basis but less frequently. Following Heaney (2008), for these funds, I fill the gaps with a linear interpolation of the AUM between two reporting dates.

[64] This can happen for a number of reasons, including bankruptcy, because the AIFs stopped reporting (voluntarily) to TASS, because it does not have anymore large enough long positions to report in 13F forms, because the AIF shrunk below the USD 100 million threshold, or because of a merger, among others.

Table 3.1: Presence of AIFs by Year

This table details the number of AIFs present in the sample in each year. It also reports the number of AIFs entering and exiting the sample each year. Entries are calculated as the difference between the AIFs that were not present in the previous year and are present in the current year, and inversely for exits. This is except for year 1994, where entries are calculated as the AIFs that were not present in January but appeared during the year, and exits are calculated as the AIFs that were present in January but disappeared during the year. The last column gives the attrition rate (Exits/AIFs in Database). The figures for 2011 only run until the end of June.

Year	N AIFs in Database	N AIF Entries	N AIF Exists	Attrition Rate (%)
1994	24	6	2	8.33
1995	28	5	1	3.57
1996	34	7	1	2.94
1997	39	7	2	5.13
1998	57	18	0	0.00
1999	64	8	1	1.56
2000	80	18	2	2.50
2001	92	16	4	4.35
2002	98	17	11	11.22
2003	99	10	9	9.09
2004	108	18	9	8.33
2005	109	14	13	11.93
2006	103	10	16	15.53
2007	101	12	14	13.86
2008	88	13	26	29.55
2009	79	3	12	15.19
2010	69	1	11	15.94
2011 (until end of June)	53	0	16	30.19
Mean	73.61	10.17	8.33	10.51

3.4.2 Summary Statistics

I report summary statistics about the returns in Table 3.2. I differentiate between the *observable* returns obtained from 13F data and the *total* returns obtained from TASS. I additionally provide information about the original universe of 1,110 equity hedge AIFs in TASS, which I cannot use because of the reasons described in above.

Starting with the final sample, which consists of 193 AIFs and 14,485 AIF-month observations, we see that the returns reported in TASS are higher on average (0.86% per month vs. 0.47%), thus showing that some AIFs provide performance beyond their *observable* positions. Interestingly, the median is higher in 13F returns (0.93% vs. 0.80%), which suggests that the higher *total* return average from TASS is driven by a limited number of well performing AIFs, as is confirmed by the positive skewness (0.85). The kurtosis is also higher in TASS (25.94) than in the 13F (9.51), signaling the presence of outlier and thus of more peaked returns.

Table 3.2: Returns Summary Statistics

This table gives returns statistics about the original universe of AIFs and the final sample, as well as about the difference between the two. For the final sample, the 13F values are also reported along with the ones from TASS. The abbreviation *(n. s.)* means 'not significantly different from zero.' The period covered is January 1994 to June 2011.

	Final Sample		**Original Universe**	**Difference Between Original And Final**
Data Source	**SEC 13F**	**TASS**	**TASS**	**TASS**
Number of AIFs	193	193	1,110	917
Number of AIF-month obs.	14,485	14,485	64,056	49,571
Average monthly return	0.47%	0.86%	1.01%	*(n. s.)* 0.15%
Median monthly return	0.93%	0.80%	0.82%	0.02%
Monthly returns std. dev.	7.73%	5.63%	6.64%	1.01%
Returns standardized kurtosis	9.51	25.94	26.41	0.47
Returns skewness	0.13	0.85	1.28	0.43
Minimum monthly return	-49.28%	-62.74%	-62.74%	0.00%
Maximum monthly return	131.96%	122.46%	122.46%	0.00%

Contrasting the above with the original universe, we see a large and proportionally similar difference in the number of AIFs (917) and in the number of AIF-month observations (49,571) covered. The returns of this group are, however, close to the original sample. The mean return is different by a monthly, not significantly different from zero, 0.15%. The median is almost identical, while the standard deviation changes by 1.01%. The kurtosis changes very little, but the skewness is about half as much as the original, which indicates a more symmetric distribution of the returns. Finally, the most extreme (minimum and maximum) returns are the same, therefore indicating that the final sample also comprises the most extreme observations of the original universe. All in all, this final sample, although reduced, looks representative of the original universe.

Table 3.3 reports summary statistics about observations and holdings in the final sample. The median AIF has 61 months of observations (75.05 for the average), but the variation is high since some AIFs only have 18 months of data (the minimum to be included in the sample), while the highest number of observations is 210. The average stock holding period per AIF[65] ranges from a minimum of 4.09 months to a maximum of 52.33 with an average of 15.9 and a median of 14.07, so on average, an AIF tends to hold its positions for about one year and a quarter.[66]

Table 3.3: Holdings and Observations Summary Statistics

This table details statistics about the number of months of observations available for each AIF, as well as information about the stock holding periods, the number of stocks in the portfolio, and the quarterly portfolio turnover. Average stock holding periods for each AIF are computed as the average holding periods across all stocks they declared in their portfolio. Average numbers of stocks for each AIF are computed as the average number of stocks they declared in portfolio across all observation dates. Average quarterly portfolio turnover rates for each AIF are computed as the average of the quarterly turnovers across all observation dates. Stock Holdings are computed as the last available information for each AIF in the database, so the observation periods differ but each AIF is represented only once. All figures are from 13F files and concern the final sample of 193 AIFs. The period covered is January 1994 to June 2011.

	Number of Months of Data	**Average Stock Holding Period (Months)**	**Average Number of Stocks in Portfolio**	**Average Quarterly Portfolio Turnover Rate**	**Stock Holdings (M $)**
Mean	75.05	15.90	106.30	25.09%	1,722
Median	61	14.07	62.54	22.20%	148
Standard Dev.	48.72	8.42	140.83	14.36%	4,605
Minimum	18	4.09	2.17	3.40%	0.117
Maximum	210	52.33	1,148.53	68.70%	30,713

The average number of stocks in portfolio is also varied. While the less diversified AIF holds an average of 2.17 stocks, the most diversified one holds 1,148.53. The average and median AIFs respectively hold about 106 and 62 stocks in their portfolio. The mean quarterly portfolio turnover rate is at 25.09% so that on average AIFs buy or sell for the equivalent of one fourth of the value of their long large holdings each quarter. This value can however range from 3.40% for the less active AIF to 68.70% for the most active one. While the mean number is in line with what can be observed in the mutual fund industry, the dispersion is much greater thereby indicating more diversified investment styles than in this latter industry; see for instance Falkenstein (1996) or Carhart (1997). On the holdings side, the average AIF reports holdings for a value of USD 1.772 billion. This number is driven by large AIFs since

[65] The average number of stocks held by each AIF is computed as the average of the number of stocks they have in portfolio across all observation dates.

[66] These figures are consistent with the ones documented by Brav, Jiang, Partnoy, and Thomas (2008).

the median investment firm only reports USD 148 million. The biggest (smallest) firm holds more than USD 30 billion (less than USD 117 thousand) in long security holdings.[67]

3.5 AIFs' Performance

This section reports my results about AIFs' performance. I first analyze the *observable* long equity positions in terms of global risk-adjusted performance, market timing, and stock picking. Second, I analyze the *total* performance under the same terms, but stock picking. Finally, I investigate whether the *observable* long equity positions are an additive or a diversifying component in AIFs' portfolios.

3.5.1 Performance of Observable Positions

I start by analyzing the *observable* performance, so the data obtained from the returns computed from the equity holdings reported in AIFs' 13F filings. These filings only contain large long positions of AIFs' portfolios, and therefore, the returns computed thereof are not influenced by smaller positions, short positions, intra-quarter trading activity, or investment costs. Table 3.4 reports the results.

3.5.1.1 Global Risk-Adjusted Performance

The left-hand side of Table 3.4 displays the global risk adjusted performance under the conditional CAPM model and the Fama and French three factor model. For each factor, it reports the mean exposure across all AIFs, as well as the mean exposures across the AIFs that are significantly exposed to that factor at the 5% level of significance. Similarly, it also reports the proportion of AIFs that fall into these 5% significance groups. The exposures to the conditional factors under the conditional CAPM specification are not reported since their interpretation makes limited sense.

[67] These stock holdings numbers are calculated based on the last available SEC 13F filing for each reporting AIF, so the reporting dates may not be the same for all of them, but they all appear only once in the computations.

Starting with the conditional CAPM, we see that the average outperformance (alpha) across all AIFs establishes at a monthly 0.41% or about 5% a year. This number is, however, impacted by a limited number of especially well performing AIFs since the 6.73% of entities that significantly outperform display an average alpha of 4.91% a month or about 77%. Concurrently, the 4.66% of AIFs that significantly underperform have an average monthly alpha of -5.78% or about -51% a year. It remains, however, that the immense majority of AIFs neither underperform nor outperform since almost nine AIFs out of ten do not have any significant alpha. Expectedly from long equity holdings, the average market beta is very close to one, while 80.31% of AIFs are significantly long on this factor and none is short.

If we switch to the Fama and French (1992) model, we can see some differences, even though the general picture remains the same. First, the average alpha across all AIFs is now a negative -0.10% a month or about -1% a year. There is strong decrease in the number of AIFs that significantly outperform since they now only represent 1.55% of the sample (3 AIFs out of 193), with an average monthly alpha of 0.94% a month or about 12% per year. Comparatively, the proportion of significantly underperforming AIFs increases to 9.84% with a monthly alpha of -1.31% or about -15% a year. Here again, it remains that about nine AIFs out of ten do not produce any significant alpha, may it be positive or negative. The market beta remains close to one in average while more than 95% of the AIFs are significantly exposed to it. Looking at the other factors, we see that almost 60% are significantly exposed to the size spread (SMB), while about 45% are significantly exposed to the spread between value and growth stocks (HML). This shows that these old and well-known investment strategies are still followed by many managers, although sometimes in a contrarian way. This model also appears to be better suited to measuring AIFs' *observable* performance since both the average adjusted R-square and the F statistic are higher than for the conditional CAPM.

Table 3.4: Performance of Observable Positions

This table reports the results of AIF by AIF regressions of observable returns (13F). The left-hand side reports the global performance under the conditional CAPM and the Fama and French (1992). The first half of the right-hand side reports the market timing measured with the Goetzmann et al. (2000) model. The second half of the right-hand side reports stock picking ability measured with the Ferson and Khang (2002) model under three different information sets Z_t. For each model, the first column (All AIFs) presents the average exposure to a given factor. The other two columns report the mean exposures of the AIFs which have a significantly positive and a significantly negative exposure to the factor at the 5% level. The proportions of AIFs in each of these 5% significance groups are reported in italic for each factor. The coefficients on the conditional factors are not reported. The period covered is January 1994 to June 2011.

	Global Performance						**Market Timing**			**Stock Picking**		
	Conditional CAPM			**Fama and French (1992)**			**Goetzmann et al. (2000)**			**Ferson and Khang (2002)**		
	All AIFs	**Positive at 5%**	**Negative at 5%**	**All AIFs**	**Positive at 5%**	**Negative at 5%**	**All AIFs**	**Positive at 5%**	**Negative at 5%**	**All AIFs**	**Positive at 5%**	**Negative at 5%**
Alpha (%)	0.41	4.91	-5.78	-0.10	0.94	-1.31	0.50	3.28	-3.42			
		6.73%	*4.66%*		*1.55%*	*9.84%*		*11.39%*	*4.67%*			
Rm – Rf *(β_1)*	1.09	1.35	–	1.14	1.16	–	1.07	1.14	–			
		80.31%	*0.00%*		*95.85%*	*0.00%*		*90.67%*	*0.00%*			
SMB *(β_2)*				0.41	0.61	-0.35	0.41	0.63	-0.35			
					56.48%	*2.07%*		*56.48%*	*20.73%*			
HML *(β_3)*				-0.02	0.60	-0.58	-0.05	0.62	-0.65			
					24.35%	*19.17%*		*23.31%*	*21.24%*			
Timing Factor *(β_4)*							-0.07	0.30	-0.31			
								5.18%	*15.54%*			
CWM (%) Z_t = General										0.13	0.79	-0.91
											8.88%	*10.88%*
CWM (%), Z_t = Gen & Corporate										-0.03	0.75	-1.11
											8.29%	*10.88%*
CWM (%), Z_t = Gen, Corp, Analyst										-0.16	0.70	-1.20
											8.88%	*11.40%*
Adjusted R^2		0.65			0.70			0.71			0.05 | 0.07 | 0.07	
F Statistic		53.45			86.32			79.93			2.01 | 4.78 | 4.77	
N AIFs		193			193			193			193 | 193 | 193	

Regardless of the performance model used, it appears that a vast majority of AIFs are not able to produce outperformance with their *observable* long equity holdings. This is in line with most studies about mutual fund performance; see, for instance, Grinblatt and Titman (1995) for a review. Considering this scarce presence of performance, the following two sections investigate the presence of particular investment skills, which are market timing and stock picking.

3.5.1.2 Market Timing

Table 3.4 reports the results for market timing under the Fama and French (1992) model, augmented by the timing factor of Goetzmann et al. (2000). Directly starting with the variable of interest, the timing factor, we see that on average across all AIFs, market timing is poor and the exposure is established at -0.07. This number means that with respect to what it could have been possible to produce through perfect timing, the average AIFs destroyed 7% value. This contrasts with the average value of -0.0136 found by Goetzmann et al. (2000) for a sample of mutual funds. As it appears, on average, AIFs are worse timers that mutual funds if we only concentrate on their long holdings. The picture is different if we look at the 5% significance groups. In fact, there are about three times as many significantly poor market timers as significantly good ones (15.54% vs. 5.18%). Moreover, it appears on average that the good and poor timers do, with the same magnitude, about 30% of what could be reached through perfect market timing. Additionally, this also contrasts with the findings of Goetzmann et al. (2000), who only identify a proportion of about 2% of outperforming mutual funds. This shows that while mutual funds are on average better timers than AIFs, the timing skills of AIFs are more dispersed. Still, the largest proportion of AIFs, 80%, does not show any significantly good or poor market timing skills. These results rejoin the fact that most AIFs are already not able to outperform in general, so the proportion with specific skills is scarce too.

3.5.1.3 Stock Picking

I examine managers' stock picking ability as measured by the CWM computed with the model of Ferson and Khang (2002). I directly use the AIFs' stock holdings obtained from their 13F filings. The lag, *k*, is equal to 3 months while the input betas are estimated over a 24-month moving window. The CWM is estimated AIF by AIF. As illustrated in Table 3.4, the mean CWM conditional on general factors (dividend yield, credit spread, size spread, and Treasury bill), establishes at a level of 0.13% per month or about 1.6% per annum. Approximately 8.88% of the managers show a significantly positive ability of 0.79% a month while about 10.88% have a significantly negative one with -0.91%. The remaining 80% have a neutral performance. This means that, when the information set is limited to general publicly available information, AIFs' stock picking ability does add some value *on average,* but for most AIFs, it does not. Moreover, there are more AIFs which destroy value than AIFs which create value with their stock picking. These findings contrast with the average CWM of 0.03% per quarter, or 0.12% per year, documented by Ferson and Khang (2002) in their sample of mutual funds. This suggests that, on average, hedge fund managers are better stock pickers than mutual fund managers. Their findings do not, however, allow drawing conclusions about the proportion of significantly positive and negative stock pickers, so we do not know the dispersion of stock picking ability in their sample.

Next, I augment the information set to include corporate related factors, which are changes in credit ratings, secondary offerings, mergers and acquisitions, and stock repurchases. Increasing the size of the information set does have some effect on the average CWM level, which now decreases to -0.03% per month or about -0.4% per year. This is now lower than the findings of Ferson and Khang (2002) for mutual funds. Also, there are somewhat fewer managers with a positive ability (8.29%) and a decreased stock picking ability at 0.75% a month, and exactly the same number of AIFs with a significantly negative ability (10.88%)

and a lower negative ability of -1.11% per month. Nevertheless, the proportion of neutral managers still represents the vast majority.

Finally, I further augment the information set to now encompass analysts' related information, which are changes in analysts' recommendations and earnings surprises. We see a decline in average CWM, to -0.16% per month or about -2% per year, which is also lower than the findings of Ferson and Khang (2002) for mutual funds. The proportion of significantly positive CWM increases back to its original level slightly to reach 8.88%, but the proportion of significantly negative CWM goes down to 11.4%. In total, under this information set, there is a slight decrease in the proportion of AIFs with a neutral stock picking ability.

In a nutshell, we see that there are about one tenth of the AIFs who show a positive and significant stock picking ability but that there is a similar (though somewhat higher) number of them who have a significantly negative ability. However, these AIFs represent a small fraction of the total number of managers since a majority of them do not have any significant stock picking ability. Finally, we see that the choice of the information set matters because if it is not large enough, what should be interpreted as information contained in public information could be understood as stock picking skill. Based on this, it appears the performance of hedge fund managers needs to be measured over a larger information set to reach similar conclusions as the ones about mutual fund managers. This suggests that the former are better at interpreting general public information than the latter. Also, adding analysts' information on top of the corporate related events increases the proportion of both outperforming and underperforming managers. This is in line with Teo and Chung (2011), who find that the analysts are actually often influenced by hedge fund holdings and not the other way around.

3.5.2 Total performance

Considering the widespread lack of performance of AIFs when looking at their *observable* performance, I now switch to the analysis of *total* performance. This is the total performance as reported by the investment firms; this includes all positions and is net of investment costs and fees. The results are reported in Table 3.5.

3.5.2.1 Global Risk-Adjusted Performance

Starting with the conditional CAPM displayed in the left-hand side of Table 3.5, we see an average alpha across all AIFs, which establishes at 0.79% per month or about 9.9% per annum. This number is almost twice as high as the one obtained from the *observable* performance. If we look at the AIFs with a significantly positive performance, we see that on average, they produce a lower alpha than the long-only position since it establishes at 2.06% per month. Nevertheless, there is a much larger proportion of AIFs that are able to outperform since there is almost one firm out of three that does so (compared to less than 7% for the long positions). Also, while the underperformance of the significantly negative group is a high -11.36% a month, this only concerns 2 firms out of 193 (1.04%). This still leaves about 70% of the AIFs with no significant performance. The market beta establishes an average of 0.51. This figure is interesting since—considering there are historically slightly more days when the market goes up than when it goes down—it is the exposure that would be expected from a perfect market hedger, fully exposed when the market goes up (beta=1) and not exposed at all (beta=0) when the market goes down. This is, of course, a rough interpretation, but it suggests that, on average, equity hedge funds hedge. It remains, however, that the variations between AIFs is high since there are about 56.5% of AIFs which are significantly exposed to the market, while about 3% are negatively exposed.

If we move to the Fama and French (1992) model, we see a decrease of the average outperformance to 0.49% per month or about 6% per annum. Importantly, and contrarily the findings about *observable* performance, there is still about one AIF out of three that is able to significantly outperform with a monthly alpha of 1.06%, and there are only 3.11% that underperform significantly with an average negative alpha of -1.6% per month. This shows that in terms of *total* performance, there is a number of AIFs who are able to outperform even when a number of risk factors are taken into account. The market exposure remains stable around 0.50 on average, but the proportion of AIFs that are significantly long on the market increases to 74% while the proportion that are short remains at 3.11%. About 37% of the AIFs are significantly exposed to the size spread, mostly positively. This is in line with the findings of Fung and Hsieh (2004a), who show that equity hedge funds are mainly exposed to the size spread and the market. The exposure to HML is close to 0 on average, while there are two similarly sized groups, each representing about 20%, which are significantly long and significantly short on this factor.

All things considered, it appears that contrarily to what can be found when looking at the performance from *observable* holdings, in *total*, there is a number of AIFs that are able to significantly outperform. At the same time, there is a relatively limited proportion that significantly underperforms, which is in line with what should be expected from a hedge fund. This indicates that hedge funds' long equity holdings are actually only part of a more global investment strategy. It remains, however, that most AIFs do not produce any significant outperformance. Considering this, I investigate the presence of market timing in the next section.

3.5.2.2 Market Timing

I employ the same Fama and French (1992) model augmented with the Goetzmann et al. (2000) factor as documented in the previous section. The results are reported in the right-hand side of Table 3.5.

Table 3.5: Total Performance

This table reports the results of AIF by AIF regressions of total returns (TASS). The left-hand side reports the global performance under the conditional CAPM and the Fama and French (1992). The right-hand side reports the market timing measured with the Goetzmann et al. (2000) model. For each model, the first column (All AIFs) presents the average exposure to a given factor. The other two columns report the mean exposures of the AIFs with a significantly positive and a significantly negative exposure to the factor at the 5% level. The proportions of AIFs in each of these 5% significance groups are reported in italic for each factor. The coefficients on the conditional factors are not reported. The period covered is January 1994 to June 2011.

	Global Performance						**Market Timing**		
	Conditional CAPM			**Fama and French (1992)**			**Goetzmann et al. (2000)**		
	All AIFs	**Positive at 5%**	**Negative at 5%**	**All AIFs**	**Positive at 5%**	**Negative at 5%**	**All AIFs**	**Positive at 5%**	**Negative at 5%**
Alpha (%)	0.79	2.06	-11.36	0.49	1.06	-1.60	0.81	2.27	-2.41
		29.53%	*1.04%*		*31.09%*	*3.11%*		*29.01%*	*2.59%*
Rm – Rf *(β_1)*	0.51	0.82	-1.31	0.48	0.63	-0.63	0.44	0.68	-0.45
		56.48%	*3.11%*		*74.09%*	*3.11%*		*62.17%*	*3.11%*
SMB *(β_2)*				0.21	0.45	-0.26	0.22	0.45	-0.28
					35.75%	*1.04%*		*36.27%*	*1.04%*
HML *(β_3)*				-0.03	0.46	-0.51	-0.04	0.52	-0.50
					23.83%	*20.73%*		*20.73%*	*21.76%*
Timing Factor *(β_4)*							-0.04	0.28	-0.27
								5.70%	*12.95%*
Adjusted R^2		0.44			0.43			0.45	
F Statistic		16.24			22.39			20.96	
N AIFs		193			193			193	

As for the *observable* positions, market timing in terms of *total* performance is poor. On average, it established at -0.04. This value comes close to the value of -0.0136 found by Goetzmann et al. (2000) for the mutual funds sample. As it appears, on average, AIFs are still worse timers than mutual funds, even if *total* performance is considered. There are again about 6% of the AIFs that are able to create value through market timing by exploiting about 28% of what a perfect market timer would do. On the other hand, there are about twice as many AIFs (12.95%) who destroy value with their market timing with a magnitude of 27% of what could be possible. These numbers are still much higher than the 2% of significantly good timers identified by Goetzmann et al. (2000). Still, there are more than 80% of the AIFs which do not show any evidence of market timing skill, may it be positive or negative. This suggests that in terms of *total* performance, at least some of them must possess some particular skills that allow them to outperform.

3.5.3 Long Equity Holdings: an Additive or Diversifying Performance Component

Considering the contrasting results between *observable* and *total* performance, in this section, I investigate whether AIFs' long and large equity positions are an additive or a diversifying component of their *total* performance. Concretely, I propose to analyze whether being skilled in producing performance from *observable* holdings is linked with producing *total* performance. For this purpose, I use the methodology described below.

As underlined in the work of Barras, Scaillet, and Wermers (2010), in a regression setting, some proportion of entities are expected to be found to outperform solely by luck. Building on this work, Chen, Cliff, and Zhao (2012) use the Dempster, Laird, and Rubin (1977) Expectation-Maximization algorithm and propose a methodology that allows extracting multiple distributions (performance groups) and their attributes from the empirical mixture of performance distributions observed. This methodology then permits assigning a probability for each AIF to be in a given performance group. I use this method and compute the probability for each AIF to be skilled (performance>0), neutral (performance=0), and unskilled (performance<0), as measured with the conditional CAPM model as well as with the model of Fama and French (1992). Based on the probabilities obtained, I assign each AIF to the performance group where its probability is the highest. I do this operation both for *observable* and for *total* performance and report my results in a contingency table for analysis. Results are reported in Table 3.6.

Panel A reports the results for the conditional CAPM. As it appears, there is not any AIF that is truly unskilled, neither in terms of *observable* performance nor in terms of *total* performance. This means that this 3x3 contingency table can actually be analyzed as if it were 2x2.

Table 3.6: Additive or Diversifying Performance Component

These two contingency tables report the results of the classifications obtained from the Chen et al. (2012) methodology. The AIFs are classified into skilled, neutral, or unskilled based on the probabilities returns by the algorithm with respect to their observable performance and to their total performance. Panel A reports the results under the conditional CAPM model. Panel B reports the results under the Fama and French (1992) model. The period covered is January 1994 to June 2011.

Panel A: Conditional CAPM

		Total Performance			
		Skilled	**Neutral**	**Unskilled**	**Total**
	Skilled	53	31	0	84
Observable	**Neutral**	99	10	0	109
Performance	**Unskilled**	0	0	0	0
	Total	152	41	0	193
$\chi^2 = 21.80$	Pr = 0.000	Cramer's V= -0.336			

Panel B: Fama and French (1992)

		Total Performance			
		Skilled	**Neutral**	**Unskilled**	**Total**
	Skilled	0	0	0	0
Observable	**Neutral**	104	20	0	124
Performance	**Unskilled**	59	10	0	69
	Total	163	30	0	193
$\chi^2 = 0.09$	Pr = 0.764	Cramer's V= -0.0216			

From the 193 AIFs of the sample, 53 AIFs that are skilled in terms of their choices of long equity positions also appear skilled when it comes to producing *total* performance. At the same time, about 40% less (31) turn to neutral. On the contrary, there are 99 AIFs that are neither skilled nor unskilled in their long holdings but skilled in terms of *total* performance, while only 10 stay neutral. A vast majority of the AIFs (152 out of 193) appear to be classified as skilled in terms of *total* performance. This contrasts with the 30% of AIFs that displayed a significantly positive alpha in the previous section. These figures cannot be compared directly, however, since what the methodology I use here states is that there are 152 AIFs out of the 193 that most likely belong to a performance group with a positive average return and are therefore most likely skilled. It does not state whether they actually did achieve a statistically significant positive performance but that they most likely belong to a group which, on average, is expected to do so. Looking at the dependence statistics, the high χ^2 (21.80) along with its corresponding probability (0%) indicates that there is a significant dependence between *observable* and *total* performance. Cramer's V (-0.336) shows a negative relationship, which indicates that being in one performance group in terms of *observable* performance tends to result in being in the other group in terms of *total* performance. In our case, this is mostly driven by the fact that being a neutral performer in terms of long holdings tends to result in being in the skilled group in terms of *total* returns. Even though most skilled AIFs tend to be skilled in both groups, they are less numerous, thus the negative relationship.

If we move to Panel B, which displays the results for the Fama and French (1992) model, the outlook is different from above. First, there appears to be no AIF that is skilled in terms of *observable* performance, while there is no AIF that is unskilled in terms of *total* performance. This means that we again have the equivalent of a 2x2 table but that the categories are different for both types of performance: neutral and unskilled vs. skilled and neutral. As it appears, the immense majority of AIFs classified either as neutral or as unskilled in terms of *observable* performance then appear as skilled in terms of *total* performance. This is in line with the findings in the previous sections since there were almost no AIFs with positive *observable* performance over the Fama and French (1992) model while there were many in terms of *total* performance. The remaining 30 AIFs are classified as neutral in terms of *total* holdings, which either represents an upgrade from *observable* performance or a stay in the same performance group. The low χ^2 (0.09) and the high related probability (76%) show that there is no clear dependence between the classification groups.

All in all, these results suggest that the greatest part of *observable* positions is more of a diversifying component than an additive one. Indeed, it appears that the performance of *observable* positions is limitedly linked to *total* performance. If anything, most AIFs tend to be skilled in terms of *total* performance regardless of their *observable* performance.

3.6 Discussion and Conclusion

This research contributes to the existing literature by offering a different methodology in assessing the "abnormal performance" of EHFs and by shedding new light on the information content of SEC 13F disclosures. In a first step, I explicitly examine the performance that is revealed by large long equity positions at the investment firm level and find that there are not many AIFs who are able to outperform with these positions. Moreover, the presence of stock picking and market timing, which should be the pillar of long equity choices, appears to be scarce. In particular, using a stock picking measure that was not previously employed in hedge funds, I show that most AIFs do not have any stock picking ability beyond what can be reached by inferring from easily collectable public information. These findings are in line with previous research mutual funds. In a second step, I examine the total performance reported by AIFs and find evidence that there are about one third that are able to produce significant outperformance, therefore showing that long equity holdings are not used to generate performance on their own; they are part of a global strategy. It remains that market timing skills are still scarce and that the majority of AIFs are not able to outperform. Finally, I try to see whether there is any link between being skilled in terms of the choice of long and large positions and being skilled globally. I find that these two types of performance are little related, thus suggesting that long and large equity holdings are most likely used as a diversifying component of performance rather than as an additive one.

These results lead to the conclusion that most AIFs are unable to outperform, but about one third of them are. Moreover, it appears that information content of *observable* positions does not allow explaining the *total* performance of AIFs. The implication for potential investors in EHFs is that it is necessary to carefully choose the manager they want to invest with since, while some of them do possess actual skills, most of them do not. Finally, the implications for the regulators are twofold. On the one hand, since AIFs' holdings do not apparently contain all the relevant information to replicate their performance, it means that they produce performance with the hidden part, so that further divulgations might well end up allowing followers to arbitrage away the remaining performance. On the other hand, given the fact that most AIFs are not able to outperform, the limited reporting obligations they are subject to give them a convenient opportunity to hide the evidence about this lack of skill from the public. In this context, further divulgation requirements would certainly lead to a better efficiency in the market by uncovering unskilled managers at the cost of skilled ones.

Appendix 3.A: Estimation of the Conditional Weight-Based Measure

I here give some computational details about the estimation of equation (4):

$$CWM_{P,t} = E\left[\sum_{j=1}^{N_P}\left(w_{j,t} - w_{b,j,t,k}\right)\left(r_{j,t+1} - E\left(r_{j,t+1}\middle|Z_t\right)\right)\middle|Z_t\right]$$

As underlined in Ferson and Khang (2002), the benchmark choice is open. It can either accommodate the weights of an external index (in the case of an index tracking fund, for instance) or be internalized based on the fund's previous holdings. Since hedge funds are assumed to be uncorrelated investments (see Brown et al. (1999), Agarwal and Naik (2004), or Lhabitant (2006, p. 25)), an external benchmark is inappropriate. I therefore follow Ferson and Khang (2002) and Grinblatt and Titman (1993) and define the benchmark weights to the ones obtained from a buy-and-hold strategy:

$$w_{b,j,t,k} = w_{j,t-k}\prod_{\tau=t-k+1}^{t}\left(1+r_{j\tau}\right)\Big/\left(1+r_{P\tau}\right),$$

where $r_{P\tau}$ is the buy-and-hold return on portfolio P using the weights in period τ. Given the quarterly disclosure requirements faced by EH funds, I set *k* to 3 months. For computation purposes, I augment $\mathbf{Z}_t$ with a constant term. I follow the simple estimation procedure detailed in Wermers (2006, p. 227-228):

A) Estimation of the regression $r_{j,t+1} = \mathbf{b}_j^{'}\mathbf{Z}_t + \varepsilon_{j,t+1}$, for each stock *j*, and storage of the coefficients $\hat{\mathbf{b}}_j$, I use an estimation window of 24 months (t-25 to t-1).

B) With the coefficients obtained in A), estimation of the regression $\sum_{j=1}^{N_P}\left(w_{j,t} - w_{b,j,t,k}\right)\left(r_{j,t+1} - \hat{\mathbf{b}}_j^{'}\mathbf{Z}_t\right) = CWM + \boldsymbol{\gamma}^{'}\mathbf{z}_t + \varepsilon_{j,t+1}$

C) where *CWM* is the measure of the manager's ability and $\mathbf{z}_t = \mathbf{Z}_t - E(\mathbf{Z}_t)$ excluding the constant term. $E(\mathbf{Z}_t)$ is measured over (t-25 to t-1).

When the information set, $\mathbf{Z}_t$, is stock-dependent, the estimation of the *CWM* above has to be slightly modified by using the portfolios' benchmark-weighted exposures to the stock-specific information sets:

A) $r_{j,t+1} = \mathbf{b}_j^{'}\mathbf{Z}_{j,t} + \varepsilon_{j,t+1}$

B) $\sum_{j=1}^{N_P}\left(w_{j,t} - w_{b,j,t,k}\right)\left(r_{j,t+1} - \hat{\mathbf{b}}_j^{'}\mathbf{Z}_{j,t}\right) = CWM + \boldsymbol{\gamma}^{'}\sum_{j=1}^{N_P} w_{b,j,t,k}\mathbf{z}_{j,t} + \varepsilon_{j,t+1}$

where $\mathbf{Z}_{j,t}$ and $\mathbf{z}_{j,t}$ are stock specific.[68]

C) Test whether CMW = 0

[68] A more elegant solution would be to follow Bange, Khang, and Miller (2003, p. 24) and assign a specific $\boldsymbol{\gamma}$ to each security, but since the portfolios generally consist of dozens or even hundreds of securities, the estimation would most often not be feasible.

Appendix 3.B: Information Set Summary Statistics

Table 3.B.1 below gives some stylized facts about the components of the information sets $\mathbf{Z}_{j,t}$ for the sample period. Information about the dividend yield, credit spread, term spread, and Treasury bill would not be informative and are thus not reported in the table.

Table 3.B.1: Information Set Summary Statistics

This table gives stylized facts about the information sets. The seven columns relate the number of events linked to each stock, that is: rating changes, stock repurchases, secondary offerings, being an M&A acquirer, being an M&A target, change in analysts' recommendations, and earnings surprises. Minimum values are not displayed and equal zero for all events. The period covered is January 1994 to June 2011.

	Rating Changes	Repurchases	SEO	M&A Acquirer	M&A Target	Rec. Changes	Surprises
Mean	0.51	3.69	0.50	0.41	0.33	21.17	16.51
Median	0	2	0	0	0	8	9
StdDev	1.46	5.98	1.44	2.73	0.57	31.53	19.69
Max	18	111	18	102	7	180	70

The table displays information about the number of corporate and analyst related events across all stocks held in AIFs' portfolios. While most stocks do not encounter any rating change, SEO, or M&A event, some of them endure up to 111. The picture is similar for the analyst related information variables. This translates the fact that AIFs do not only invest in large, well-followed stocks, but are diversified over the entire stock universe. Panel B reports the distribution of these events across all years of the sample period. Finally, the (unreported) distribution of events across the years of the sample is relatively uniform. Although there are variations across years, there is no extreme year in which an event is dramatically numerous. It remains, however, that most events tend to be more frequent in the earlier years of the sample.

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