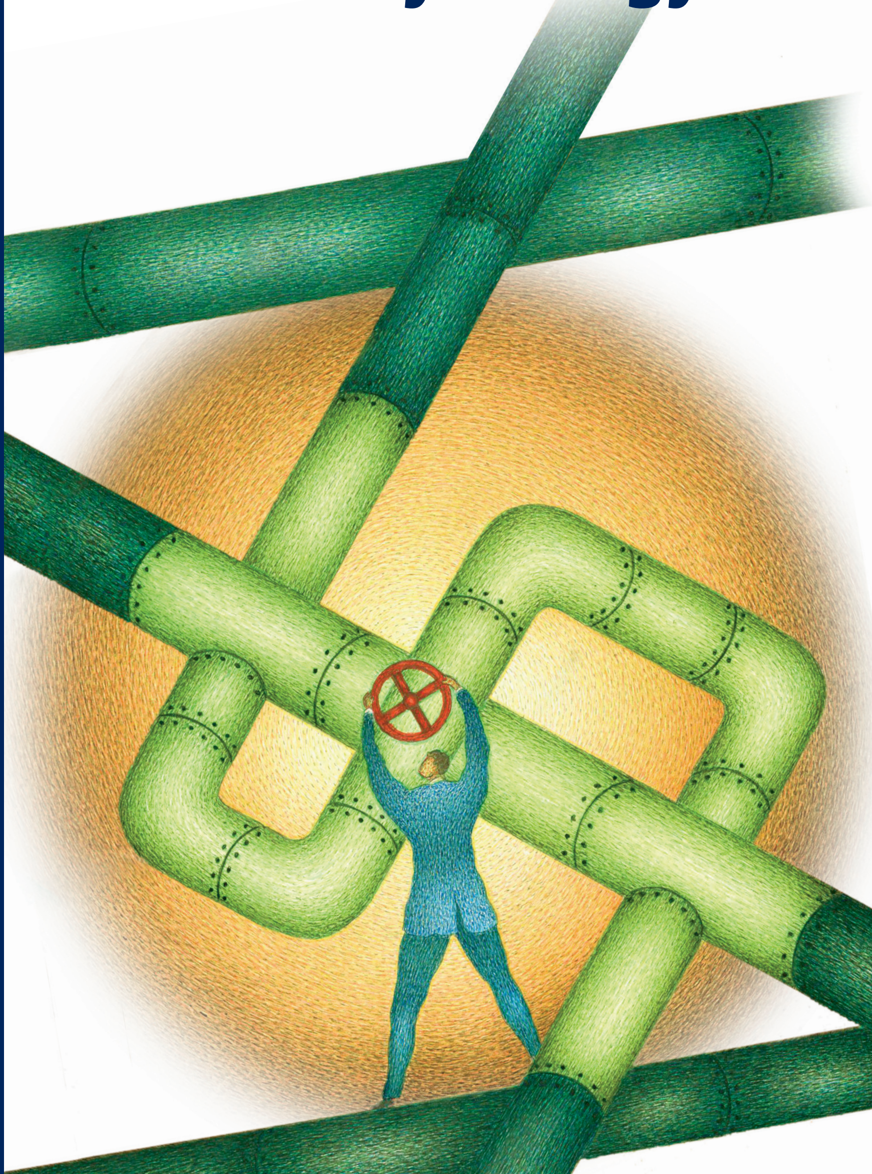
GUILLERMO BAQUERO

On Hedge Fund Performance, Capital Flows and Investor Psychology



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On Hedge Fund Performance, Capital Flows and Investor Psychology

Hedgefondsen: over kapitaalstromen, prestaties
en de psychologie van beleggers

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To Guillermo Enrique
and Constance

In memory of Edwin

"And the end of all exploring will be to arrive where we started
and know the place for the first time".
T.S. Eliot, *The Four Quartets*

Preface

Back to the year 2000, while working as a research assistant at the *Katholieke Universiteit Leuven*, I was very fortunate to become part of a research project on hedge funds, initiated by Jenke ter Horst, from *Tilburg University* and Marno Verbeek, then at *KULeuven* but already appointed at the *Rotterdam School of Management*. At that time there were only a handful of academic papers on hedge funds, most of them working papers. Little was known about this mysterious investment category, while myths and spectacular stories of rise and fall surrounded them. Six years later, we can count the number of academic papers on hedge funds on the order of hundreds, covering a multiplicity of research areas, a boom that parallels the one of the hedge fund industry itself while reflecting its rapid pace of evolution.

The seminal academic papers in the late 1990's concentrated attention, perhaps naturally, on three broad areas: the assessment of risk exposures of hedge funds, the potential survivorship biases affecting the few existing datasets, and the persistence in performance of hedge fund managers. Not surprisingly, our project had a first paper extending this literature, which eventually became the basis for Chapter 2 of this book. Jenke and Marno had a large experience investigating survivorship and selection biases, and the persistence in performance of mutual funds. Consequently, I had the best guides one could possibly have, and the most patient too. In that very first project they initiated me into the itineraries of academic research, where one finds at times agreeable hiking trails, often very narrow passages, but mostly demanding slopes, hidden crevasses, and risky ridges near the summit. What I learned from them along the path, from the very early stages until final publication, is of inestimable value. I feel honoured to have had two researchers of such stature as co-authors and guides, and my first words of deep gratitude go to them both.

Thereafter, a combination of circumstances and fortuitous encounters with several people steered the research focus of this thesis into the behaviour of investors and their motivations to open or close the valves of dollar flows to hedge funds. The interconnections between money flows and the performance of financial intermediaries has been a rising field of research during the last ten years. I am especially indebted to Susan Christoffersen, Ignacio Palacios-Huerta and Wessel

Marquering, for opportunely drawing my attention to several key theoretical articles that gave whole sense to my empirical research. Their encouraging words constituted a very timely boost of confidence to continuing ahead. Susan had the extreme kindness to read through my initial research proposal on capital flows and I am grateful to her for the many valuable insights she gave me in those early and crucial stages. My brief encounter with Ignacio at *CEMFI* paved the way for an empirical test to link the patterns of money flows to potential psychological biases, as implemented in Chapter 4. I owe him many thanks for his openness and very inspiring talks in Behavioural Economics. I am extremely grateful to Wessel Marquering for introducing me to the literature on Behavioural Finance and for the innumerable exchanges of ideas we had about these topics. We taught a course in Behavioural Finance together over the last four years, which proved to be the source of innumerable discoveries and research possibilities, partly already reflected in this book. Wessel became not only my closest colleague and a co-author but also the most supportive and hospitable friend I had in Rotterdam.

Several colleagues and friends have read through the entire manuscript of this book, or parts of it, and provided detailed comments and valuable suggestions. My special thanks go to Ben Jacobsen, Marieke van der Poel, Gail Whiteman and the members of my doctoral committee, Kees Koedijk, Frank de Jong and Ronald Mahieu.

I am indebted to ERIM, a truly doctoral school with strong impetus, for its unconditional financial and academic support. I thank Tineke van der Vhee and Olga Novikova for their outstanding administrative work. I gratefully acknowledge the financial support from the *Department of Financial Management* of RSM, the *Vereniging Trustfonds* and the *Centre for Economic Studies* (CES) of the *KULeuven*.

Along my itineraries between Leuven and Rotterdam, two close friends and colleagues were influential in many ways in the progression of this thesis, Marco Lyrio and my *paranimf* Wim Koevoets. I have spent with them countless hours of enjoyable and stimulating conversation on any possible topic, while sharing the vicissitudes of academic life. I owe them too many lessons. They have qualities that I lack so much, and they stand as examples of amazing discipline and rigor to be emulated.

Being a Latin-American, to adapt to the life in the Netherlands proved to be more than a challenge in four broad areas: the language, the notions of time and space, the sense of humour and… housing. I must admit, with much regret, that I have less than fully adapted in all four of them, in spite of much struggle. I would like to thank my colleagues from ERIM and the *Department of Financial Management* for their understanding, enormous patience, and help in those four essential aspects, and for creating a very agreeable and stimulating working environment. As a matter of fact, they all proved to be far more adaptable to my -sometimes- unconventional notions of time and space. My special thanks go to Martine Cools, Jana Firdrmuc, Reggy Hooghiemstra, Gerard Moerman, Arjen Mulder, Paolo Perego, Ben Tims, and with particular esteem to my office-mates along these years: Sara Lelli, Erik Kole, Joop Huij and Marieke van der Poel.

I read somewhere stated that a PhD thesis is primarily an indication of survival. There are many people (so many!) in this story of two cities to be thanked for assuring that I am still alive. Both in Leuven and Rotterdam, I was exceedingly fortunate to be adopted by two groups of (mostly) foreign PhD candidates who gave me a vital sense of belonging that is rarely experienced while living abroad. They became an emotional anchoring indispensable to continuing ahead. To name but a few of them, in Leuven: Helena Kim, Jürgen Germeys, Rocio Lozano, Azeta Cungu, Steven Simon, Marianna Grimaldi and Peter De Goeij; genuinely a family. In Rotterdam: ladies first, entrepreneurial, marvellously creative and warm hosts, Julia Kotlarsky, Viara Popova, Irina Kotliar, Catia Pimenta de Sousa, Marisa De Brito, Eliane Haseth and Luciana Ferreira. The gentlemen, and late hours companion workers, Xueyuan Zhang, Willem Smit, Guido Berens, Manuel Hensmans, and my *paranimf*, Julien Mostard. To all, my deep appreciation.

Marno Verbeek deserves a special place in this preface. All the way since we first met in Leuven, I counted on his exceptional mentoring whenever it was necessary. We have extensively discussed together each chapter of this book. His guidance on the most appropriate econometric techniques for each particular situation was crucial, while he challenged and gave shape to my views about a number of econometric and finance issues. I only hope that, in retribution, our joint work continues being the source of personal satisfactions. But Marno has been far more than a fully committed thesis advisor and co-author. I owe him an immense debt of gratitude for believing on me when I most hesitated along the route. And when several personal circumstances hindered the achievement of this project, his supportive hand was decisive. Those, I believe, are the qualities of a truly educator. In turn, along the journey, I am glad to have contributed to bring Marno a little bit closer to the behavioural camp (if not entirely!), and I sincerely wish we can continue many more years of collaboration.

Mi final word of gratefulness goes to my parents, Guillermo Enrique and Constance. Their everyday support and close presence, in spite of the 8000 km of land and ocean separating us, were the most precious solace along these years. What could ever compensate the immense sacrifice for such a long physical distance! This book is dedicated to them.

I myself am entirely responsible for any errors and omissions.

Guillermo Baquero Vinces
Rotterdam, October 2006

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"It's true that the best minds are drawn to the hedge fund business.
But there are not as many great minds out there
as there are hedge funds being started"
(The Wall Street Journal, June 1998)

Chapter 1

Introduction

1.1 Motivation

One of the most debated issues in financial economics remains the fact that the industry of actively managed portfolios has grown at rapid pace in spite of having underperformed both market indices and passive investment portfolios. In two seminal and influential papers, Lakonishok, Shleifer and Vishny [1992] and Gruber [1996] pointed out at this issue while studying the pension fund and mutual fund industries respectively, and raised the puzzling question of what accounts then for the enormous appeal that these financial intermediaries have among investors. This question spawned a vast academic literature over the last ten years devoted to understanding the behaviour of investors in this industry. However the puzzle deepened with the uncontested evidence that investors are in fact powerfully attracted by the best performing managers in the previous year (see e.g. Sirri and Tufano [1998]), while most studies on performance persistence of fund managers indicate that at annual horizons past performance is uninformative of future performance, consistent with standard finance models based on market efficiency (see e.g. Carhart [1997]). Different theoretical models of learning have attempted to explain the seeming inconsistent behaviour of investors, either in a frame of fully rational and competitive markets (see Berk and Green [2004]), either questioning investors' rationality (see Rabin [2002]), either appealing to asymmetric information arguments (see Palomino and Uhlig [2001]). Yet, another stream of studies have suggested that investors appear to be able to choose the best performing managers in the future (see Zheng [1999], Wermers [2003]).

The present thesis speaks to this controversy by extending the debate to the rapidly evolving industry of hedge funds. The rationale behind the choice of the hedge fund industry as our object of study lies in three main considerations. First, its stunning growth and its increasingly dominant presence in financial markets; second, the increasing concerns that, despite growth, capital is inefficiently allocated across hedge funds; and third, the several distinctive institutional features of this industry that are likely to limit investors actions or prevent them from taking timely decisions. By the end of 2004, the amount of money managed by hedge funds had risen to $1 trillion dollars, from nearly $100 billion in 1994. Over the same period, the average quarterly return was 2.7% [1], underperforming the S&P500 by nearly 30 basis points. The industry is well known for one major feature: it is subject to limited regulation and disclosure requirements[2]. Not surprisingly, blow ups and cases of fraud are relatively frequent. In spite of the industry's polemic nature and the poor quality of information, investors' overwhelming response is disconcerting. Recent surveys indicate that 56% of institutional investors are willing to increase even further their allocations to hedge funds[3], while company and public pension plans constitute the fastest growing segment among institutional investors having shares in this industry. But also access to less sophisticated investors is becoming easier as minimum investment requirements, typically above $1 million dollars, are been lowered down. Additionally, funds of hedge funds are an increasingly popular and convenient avenue for small investors. This increasing and widespread acceptance of hedge funds as an alternative to other investment vehicles has sparked a debate on the regulatory side, on concerns of insufficient levels of investor protection and a questionable ability of investors to make the right investment choices in hedge funds.

Several organizational aspects unique to the hedge fund industry have direct implications for understanding the links between investors' behaviour and growth. First, there are several consequences of limited regulation. The lack of formal disclosure requirements together with restrictions on public advertising faced by hedge funds in most countries, means that information hurdles for investors are high, calling for more circumspect choices. Further, limited regulation gives funds large flexibility in the types of positions they can take (namely, by using short selling, leverage and derivatives). It allows them to have a dynamic activity by holding diverse asset categories and actively shifting their factor exposures. The typical dynamic trading strategies employed by hedge fund managers have option-like returns

[1] Average quarterly return of the CSFB/Tremont Hedge Fund Index.
[2] Neither domestic hedge funds, nor off-shore funds are subject to SEC regulations. Domestic hedge funds are exempted from regulations and disclosure requirements because they are typically limited partnerships (i.e. fewer than 500 investors). Off-shore funds are not subject to SEC regulations because they are non-US corporations and are typically registered in a tax-haven.
[3] Source: Deutsche Bank, 2005 Alternative Investment Survey.

that cannot be captured by the usual factor models based on standard asset benchmarks (as in Sharpe [1992]). Therefore, understanding and evaluating the arbitrage strategies of hedge fund managers requires time and financial expertise. In sum, hedge fund investors are confronted to high searching costs, large information asymmetries and a complex evaluation procedure, all of which is likely to delay the decision to select a fund manager.

Besides limited regulation, a second major feature characterizing hedge funds is the structure of managerial incentives. Hedge fund managers on average receive 1% of assets under management as a fee for administering the fund, but also about 20% of annual profits. This performance-based incentive rewards managers for achieving absolute returns. The incentive fee is paid under two conditions: first, returns must surpass a hurdle rate, typically set as the risk-free rate. Second, the fund's value has to surpass a "high water-mark" which requires the manager to have recovered previous losses. This incentive structure could lead to excess risk, but this is often mitigated by a substantial managerial investment in the fund and the fact that managers are general partners and thus may incur in liabilities in case the fund goes bankrupt (see Ackermann, McEnally and Ravenscraft [1999]).

A third important feature of hedge funds is their illiquidity, a distinctive characteristic of any alternative investment. Institutional investors in the US typically participate in alternative investments through a limited partnership structure. With rare exceptions, limited partnerships are not registered with the Securities and Exchange Commission. Therefore, limited partners cannot freely trade their ownership interests in the public market. Moreover, withdrawals are restricted. Lock-up periods are common and redemptions are limited to certain dates, typically the end of a month or a quarter. Investors are thus forced to have a longer term investment horizon. There are also subscription periods and minimum investments required are large to allow participation of sophisticated investors exclusively. Finally, a fund may decide to close to new investments either because of legal requirements on the maximum number of investors or because of capacity limits. All in all, hedge fund investors' decisions of supplying capital or redeeming their shares are constrained by the organizational structure on the demand side for capital.

The four essays presented in this book constitute an empirical investigation of capital flows to hedge funds. They examine the investment process of investors, the underlying factors determining their choices and the implications for investors' wealth and for hedge funds' performance. The emphasis is placed in the interconnections between capital flows and performance, where most of the academic controversy lies. The notion of delegated portfolio management entails by nature a situation of asymmetric information between managers and investors at the time of signing the contract. Investors do not observe managers' actual investment skills and must infer their ability from observed prior performance signals and other characteristics. Within this simple frame, the questions that arise pertain to: 1) the quality of the performance signal (i.e. how informative is past performance of future performance of the manager), 2) the investors' perception of performance signals (i.e. what the impact of past performance on money flows is), and 3) the effectiveness of investors learning (i.e the relation of money flows and subsequent performance). These are the central concerns of this thesis.

A situation of asymmetric information of different nature than the one described above, develops subsequent to signing the contract. Investors do not observe the true actions of the manager and the contract is designed to align managers' behaviour with investors' interests. These agency problems are not our object of investigation here, thus the question of what the optimal contract for the manager should be is not explicitly addressed. However a number of interactions between agency problems and the issues at stake in this thesis are possible, and we shall refer to them when appropriate. For example, under certain conditions, and depending on the investment horizons of investors, their responsiveness to past performance may represent an implicit incentive for managers to adopt gambling behaviour (see e.g. Chevalier and Ellison [1997]). In turn, if this is the case, it may not be optimal for investors to choose the best performer in the past, as this might be signalling higher risk (see e.g. Palomino and Uhlig [2001]). On the other hand, one of our main results suggests that a relatively fast response of investors to bad performance may have an opposite effect and restrain managers from increasing the risk of their portfolios.

The first part of this thesis consists of two essays exploring separately and in detail the three broad questions described previously, namely, the relation between past performance and future performance, the relation between money flows and past performance and the relation between money flows and subsequent performance. The two chapters in the second part attempt each to integrate the three questions under one single unifying behavioural argument.

1.2 Outline of the thesis

Chapter 2 studies the information content of performance signals. The notion that future fund performance relates to past performance is referred to as persistence. Persistence matters as investors tend to allocate their money across funds based on past performance and it is even more relevant in the case of hedge funds since investors are confronted to lock-up periods and restrictions on withdrawals. The commonly used research methodologies of persistence evaluation, however, impose a survival conditioning bias referred to as look-ahead bias (e.g. Brown et al. [1992]). As a result, spurious performance persistence might arise. Ter Horst, Nijman and Verbeek [2001] proposed a methodology to correct for this potential bias based on a weighting procedure which requires modelling the survival process and relating it to historical performance. We apply this approach in studying the persistence in performance of hedge funds. We investigate look ahead bias for different time horizons and we show that past performance is an important determinant of subsequent liquidation rates at least over four subsequent quarters: funds with low returns are more likely to disappear than funds with high returns. This suggests that look-ahead bias is quite severe. Without corrections, at four quarter horizons average returns may be overestimated by as much as 3.8% for the worst decile. The corrections are most pronounced for the extreme deciles, which might be explained given that these deciles contain the more risky funds. For the one-quarter and four-quarter horizons, the corrected results show positive persistence in raw returns for the best three decile portfolios as they provide above average expected returns in the subsequent evaluation period. Persistence is particularly strong at quarterly horizons and somewhat weaker at annual horizons. Very importantly, our results are not driven by well performing funds closed to new investments, which indicates that performance persistence is susceptible of exploitation. Finally, we also investigate the effect of style or risk characteristics on performance persistence by subtracting from raw returns the return of the corresponding style benchmark. Following the same procedure to correct look-ahead bias as with raw returns, we find that funds in the top decile outperform their style benchmark by 6.7% (annualised) at a quarterly horizon and by 6.2% at the annual horizon. Again, the look-ahead bias is most severely present in the worst decile. At the biannual horizon hedge funds underperform, in general, their style benchmark.

These results make clear that past performance contains potentially useful information for investors. But, to what extent it actually determines investors' decisions? This is the subject of the first part of Chapter 3. The interconnections between persistence and the responsiveness of flows to past performance have been addressed by various and conflicting theoretical models. While Ippolito [1992] argues that the response of investors is stronger where the performance signal is of better quality, Berk and Green [2004] contend that in equilibrium and under decreasing returns to scale, money flows chase the winning funds to the point where the risk-adjusted expected excess return is zero. In this view, there is no persistence precisely because investors rationally shift their money to the managers with the best track records. Since hedge fund persistence is stronger at quarterly horizons and weaker at annual horizons, as shown in Chapter 2, the latter argument implies a weaker flow-performance relation at quarterly horizons compared to annual horizons. To test this hypothesis, we undertake an investigation of the flow-performance relation for hedge funds by explicitly separating the investment and divestment decisions of hedge fund investors. This separation has been overlooked in previous studies in mutual funds and hedge funds and it has several major implications. First, if money inflows and outflows are not modelled as two distinct regimes, the impact of past performance and several control variables like size, age and style upon money flows is improperly estimated. Using a regime switching model with endogenous switching reveals a number of important asymmetries between both regimes of money flows that we interpret in terms of both high searching costs and liquidity restrictions which affect differently inflows and outflows. Second, this separation allows us to identify a different response time of inflows and outflows to past performance, which implies a different shape of the flow-performance relation across evaluation horizons in the way predicted by Berk and Green [2004]. While money inflows chase the winners at annual horizons, outflows are highly responsive to the losers at quarterly horizons. This immediate and sustained response of investors to poor performance over the following two or three quarters remained hidden in previous studies over annual horizons.

Several economic implications follow, which are addressed in the second part of Chapter 3. We study the performance of the portfolio of hedge fund investors and the extent of investors' ability to exploit persistence patterns by looking into detail at the performance of aggregate investors allocations and de-allocations. Our evidence indicates that inflows are not fast enough to exploit and compete away the quarterly performance persistence among the winners, following Berk and Green [2004]'s argument. Put differently, hedge fund investors are limited in identifying and directing their capital towards the best performers in the short run. They invest mostly in funds that subsequently perform poorly, underperforming an equally-weighted allocation by nearly 50 basis points per quarter on average. Conversely, investors are fast and successful in de-allocating from the persistent losers, ensuring a disciplining mechanism for low-quality funds. Fast outflows pose a credible threat of termination that mitigates the incentives of hedge fund managers to increase volatility to meet their high watermark. We interpret our results as a consequence of the asymmetric response time of investors' purchasing and selling decisions. Our findings do not support the existence of smart money, and put under question investors' rationality.

Chapter 4 investigates the possibility that investors are less than fully rational. It asks whether the momentum strategies followed by investors as documented in Chapter 3, are at least partly the result of a well known cognitive bias referred to as *the law of* *small numbers*. Believers in the law of small numbers tend to overinfer the outcome of a random process after a small series of observations. They believe that small samples replicate the probability distribution properties of the population. We provide empirical evidence indicating that investors are mistakenly driven by this psychological bias when hiring or firing a fund manager after a successful (or losing) performance streak, in line with the theoretical model of Rabin [2002]. We analyze actual money flows into and out of hedge funds and their relationship with the length of the streak. We first show that persistence patterns have a predictive ability of future relative performance of a manager, consistent with our results in Chapter 2: the longer the winner streak, the larger the probability for a fund to remain a winner. Investors, in turn, appear to be aware of quality dispersion across managers and respond by following a momentum strategy: the longer the winning (losing) streak, the more likely they will invest in (divest from) that fund. Yet, we find that investors place excessive weight in the managers' track record as a criterion for decision. Our model shows that the length of the streak has an economically and statistically significant impact on money flows beyond rationally expected performance, which confirms a "hot-hand" bias driving to a large extent momentum investing, with potential adverse effects on investors' wealth.

Finally, Chapter 5 explores the hypothesis that one component of investors' learning takes place at the style level as the result of extrapolative expectations. This is a prevalent and a key assumption in several models of aggregate capital flows in financial markets (see e.g. Barberis and Shleifer [2003], Shleifer and Vishny [1997]). Therefore, we conduct a study of aggregate money flows by decomposing the allocation process of hedge fund investors between style allocation and fund selectivity. We first estimate a model of money flows from a number of fund specific features and style-adjusted performance. From this model we obtain an estimate of expected money flows driven by fund selectivity while we link the aggregate residuals to the performance of style indices. On the one hand, we find evidence that investors chase the winning styles in the previous one to three quarters. However, we do not find evidence of style-timing abilities, nor indications of momentum in style index performance at quarterly horizons. This suggests that momentum investing among styles is the result of a biased perception of relative performance of style indices and reflects correlated sentiment. Overall, our study raises concerns about the efficiency of investors' allocations across hedge funds.

"I know of no way of judging of the future but by the past"
Patrick Henry, Virginia Convention Speech, March 23, 1775

Chapter 2

Survival, Look-Ahead Bias and the Persistence in Hedge Fund Performance[4]

2.1 Introduction

During the last decade, hedge funds have gained tremendous popularity, particularly in the U.S. Hedge funds are similar to mutual funds in that they provide actively managed portfolios in publicly traded assets. Unlike mutual funds, however, they have broad flexibility in the type of securities they hold and the type of positions they take. For instance, hedge funds can invest in international and domestic equities and debt, and the entire array of derivative securities, and they can take undiversified positions, sell short or lever up the portfolio (see, e.g., Fung and Hsieh [1997], Liang [2000]). According to Brown and Goetzmann [2003], hedge funds are best defined by their freedom from regulatory controls stipulated by the Investment Company Act of 1940. These non-standard features of hedge funds make them an interesting investment alternative given the potential diversification benefits they offer an existing portfolio.

The question of whether mutual funds and hedge funds show persistence in their performance receives much attention in the literature (see, e.g. Gruber [1996], Carhart [1997], Agarwal and Naik [2000], Boyson [2003], and Bollen and Busse [2005]). The underlying idea behind these studies is that investors usually invest more in funds that recently performed well with the expectation that these funds will continue to do so in

[4] This chapter is based on Baquero, ter Horst and Verbeek [2005]. I am grateful to Bing Liang, Stephen Brown, Narayan Naik and Theo Nijman for many helpful comments and suggestions.

the future. In the mutual fund literature it is common that the well-performing funds attract much larger money-flows than badly performing funds (see, e.g. Sirri and Tufano [1998]). Agarwal, Daniel and Naik [2004] report similar findings for the hedge fund industry. Apparently, it is also the case in the hedge fund industry that money flows chase recent performance. Although the evidence is somewhat ambiguous, the majority of empirical studies concerning mutual funds show that active selection, on average, underperforms passive investment strategies. As Berk and Green [2004] argue, the absence of persistence in mutual fund returns might be due to the fact that persistence in returns is competed away by mutual fund investors rationally shifting their capital in search of superior investments. For hedge funds, however, there are substantial hurdles to the quick and cheap movements of capital. Hedge fund investors are often confronted with lockup periods, which may be as long as one year, during which the invested money cannot be withdrawn. Moreover, many funds apply a redemption notice period of up to 90 days. Therefore, one might expect to see more persistence for hedge funds than for mutual funds.

A major problem in evaluating hedge fund performance and its persistence is the relatively high attrition rate of funds. For example, Brown, Goetzmann and Ibbotson [1999] report an attrition rate of about 14% per year from 1987-1996. If fund survival (directly or indirectly) depends upon historical performance, it is well known that standard methods of analysis may lead to biased results (see, e.g. Brown et al. [1992], Carpenter and Lynch [1999], or ter Horst, Nijman and Verbeek [2001]). Spurious persistence patterns may arise, the form of which depends upon the survival process and the underlying heterogeneity in fund characteristics. While most studies attempt to eliminate survivorship bias by taking fund returns into account until the moment of disappearance, a second ex-post conditioning bias, the so-called look-ahead bias, is not usually taken into account. This bias develops because the employed methodology implicitly or explicitly conditions upon survival over a number of consecutive periods. When analyzing performance persistence, for example, the fact that funds dissolve in a non-random way during the ranking or evaluation period may cause a bias (see e.g. Brown et al. [1992], or Carhart [1997]). As ter Horst, Nijman and Verbeek [2001] stress, the elimination of look-ahead bias requires that the methodology be adjusted. An essential step in the correction procedure (see Brown, Goetzmann and Ross [1995]) is to model the survival process of hedge funds and how it relates to their (historical) performance.

As Fung and Hsieh [1997, 2000] and Liang [2000] note, practical problems may complicate this issue. Because the hedge fund industry is highly unregulated, and data sets may be subject to backfilling biases, a careful analysis is required. A wide range of empirical problems needs to be taken into account in order to prevent biased results (see, e.g. Fung and Hsieh [1997], Ackermann, McEnally and Ravenscraft [1999], Agarwal and Naik [2000]). One of these potential biases is a self-selection bias that arises because hedge funds voluntarily report to a data vendor. Since hedge funds are not allowed to advertise publicly, these data vendors serve as an important distribution channel. Thus, self-selection bias exists either because underperformers do not wish to make their performance known, because funds that performed well have less incentive to report to data vendors to attract potential investors, or because funds do not wish intervention in case SEC interprets reporting as illegal advertising. In contrast to mutual funds, where fund attrition is usually related to bad performance, hedge funds disappear from a database because the fund is liquidated, is closed to new investments, or the manager voluntarily decides to stop reporting. Of these reasons, liquidation is the relevant event related to the issue of survival. In our analysis, we focus on the case where death is due to liquidation, as opposed to the case where the fund continues to exist but stops reporting to the database vendor. Empirically, about two thirds of hedge fund attrition can be attributed to liquidation.

In this paper we study liquidation, look-ahead bias and the performance persistence of hedge funds that report returns in U.S.$ over the period 1994-2000. The contributions of this paper are threefold. First, and most importantly, we find that, compared to the mutual fund literature, look-ahead bias for hedge funds is quite severe, especially at one-year horizons and for funds with high attrition rates. Ignoring look-ahead bias, average returns may be overestimated by as much as 3.8% per year. In contrast, ter Horst, Nijman and Verbeek [2001], studying performance persistence of "growth" and "income" mutual funds, report only slightly different estimates after correcting for look-ahead bias. These findings show that the impact of look-ahead bias in persistence estimates is much greater for hedge funds than for mutual funds. Apparently, due to the greater total risk of hedge funds over their mutual fund counterparts, look-ahead bias is exacerbated. This is consistent with Brown, Goetzmann and Ross [1995] who document the precise relation between total volatility and return in a survival conditioned sample. Second, we extend the previous literature on hedge fund attrition, by modelling the liquidation process allowing for a flexible impact of historical returns, by incorporating fund size as well as aggregate time effects to capture economy-wide shocks that affect liquidation rates of all hedge funds, and by testing for potential sources of misspecification. Our model for hedge fund liquidation provides an alternative for Brown, Goetzmann, and Park's [2001] model, which explains survival from style-adjusted returns, the age of the fund, a measure for relative performance (i.e. the alpha), absolute performance, style-adjusted return risk and a time trend. Finally, we investigate performance persistence in hedge funds both with and without correcting for look-ahead bias using the methodology of ter Horst, Nijman and Verbeek [2001]. We conclude that correcting for look-ahead bias increases the difference in average returns of the top and bottom deciles at the annual horizon. Nevertheless, we only find a statistically significant positive persistence pattern at the quarterly horizon, no matter whether we use the corrected or uncorrected method. This corresponds to the findings of Agarwal and Naik [2000].

The remainder of this paper is organized as follows. In Section 2.2 we describe the sample of hedge funds that we employ and describe the potential biases that could arise. In Section 2.3 we model the liquidation process of hedge funds. Section 2.4 examines performance persistence for a sample of hedge funds over the period 1994 - 2000, taking into account potential biases that might be present, and discusses the robustness of our results. Section 2.5 concludes.

2.2 Hedge fund data

Hedge funds seek to deliver high absolute returns. They typically have features such as hurdle rates and incentive fees with high watermark provision, and investors in hedge funds are often confronted with lockup periods and redemption notice periods. Such withdrawal restrictions imply smaller cash fluctuations, which give fund managers more freedom in setting up long-term or illiquid positions. However, investors that follow an active selection strategy of investing in funds that recently performed well might be negatively affected by this lockup period.

As mentioned, U.S.-based (onshore) hedge funds are free from regulatory controls stipulated by the Investment Company Act of 1940. Since 1996 the number of U.S. investors allowed in unregulated funds is 500. Moreover, domestic hedge funds can accept money from “qualified investors”, who have at least $5 million to invest and have “sophisticated understanding” of financial markets. In addition they can accept money from pension funds that have at least $25 million in capital. A distinction is made between onshore and offshore funds, where the latter type is typically developed to raise capital from non-U.S. investors. Offshore hedge funds are non-U.S. corporations, typically registered in a tax-haven and, as such, they are not regulated by the SEC. While the number of net worth investors is unlimited, participation from U.S. investors is still restricted.

These distinctive features, particularly the low level of regulation and the long lockup periods, give hedge funds large flexibility in the types of positions they can take, by using short selling, leverage and derivatives. It allows them to have a dynamic position by holding diverse asset categories and moving quickly across them. Strong managerial incentives constitute a second important feature characterizing this industry. Such incentives are largely based on performance. On average, fund managers receive around 20% of annual profits, as well as an annual management fee of about 1%. There is no incentive fee until the fund has recovered past losses (i.e. returns have to surpass a threshold or "high watermark"). This incentive structure can lead to excessive risk taking, although this is often dampened by a substantial managerial investment in the fund and the fact that managers may incur in liabilities as general partners.

We use hedge fund data from TASS Management Limited. While the TASS database goes back to 1979, the initial years typically contain very few funds. By the beginning of the 1990s, however, about 200 funds were in the database, and by 1998 more than 1400 active funds were available, illustrating the increased importance of the hedge fund industry. Information on defunct funds is available only for funds that left the database in 1994 or later. For the empirical results, we therefore concentrate on the period 1994-2000. Because our interest lies in persistence at horizons of at least one quarter, we aggregate all information into quarterly levels, which has the advantage of reducing the impact of return smoothing due to the possibility that a hedge fund invests in securities that are not actively traded (see Getmansky, Lo and Makarov [2004]).

During the sample period, 612 hedge funds disappear from the sample. Using additional information provided from the TASS database, we classify these cases into "liquidation" and "self-selection" categories. The latter category refers to cases where the fund continues to exist but stops reporting to TASS. When the fund stops reporting because it is closed to new investors, at fund manager request, or fund matured, we consider it as evidence of self-selection. This is the case for 219 hedge funds. For 316 funds TASS reports that the fund is liquidated. For 77 hedge funds the reason is unknown. To make an assessment of the death reason for the funds where the disappearance reason is unknown, we estimate quarterly money flows according to the procedure mentioned in Agarwal, Daniel and Naik [2004]. We aggregate these money flows over the four quarters preceding the disappearance. If the final year money flow is negative, we classify the fund as liquidated, otherwise we consider it as self-selected. We classify 49 of the remaining cases as liquidated, and 28 funds as self-selected.

We now focus on hedge funds reporting returns in U.S.$., which results in a total of 1797 funds of which 1185 are active in the first quarter of 2000. This corresponds to an average annual attrition rate of 8.6% from 1994 to 2000[5], which is very close to the

[5] The average annual attrition rate is computed as four times the (unweighted) average quarterly attrition rate.

rate of 8.3% reported for 1994-1998 by Liang [2000] (using a similar data set). However, recall that while attrition is caused by both self-selection and fund liquidation, liquidation is the relevant event related to the issue of survival. Table I provides detailed information on the numbers of funds that enter, are liquidated or are self-selected in our data set in each quarter. For example, in the first quarter of 1997, 69 funds enter the sample, while 20 funds liquidate and 10 funds self-selected out. Given that 1069 funds were present at the beginning of the quarter, this corresponds to an attrition rate of 2.81% and a liquidation rate of 1.87%.

Table II provides average quarterly returns for different subsets of funds, as well as the returns on the S&P 500 index. The column labelled "all funds" refers to all funds that were present in a given quarter, the column labelled "active" refers to funds still active in the first quarter of 2000, and the column labelled "non-liquidated" refers to all funds that are present in a certain quarter and have not been liquidated (but may have stopped reporting) during the sample period. Finally, the column labelled "liquidated" refers to funds that had left the database by the end of the sample period due to liquidation. Clearly, Table II indicates that average returns of liquidated funds are substantially below those of non-liquidated funds. For example, the average return in the first quarter of 1995 for non-liquidated funds is 4.0%, while the average return is only 2.0% for funds that have been liquidated by 2000. Combining both subsets produces an average quarterly return of 3.4% in the first quarter of 1995. A striking result is that the difference in mean over the entire sample period between non-liquidated and liquidated funds is about 3.2% per quarter with a *t*-value of 2.89. Over the entire sample period, average returns of active funds are about 2.11% (per annum) above the average returns of all funds, a number that Malkiel [1995], Liang [2000] and others refer to as the "survivorship bias". Note that the average returns of non-liquidated funds (the combination of the subset of active funds with the funds that have been self-selected during the sample period) are about 1.52% (per annum) above the average of all funds, a number we can refer to as "liquidation bias". Both estimates are between the 1.5% of Fung and Hsieh [2000] and the numbers presented by Brown, Goetzmann and Ibbotson [1999] (3%) and Liang [2000] (2.24%). There is no clear indication of a "self-selection bias" in average returns.

While it is commonly accepted that funds with a relatively bad performance are more likely to be dissolved, it is not clear a priori over which period historical returns are important to explain liquidation. To obtain some insight into this question, Figure 1 presents conditional liquidation rates (hazard rates) by performance decile over the next eight quarters. That is, in each quarter funds are ranked on the basis of (gross, raw) returns and divided into 10 deciles. Next, for each decile, the average liquidation

Table I

Quarterly Numbers of U.S. Hedge Funds in the TASS database (1994-2000)

Table I reports the quarterly numbers of U.S. hedge funds in the TASS database that enter, liquidate, or self-select (stop reporting) during the sample period 1994-2000.

Quarter	Funds Entering	Existing	Liquidated	Self Selected	Attrition Rate	Liquidation Rate
1994 Q1	50	577	0	0	0.00	0.00
1994 Q2	38	627	0	0	0.00	0.00
1994 Q3	60	665	0	2	0.30	0.00
1994 Q4	55	723	4	1	0.69	0.55
1995 Q1	64	773	3	0	0.39	0.39
1995 Q2	47	834	3	11	1.68	0.36
1995 Q3	52	867	10	4	1.61	1.15
1995 Q4	53	905	9	1	1.10	0.99
1996 Q1	67	948	15	3	1.90	1.58
1996 Q2	51	997	17	6	2.31	1.71
1996 Q3	63	1025	17	17	3.32	1.66
1996 Q4	44	1054	21	8	2.75	1.99
1997 Q1	69	1069	20	10	2.81	1.87
1997 Q2	56	1108	16	10	2.35	1.44
1997 Q3	65	1138	15	13	2.46	1.32
1997 Q4	46	1175	11	6	1.45	0.94
1998 Q1	68	1204	12	15	2.24	1.00
1998 Q2	41	1245	20	11	2.49	1.61
1998 Q3	57	1255	24	34	4.62	1.91
1998 Q4	32	1254	19	19	3.03	1.52
1999 Q1	49	1248	15	12	2.16	1.20
1999 Q2	26	1270	17	23	3.15	1.34
1999 Q3	34	1256	25	20	3.58	1.99
1999 Q4	13	1245	39	13	4.18	3.13
2000 Q1	20	1206	33	8	3.40	2.74
Overall	1797		365	247	2.16	1.30

rate is determined for one up to eight quarters after the ranking period[6]. Figure 1 clearly shows that in the first four quarters conditional liquidation rates for loser funds (decile 1) are much higher than for winner funds (decile 10); for the last two or three quarters the relationship is almost flat. This indicates that quarterly returns are important determinants of subsequent liquidation rates over the next four or so quarters, while at eight quarters conditional liquidation rates are basically the same, independent of initial returns.

[6] The conditional attrition rate (hazard rate) corresponds to the probability of attrition in quarter $t+S$ conditional upon not being dissolved in the preceding quarters $t + 1$ to $t + S-1$, and conditional upon its performance rank in quarter t.

Table II

Average Quarterly Returns of U.S. Hedge Funds (1994-2000)

Table II reports the average quarterly returns of U.S. hedge funds from 1994-2000. The All Funds column refers to all funds present in a certain quarter; the Active column refers to funds still active in the first quarter of 2000; Non-Liquidated refers to all funds present in a certain quarter that had not been liquidated during the sample period; and Liquidated refers to funds that left the database by the end of the sample period due to liquidation.

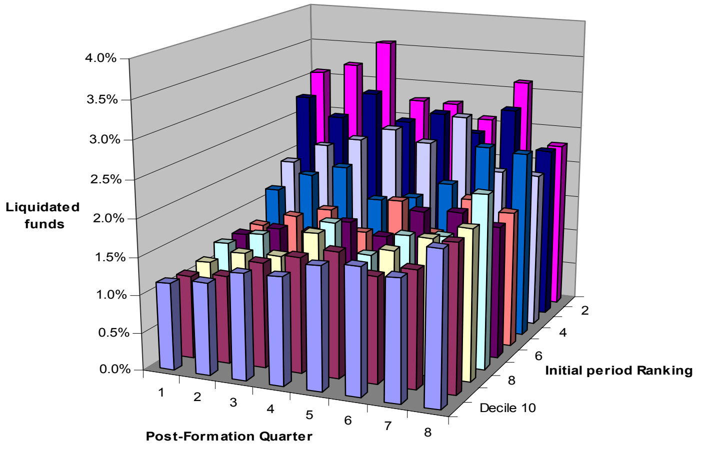
Quarter	All Funds	Active Funds	Non- Liquidated	Liquidated	S&P500
1994 Q1	-0.018	-0.015	-0.016	-0.024	-0.035
1994 Q2	0.011	0.009	0.009	0.018	0.008
1994 Q3	0.017	0.026	0.024	-0.004	0.042
1994 Q4	-0.011	-0.010	-0.011	-0.013	0.002
1995 Q1	0.034	0.040	0.038	0.020	0.100
1995 Q2	0.041	0.054	0.050	0.010	0.097
1995 Q3	0.039	0.049	0.047	0.014	0.069
1995 Q4	0.041	0.042	0.039	0.050	0.065
1996 Q1	0.031	0.036	0.036	0.014	0.067
1996 Q2	0.060	0.063	0.067	0.033	0.040
1996 Q3	0.019	0.024	0.022	0.007	0.025
1996 Q4	0.057	0.066	0.063	0.032	0.081
1997 Q1	0.045	0.046	0.046	0.042	0.030
1997 Q2	0.051	0.054	0.055	0.033	0.178
1997 Q3	0.075	0.080	0.077	0.065	0.077
1997 Q4	-0.010	-0.004	-0.007	-0.024	0.020
1998 Q1	0.048	0.058	0.055	0.010	0.146
1998 Q2	-0.012	-0.006	-0.011	-0.020	0.040
1998 Q3	-0.049	-0.049	-0.048	-0.059	-0.138
1998 Q4	0.051	0.061	0.057	0.000	0.251
1999 Q1	0.031	0.039	0.037	-0.022	0.056
1999 Q2	0.078	0.086	0.084	0.015	0.071
1999 Q3	0.005	0.007	0.006	-0.007	-0.068
1999 Q4	0.129	0.136	0.135	0.002	0.138
2000 Q1	0.060	0.063	0.063	-0.065	0.038
Overall	0.033	0.038	0.037	0.005	0.056

Data vendors commonly use a number of classification methods for hedge funds' investment styles, but none appears to be universally accepted. The TASS database employs two different classifications. The classification we use initially contains 17 styles which are mutually exclusive and closely correspond to the commonly used Tremont hedge fund style indices, simultaneously taking into account different dimensions such as asset class, geographical focus, and investment bias (i.e. U.S. equity hedge funds; European equity hedge funds; Asian equity hedge funds; pure leveraged currency; fixed income directional; and convertible fund (long only)). However, this investment style is not available for 269 funds (of which 242 are dead funds). This represents a major drawback since we intend to study survival-related

Figure 1

Conditional Liquidation Rates
from One to Eight Quarters after Initial Rank

In each quarter from 1994Q2 to 2000Q1, funds are ranked into decile portfolios based on their previous one-quarter raw returns. For the quarter subsequent to initial ranking and for each of the next 8 quarters after formation, the rate of liquidated funds as a percentage of the total number of funds still existing at the beginning of each period is determined. Thus, the bar in cell (i,j) represents the conditional probability of being liquidated in the post-formation period i given an initial ranking of decile j.



biases by investment style. To determine the style of this subsample of funds, we apply multiple discriminant analysis.

For all funds in the TASS database, we observe indications of their investment style through a set of 15 overlapping style indicators (e.g. bottom up, market neutral, fundamental). On average, each fund is characterized by at least four of these styles. The subsample of funds for which we also observe a unique style classification according to the 17 styles distinguished above, is used to determine a set of discriminant functions. These discriminant functions provide a set of scores for each of the 17 styles[7]. The discriminant functions are then used to determine the scores for the subsample of funds for which the appropriate style classification is missing. We

[7] One of these 17 style categories, pure property, contained only one fund and was not used in the discriminant analysis.

then allocate each fund to its most likely style. While such a procedure is necessarily subject to classification error, its within sample performance is rather good, with 52.3% of the funds correctly classified in one of the 17 investment styles.

Table III

Liquidated and Non-Liquidated U.S. Hedge Funds per Investment Style

Table III reports the numbers of liquidated and non-liquidated U.S. hedge funds from the TASS database by investment style.

	Onshore			Offshore		
Investment Style	Non-Liquidated	Liquidated	Total	Non-Liquidated	Liquidated	Total
Convertible Arbitrage	5	0	5	4	2	6
Dedicated Short Bias	6	0	6	6	0	6
Emerging Markets	23	9	32	139	43	182
Equity Market Neutral	46	15	61	76	23	99
Event Driven	65	5	70	78	8	86
Fixed Income Arbitrage	7	1	8	14	6	20
Global Macro	3	1	4	21	6	27
Long/Short Equity	158	19	177	154	33	187
Managed Futures	100	41	141	123	92	215
Hedge Fund Index	118	15	133	263	69	332
All Styles	531	106	637	878	282	1160

As previously mentioned, these 17 styles closely correspond to the Tremont hedge fund benchmarks. Tremont offers a series of nine hedge fund indices, computed on a monthly basis and constructed from hedge funds that have at least $10 million under management and provide audited financial statements (see, e.g. Lhabitant [2001]). In Table III, we report the number of non-liquidated and liquidated funds assigned to a Tremont index. The investment style "Hedge Fund Index" is a general hedge fund index and does not refer to a particular investment style. We assign funds without a clear investment style, such as fund-of-funds, to this category. In addition, we distinguish between offshore and onshore funds.

From Table III, it appears that "Long/Short Equity" and "Managed Futures" are the most popular investment styles, with 364 and 356 funds, respectively. Furthermore, the majority of the funds can be classified as offshore. A large proportion of about 37,4% of the funds with the investment style "Managed Futures" have been liquidated by 2000. For "Emerging Markets" this percentage is about 24.3%, while for "Dedicated Short Bias" this percentage is 0%. Clearly, these results indicate that investment style might be a significant factor in explaining fund survival. We do not observe striking differences between the liquidation rates of offshore and onshore funds, although the first group has a somewhat larger proportion of dissolved funds.

In the next section, we present a model that explains hedge fund liquidation as a function of historical returns as well as a number of fund characteristics, including investment style.

2.3 Modelling the liquidation process

Variables that are likely to affect liquidation rates of hedge funds are historical returns over a number of previous quarters, fund size, fund age, fund risk, an underwater indicator reflecting negative returns over a predetermined period, and the fund's investment style. To describe our liquidation model, let y_{it} be an indicator variable that indicates whether fund i liquidates in quarter t. Our specification describes the probability of fund liquidation (y_{it} = 0) using a longitudinal probit model, such that a fund does not liquidate if an underlying latent variable, $y^*_{it,}$ is positive. That is,

$$y^*_{it} = \alpha + \sum_{j=1}^{J} \gamma_{ij} r_{i,t-j} + \beta' x_{i,t-1} + \lambda_t + \eta_{it} \tag{1}$$

and $$y_{it} = \begin{cases} 0 & \textit{if fund i is liquidated in quarter t } (y^*_{it} \le 0) \\ 1 & \textit{otherwise} \end{cases}$$

where $r_{i,t-j}$ is the return of fund i in quarter t-j, $x_{i,t-1}$ is a vector of fund-specific characteristics, including a set of style dummies, and λ_t denotes fixed time effects describing economy-wide effects. The coefficients γ_{ij} indicate how non-liquidation (survival) is affected by the funds' returns, lagged j quarters. Compared to Liang [2000], who includes the average monthly return over the fund's history, this allows us to analyze the dynamic impact of historical returns upon fund survival. For the moment, we fix the maximum lag J at six. The γ_{ij} coefficients are assumed to be equal across funds, with the exception of those cases in which fewer than J historical returns are available -in this case, the γ_{ij} coefficients are set to zero if the corresponding return is unobserved (which is typical for funds with a recent inception date). To reduce the effect of a potential backfill bias on our estimates, information on a fund is only taken into account in the estimation of (1) the moment its age exceeds four quarters.

In Table IV we present some summary statistics of the fund-specific variables ($x_{i,t-1}$) that are included in the liquidation model (1). These descriptive statistics are based on 19245 fund/period observations. Note that 10 of the fund-specific variables are dummies. It appears that 59% of the observations are from offshore hedge funds, which, while reporting in US$, are located in tax-havens like the Virgin Islands. The average incentive fee of the fund manager is about 16%, but can be as high as 50% of realized performance. Note that these incentive fees are only obtained when the fund has recovered past losses (high water-mark). The annual management fee varies from 0% to 8% (of net asset value) and has an average of 1.6%. The age of the funds varies between 13 months and 275 months (about 23 years), with the average age of about 45 months. The average size of the hedge funds, measured by their log net asset value is 16.72, corresponding to about 18.3 million US$. Total risk is measured by the standard deviation of the previous six quarterly returns. The underwater indicator is

Table IV

Summary Statistics of Fund-Specific Variables

Table IV presents summary statistics of the fund-specific variables included in liquidation model (1). These descriptions are based on 19245 final period observations; 10 of the fund-specific variables are dummies.

Variable	Mean	Std. Dev.	Min	Max
OffShore	0.593	0.491	0.000	1.000
Incentive fees	15.925	7.902	0.000	50.000
Management fees	1.617	1.064	0.000	8.000
ln(NAV)	16.720	1.772	7.578	23.297
ln(Age)	3.808	0.659	2.565	5.617
$\ln(\text{Age})^2$	14.937	5.087	6.579	31.548
St.dev	0.084	0.083	0.001	2.189
Underwater	0.170	0.375	0.000	1.000
Emerging Markets	0.103	0.304	0.000	1.000
Equity Market Neutral	0.073	0.260	0.000	1.000
Event Driven	0.100	0.300	0.000	1.000
Fixed Income Arbitrage	0.011	0.107	0.000	1.000
Global Macro	0.022	0.146	0.000	1.000
Long/Short Equity	0.185	0.388	0.000	1.000
Managed Futures	0.218	0.413	0.000	1.000
Fund-of-funds	0.203	0.403	0.000	1.000

equal to one if a fund has a negative cumulative return over the past eight quarters[8], which occurs in 17% of the cases. About 20% of the observations belong to so-called funds-of-funds, while only 1% corresponds to hedge funds with a fixed income arbitrage investment style. We estimate (1) using all investment styles, while including style dummies to capture the possibility, as suggested by the summary statistics in Table III, that different investment styles are associated with different overall liquidation rates. Given the limited number of funds with “convertible arbitrage” or “dedicated short bias” investment styles, no dummies are included for these styles and the funds are allocated to the general hedge fund index (reference category). In addition, the model includes time dummies to capture aggregate shocks to the liquidation rates. Because fund size (NAV) is not available in each period for all funds in our sample, we use the most recent observation of net asset value available

[8] The cumulative return is determined over at least five quarters with a maximum of eight quarters.

from the TASS database. However, in 7% of the cases some observations remain for which NAV is missing and cannot be imputed. Because we do not want to eliminate these observations from our persistence analysis in Section 2.4, we also estimate a second liquidation model in which ln(NAV) is excluded. This model, based on a smaller information set, is used to correct for look-ahead bias whenever information on net asset value is missing. The estimation results, based on either 19245 or 20413 fund/period observations, are presented in Table V and Table VI, respectively[9].

Table V

Estimation Results of the Liquidation Model Including NAV

Table V reports the estimation results of the liquidation model, including net asset value (size). Coefficient estimates for the time dummies are not reported.

Parameters	Estimate	Std. Error	Parameters	Estimate	Std. Error
Intercept	2.171	0.857	St.dev	1.676	0.404
r1	0.913	0.229	Underwater	-0.387	0.070
r2	0.820	0.246	ln(Age)	-1.001	0.438
r3	1.153	0.252	$\ln(\text{Age})^2$	0.142	0.058
r4	0.290	0.252	Emerging Markets	-0.137	0.090
r5	0.101	0.234	Equity Market Neutral	-0.219	0.101
r6	-0.384	0.203	Event Driven	0.165	0.131
OffShore	-0.136	0.057	Fixed Income Arbitrage	-0.194	0.223
Incentive Fees	-0.007	0.004	Global Macro	-0.145	0.206
Management Fees	-0.021	0.026	Long/Short Equity	-0.083	0.088
ln(NAV)	0.171	0.017	Managed Futures	-0.076	0.078
Observations:	19245				
Log likelihood:	-1358.2194		χ^2 test: 548.25 (DF =42)		
Pseudo R^2:	0.1679		(p=0.0000)		

Table VI

Estimation Results of the Liquidation Model Excluding NAV

Table VI presents estimation results of the liquidation model, excluding net asset value (size). Coefficient estimates for the time dummies are not reported.

Parameters	Estimate	Std. Error	Parameters	Estimate	Std. Error
Intercept	4.189	0.797	St.dev	0.735	0.377
r1	1.052	0.218	Underwater	-0.453	0.068
r2	1.044	0.236	ln(Age)	-0.599	0.414
r3	1.374	0.243	$\ln(\text{Age})^2$	0.098	0.055
r4	0.447	0.235	Emerging Markets	0.031	0.086
r5	0.307	0.225	Equity Market Neutral	-0.184	0.096
r6	-0.065	0.194	Event Driven	0.245	0.126
OffShore	-0.104	0.055	Fixed Income Arbitrage	-0.066	0.219
Incentive Fees	-0.008	0.003	Global Macro	0.089	0.208
Management Fees	-0.031	0.025	Long/Short Equity	-0.054	0.084
			Managed Futures	-0.284	0.073
Observations:	20413				
Log likelihood:	-1452.3809		χ^2 test: 455.82 (DF =41)		
Pseudo R^2:	0.1356		(p=0.0000)		

[9] The estimates for the time dummies are available from the authors.

The results show that the impact of historical returns upon fund survival is positive and significant: funds with high returns are much less likely to liquidate than funds with low returns. The impact of the individual quarters decreases with each lag. Consistent with Brown, Goetzmann and Park [2001], the underwater indicator has a highly significant and negative impact upon survival, indicating that a negative aggregated return over the previous two years increases the probability that a fund will liquidate. A comparison with the results for mutual funds in ter Horst, Nijman and Verbeek [2001] suggests that hedge fund survival is more strongly related to historical performance, both economically, as measured by the coefficient magnitudes, and statistically, as reflected by the corresponding *t*-ratios. As the χ^2 test indicates, the variables in the models are jointly highly significant, while many of the variables are also individually significant. For example, fund size has a strong negative impact upon liquidation: smaller funds are, ceteris paribus, much more likely to be liquidated than large funds. Surprisingly, the magnitude of the incentive fee for a manager affects the probability of survival in a negative and significant way, i.e. the higher the incentive fee, ceteris paribus, the more likely it is that the fund will liquidate in the next quarter. Age has a significant nonlinear effect: young hedge funds have a high probability of disappearance, but as funds become more mature, the liquidation probability decreases. Most investment style dummies have a significant impact on survival probabilities. The funds with an "event driven" style have, ceteris paribus, the highest probability to survive, while funds classified as "equity market neutral" have the lowest survival probability. Interestingly, no significant effect is found for the "managed futures" style when fund size is included in the specification, whereas it is highly significant and negative when size is dropped.

The results of Brown, Goetzmann and Park [2001], who estimate several alternative models for hedge fund failure, indicate a positive and statistically significant impact of style-adjusted return risk upon fund failure, which is consistent with the idea that high risk funds are more likely to experience extreme returns and therefore are more likely to terminate (Brown et al [1992]). However, in the current specifications explaining fund liquidation, standard deviation is statistically insignificant when fund size is excluded (Table VI), but becomes significant and positive when fund size is added (Table V), suggesting that with a given return history and fund size, high risk funds experience a somewhat lower liquidation probability[10]. This is not inconsistent with the finding that high-risk funds are more likely to liquidate, but it does indicate

[10] The results in Tables V and VI are not driven by outliers. Moreover, the results are similar if alternative measures for standard deviation are used (e.g. based on monthly returns).

that high-risk funds are allowed to have more extreme negative returns than low-risk funds before they decide to liquidate.

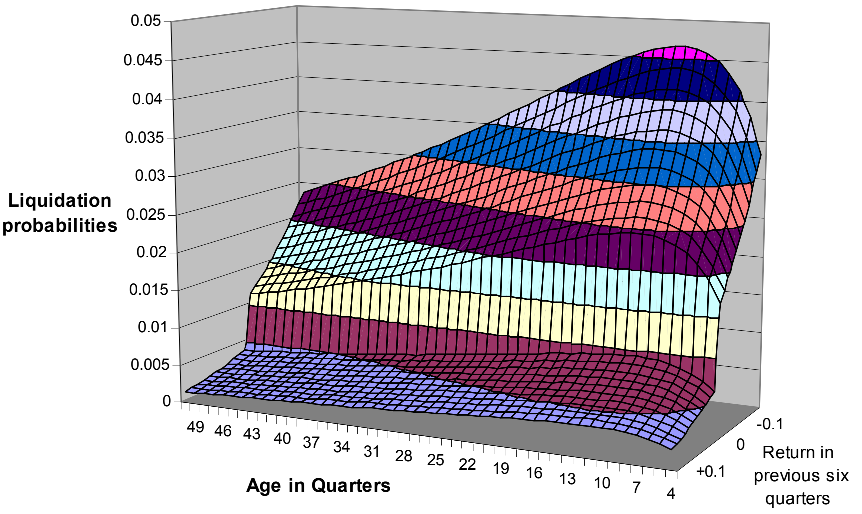
The specification reported in Table V is tested against a number of more general alternatives. For example, we test whether the model is significantly improved when returns lagged seven, eight and nine quarters are added. The value of the likelihood ratio test statistic is 4.82, which is insignificant at the 10% level[11]. Furthermore we test the logarithmic specification in size against a more general alternative. The likelihood ratio test on the inclusion of $\ln(NAV)^2$ produces an insignificant value of 0.09. In summary, the results of these tests do not indicate serious shortcomings of the current specification.

To obtain an indication of the probability that an arbitrary hedge fund will liquidate in the next quarter given its past record of returns and its age, we use the estimates of (1) to compute the liquidation probability. In Figure 2 we report the liquidation probabilities for funds with different ages, with a minimum of 5 quarters, where historical returns vary from -10% to +10% for each of the last six quarters. The underwater indicator is set equal to one if the cumulative return over the previous six quarters is negative. All other variables are fixed at their sample average. It appears that for a fund with an age of 12 quarters and a return record of -10% for each of the last six quarters, the probability of liquidation in the next quarter is about 4.6%, while for a fund with the same age but a return record of +10% for each of the last six quarters, the liquidation probability is only 0.5%. Note that the underwater indicator has a strong impact on the probability of liquidation. If a fund is underwater, implying that the manager will not receive the incentive fee, the probability that a fund will disappear increases from almost 1% to about 2.5% for a 12-quarter old fund with past average returns around 0%. Clearly, fund age affects liquidation nonlinearly. Apparently, liquidation rates of young funds are less affected by poor historical performance than those of funds that have been around for several years, however, relatively older and established funds are also less likely to liquidate. These results are consistent with Boyson [2003], who investigates the relation between survival, past performance and manager tenure. According to her results, young managers are much more likely than old managers to be terminated for poor performance.

[11] The asymptotic distribution is χ^2 with 3 degrees of freedom.

Figure 2
Liquidation Probabilities Implied by Estimated Survival Model

Figure 2 shows liquidation probabilities by fund age and the previous six quarters' returns as implied by the estimated liquidation model.



2.4 Estimating Persistence in Performance

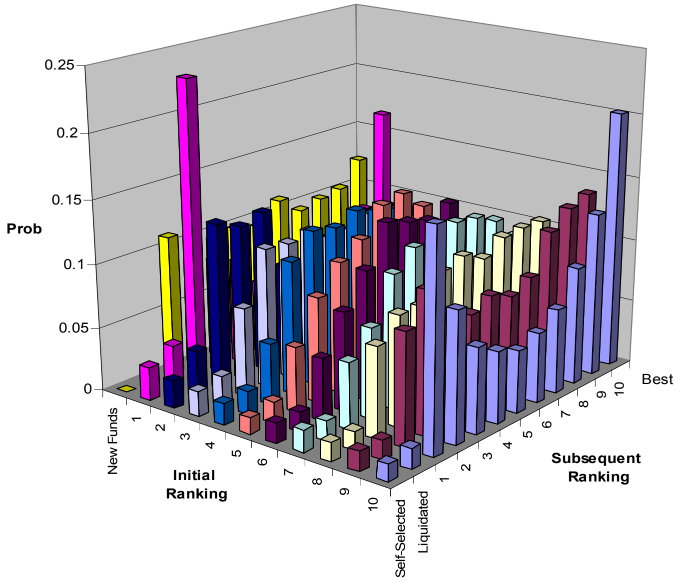
The question whether hedge funds exhibit performance persistence has received much attention in the recent literature. For example, Brown, Goetzmann and Ibbotson [1999] use annual returns of offshore hedge funds and do not find persistence in their sample. Agarwal and Naik [2000] use quarterly, half-yearly and annual (post-fee and pre-fee) returns and examine short- as well as long-term persistence. They find that persistence is highest at the quarterly horizon and decreases when moving towards a yearly horizon. However, persistence in quarterly returns can be affected by the fact that most hedge funds only report on an annual basis. The investment style of hedge funds is not relevant for the persistence pattern that Agarwal and Naik [2000] find.

In this section, we first examine whether there is performance persistence in raw returns. Basically, we examine whether winning funds are more likely to be winners in the next period. To obtain an indication of the probabilities that hedge funds from the top deciles will remain in the top deciles, Figure 3 reports a contingency table of quarterly performance. Each quarter all funds are ranked in ten deciles, and this is compared with their rank in the previous quarter. The table also incorporates liquidated funds and new funds that enter the database (after a backfill period of four quarters) and is, therefore, not affected by look-ahead bias. Funds that are in the top decile (decile 10) have a probability of about 20% of being a top performer in the next quarter again, and have a probability of about 17% of ending up in the loser decile (decile 1). The funds that performed worst (decile 1) in the ranking period, have the highest probability of being a loser again (about 24%), and a probability of about 4% of being liquidated in the next quarter. Moreover, these funds have a high probability (more than 16%) of ending up in the winner decile. The most likely explanation for this finding is that funds in the extreme deciles (deciles 1 and 10) are more risky than those in the other deciles, as more risk is associated with higher average returns, but also with greater chances of extremely good and extremely poor outcomes. Such funds are more likely to move from the winner to the loser decile or vice versa. We observe that funds from the middle deciles are more likely to remain in the middle deciles than to move to one of the extreme deciles. The probability of being liquidated in the next quarter is relatively high for the lower deciles.

Figure 3

Contingency of Quarterly Performance
(ranking criterion: past one-quarter raw returns)

Hedge funds are sorted each quarter from 1994Q1 to 2000Q1 into ten rank portfolios based on their previous one-quarter net raw returns, provided they have a return history of at least 4 quarters to correct for backfilling bias. This initial ranking is compared to the fund's subsequent one-quarter return ranking. The bar in cell *(i,j)* represents the conditional probability of achieving a subsequent ranking of decile *j* given an initial ranking of decile *i*. New funds are placed in a separate category. In this case bar in cell *(i,j)* represents the conditional probability of achieving a ranking of decile *j* in the quarter subsequent to the starting-operations quarter.



The previous analysis does not provide information about the levels of average returns across the different deciles. To investigate this, we rank the funds in the so-called ranking period on the basis of past average returns over the previous quarter, the previous year or the previous two years. This ranking is broken down into 10 deciles. To avoid double counting, fund-of-funds are excluded from this exercise. In the subsequent evaluation period we calculate the average returns for each of these deciles. For instance, for the one-year ranking period this implies that the first ranking is based on returns over the year 1994 (i.e. the first year of our sample), while the evaluation period is the year 1995. The procedure is repeated over the entire sample period, moving forward by one quarter at the time and adjusting the sample to include those funds that have a sufficiently long return history. As a result, these rankings are conditional upon survival over the ranking and evaluation periods, and thus, multi-period selection bias or look-ahead bias may distort the empirical results. As before, we take account of potential backfill biases by only using information on a fund once its age exceeds four quarters.

As is well known, spurious performance persistence patterns that are due to look-ahead bias might arise (Carpenter and Lynch [1999]). Following the correction procedure introduced by ter Horst, Nijman and Verbeek [2001], we present persistence results that are corrected for look-ahead bias. Basically, the correction method implies a multiplication of the performance measure (e.g. the average return over the ranking period) with a weight factor, which is the ratio of an unconditional non-liquidation probability in the numerator and a conditional non-liquidation probability in the denominator. The latter one can be obtained from the estimated liquidation process that is reported in Section 2.3, while the unconditional probability can be estimated by the ratio of the funds that were not liquidated during the ranking period to the number of funds present in the sample at the beginning of the ranking period. The correction for the average returns over the evaluation period is similar, except that the unconditional probabilities are conditional upon the fund's decile during the ranking period (but not upon the entire return history)[12].

Consider the case of interest here, namely persistence in raw returns at the annual horizon. This implies that we can only use information on funds that have reported returns for at least four consecutive quarters. Let $Y_{it} = 1$ if fund i has survived during quarters t to $t + 3$ ($Y_{it} = 0$ otherwise) and let R_i denote the entire vector of fund returns. The probability that a fund is observed in quarters t to $t + 3$, after a backfill period of

[12] The correction assumes that self-selection is determined exogenously.

four quarters, and given both its returns and characteristics X_{it} (age, management fees, investment style, net asset value), can be obtained from the liquidation model. Assuming that liquidation is independent of current or future returns, this probability is

$$P\{Y_{it} = 1 \mid R_i, X_{it}\} = \prod_{s=t}^{t+3} P\{y_{i,s} = 1 \mid r_{i,s-1}, \ldots, x_{i,s-1}\}. \tag{2}$$

Estimates for the probabilities at the right-hand side are directly obtained from the probit model. The unconditional non-liquidation probability can easily be estimated by the ratio of the appropriate number of funds that did not liquidate between quarter t and $t + 3$ and the number of funds that were in the sample in quarter $t-1$. As ter Horst, Nijman and Verbeek [2001] show, multiplying the returns for funds used in the analysis by the resulting weight factors provides the unconditional distribution of returns of interest to us.

In Table VII we report the empirical persistence of raw returns at quarterly and annual horizons, both with and without correcting for look-ahead bias. The results for the annual horizon are also represented graphically in Figure 4. All estimates are based on the full sample of hedge funds, excluding fund-of-funds. The results in Table VII show some interesting patterns. At the annual level, we see that the persistence pattern without corrections is slightly J-shaped. Given the results of Hendricks, Patel and Zeckhauser [1997], Brown, Goetzmann, Ibbotson and Ross [1997], and ter Horst, Nijman and Verbeek [2001], a pattern like this may be attributable to look-ahead bias. Correcting for look-ahead bias flattens the J-shaped pattern. Without corrections, average returns may be overestimated by as much as 3.8% (decile 1), which is statistically significant with a *t*-value of 2.59. This shows that the impact of look-ahead bias upon persistence measures may be quite severe. In contrast, ter Horst, Nijman and Verbeek [2001], studying persistence in performance of "growth" and "income" mutual funds, report only slightly different estimates after correcting for look-ahead bias. These findings show that the impact of look-ahead bias in persistence estimates is much larger for hedge funds than for mutual funds. The most likely explanation for this is the stronger relation between hedge fund survival and historical performance. The corrections for look-ahead bias are most pronounced for the extreme deciles, which is to be expected given that these deciles typically contain the more risky funds. The finding that look-ahead bias has a U-shaped pattern is due to the cross-sectional dispersion in fund specific risk: funds ranked in one of the extreme deciles are more likely to be high risk funds and thus are less likely to survive. Conditional upon the fact that a fund has not been liquidated during the evaluation period, it will make better returns than average (see ter Horst, Nijman and Verbeek [2001] for additional discussion).

Table VII

Persistence Estimates for One-Quarter and Four-Quarter Raw Returns

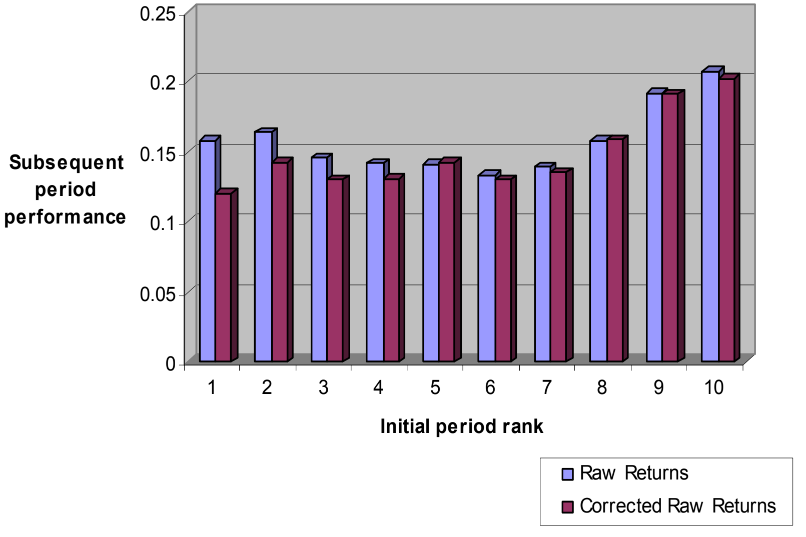
Each quarter funds are sorted into 10 rank portfolios based on their previous one- or four-quarter returns, respectively. Next, average returns over the next one or four quarters are computed for each decile. Using returns from 1994-2000, this produces a time series for each decile of 22 average one-quarter returns and 16 (overlapping) average four-quarter returns. The numbers in the table are the annualized time-series averages and their standard errors are in parenthesis. The standard errors are corrected for autocorrelation based on the Newey-West approach. The corrected figures employ a weighting procedure to eliminate look-ahead bias.

	Average Performance (Raw Returns)			
	One-Quarter		Four-Quarter	
Decile	Non-corrected	Corrected	Non-corrected	Corrected
1 (losers)	0.092	0.083	0.159	0.121
	(0.076)	(0.077)	(0.097)	(0.099)
2	0.116	0.117	0.164	0.143
	(0.048)	(0.047)	(0.064)	(0.056)
3	0.124	0.124	0.146	0.131
	(0.034)	(0.033)	(0.048)	(0.045)
4	0.118	0.116	0.142	0.131
	(0.030)	(0.030)	(0.041)	(0.037)
5	0.121	0.124	0.141	0.143
	(0.021)	(0.021)	(0.027)	(0.029)
6	0.130	0.126	0.134	0.131
	(0.024)	(0.024)	(0.034)	(0.035)
7	0.143	0.141	0.139	0.135
	(0.025)	(0.026)	(0.041)	(0.042)
8	0.165	0.168	0.159	0.159
	(0.034)	(0.034)	(0.034)	(0.035)
9	0.197	0.197	0.192	0.191
	(0.045)	(0.044)	(0.051)	(0.051)
10 (winners)	0.206	0.204	0.208	0.203
	(0.067)	(0.066)	(0.109)	(0.109)
Winners-Losers	0.115	0.121	0.049	0.082
	(0.076)	(0.079)	(0.074)	(0.080)

At the quarterly horizon, we clearly observe positive persistence in hedge fund returns, particularly for the four best deciles. For example, the top decile provides an average return over the next quarter of 20.4% (annualized) while the bottom decile provides only about 8.3%. This corresponds to the findings of Agarwal and Naik [2000], who also find strong persistence at a quarterly horizon over the period 1982-1998. However, in their study the issue of look-ahead bias is not taken into account. The corrections for look-ahead bias reduce most of the averages somewhat, although the bias is much less than in the case of an annual horizon. Because these estimates refer to only one quarter, it is not surprising that the look-ahead bias is less severe.

Figure 4

Annual Persistence in Raw Returns



The results for a two-year horizon are reported in Table VIII. Compared to Table VII, the number of funds that can be used to estimate persistence is substantially reduced. Both the corrected and uncorrected persistence estimates show an increasing pattern over the deciles, with the exception of the top decile. Nevertheless, the winners outperform the losers by a statistically insignificant 7%. To investigate the impact of the extreme observations, we also compute average returns in the evaluation period giving zero weight to the 1% lowest and 1% highest returns. We anticipate this to result in more robust estimates for the expected returns during the evaluation period. The results are reported in the last column of Table VIII and reduce the performance of the winner-loser portfolio to 4.4%.

One explanation for positive persistence in raw returns, after correcting for look-ahead bias, is the presence of cross-sectional variation in expected fund returns due to heterogeneous style or (systematic) risk characteristics. As Boyson [2003] argues, controlling for style is important in an analysis of performance persistence among hedge funds. Therefore, we also examine persistence in risk-adjusted returns. For hedge funds this is somewhat more complicated than for mutual funds. Hedge fund returns typically have low correlations with returns on standard asset pricing factors like the return on the market portfolio. This is an important feature of hedge funds and makes them an interesting investment vehicle for diversification opportunities. The reason for the low correlation is that hedge funds often follow highly dynamic

Table VIII

Persistence Estimates for Eight-Quarter Raw Returns

Each quarter funds are sorted into 10 rank portfolios based on their previous eight-quarter returns. Next, average returns over the next eight quarters are computed for each decile. Using returns from 1994-2000, this produces a time series for each decile of 8 (overlapping) average eight-quarter returns. The numbers in the table are the annualized time-series average returns and their standard errors are in parenthesis. The standard errors are corrected for autocorrelation based on the Newey-West approach. The corrected figures employ a weighting procedure to eliminate look-ahead bias. The robust estimates give zero weight to the 1% lowest and 1% highest returns.

	Average Performance (Raw Returns)		
	Eight Quarter		
Decile	Non-corrected	Corrected	Corrected (Robust Estimates)
1 (losers)	0.039	-0.021	0.020
	(0.041)	(0.046)	(0.024)
2	0.076	0.050	0.044
	(0.096)	(0.093)	(0.059)
3	0.116	0.113	0.102
	(0.059)	(0.063)	(0.045)
4	0.110	0.107	0.105
	(0.021)	(0.029)	(0.030)
5	0.121	0.116	0.113
	(0.033)	(0.038)	(0.040)
6	0.131	0.115	0.115
	(0.042)	(0.043)	(0.044)
7	0.159	0.159	0.145
	(0.057)	(0.052)	(0.041)
8	0.174	0.162	0.153
	(0.068)	(0.052)	(0.033)
9	0.152	0.155	0.156
	(0.047)	(0.055)	(0.049)
10 (winners)	0.083	0.050	0.064
	(0.082)	(0.100)	(0.082)
Winners-Losers	0.044	0.070	0.044
	(0.095)	(0.104)	(0.079)

investment styles, and are allowed to invest in derivatives, to take short positions or to make use of leverage. The question of how to obtain risk-adjusted hedge fund returns receives a lot of attention in the current literature. Basically, two approaches can be found, the first approach makes use of indices that have option like pay-off structures (see, e.g. Fung and Hsieh [1997], [2001], and Agarwal and Naik [2004]), while the second approach uses peer group hedge fund indices (see, e.g. Lhabitant [2001]). The idea behind the first approach is that hedge fund strategies generate option-like returns that should be reflected in the benchmark indices. The second approach avoids the problem and simply makes use of indices constructed out of other hedge funds with the same reported style as the funds under consideration. The first approach is only suitable for very specific trading strategies, while the second approach is much more general. However, it is more appropriate to denote the obtained returns generated from the second approach as style-adjusted or relative returns instead of risk-adjusted returns. Given that in our study the focus is on persistence in hedge fund returns in general, and not for a specific investment style, we decided to follow the second approach, and examine whether hedge funds show persistence in style-adjusted or relative returns. The style benchmarks we employ are the Tremont hedge fund style indices, which correspond to the investment styles of the hedge funds in our sample (see Table III). Basically, we subtract from the raw return of a hedge fund the return on the style benchmark the fund belongs to. Similarly to the procedure followed in case of raw returns, we examine whether there is persistence in relative returns.

In Table IX we report persistence of relative returns at quarterly and annual horizons, with and without corrections for look-ahead bias. Figure 5 presents a visual representation of the results at the annual frequency. Results for the biannual horizon are reported in Table X. At the annual horizon we find that the top three deciles (decile 8, 9 and 10) outperform their style benchmark. The outperformance, although statistically insignificant, increases from about 1% (decile 8) to somewhat more than 6% for decile 10 at an annual basis (corrected relative returns). For the remaining deciles we find underperformance and insignificant persistence of negative relative returns. The effect of look-ahead bias is most severe for decile 1, where the bias is about 3%. At a quarterly horizon the persistence of relative returns is stronger. For decile 7 this outperformance is about 2% and increases to about 6.7% for decile 10. Similar to the results of the raw returns, the effect of look-ahead bias is much smaller at a quarterly horizon than at an annual horizon. At a biannual horizon, reported in Table X, we do not observe any persistence of relative returns. Almost all funds show, on average, underperformance with respect to their corresponding style benchmark. When the 1% highest and lowest observations are omitted from the evaluation period, we find qualitatively similar results.

A major explanation for the fact that we observe more persistence in hedge fund returns than what is usually found for mutual fund returns, is that liquidity in the hedge fund industry is severely restricted. While Berk and Green [2004] argue that past performance is unable to predict future returns of mutual funds due to the fact that mutual fund investors chase performance by investing more in funds that recently performed well (see, e.g. Chevalier and Ellison [1997], Sirri and Tufano [1998]), hedge funds are characterized by lockup periods and redemption notice periods. Moreover, regulatory restrictions may limit the growth of (onshore) hedge funds. When investment strategies employed by hedge fund managers cannot be scaled up without limit, performance fees and high watermark contracts provide incentives to the manager to close the fund for new investors or otherwise limit the inflow of new money (see Goetzmann, Ingersoll and Ross [2001]). However, the persistence found above may not be exploitable if the funds in the top deciles are closed for new investments. To address this issue[13], we analyze the subsequent performance of the top three deciles, while concentrating only on those funds that are actually taking new money. While our database provides information about whether or not a fund is closed

Table IX

Persistence Estimates for One-Quarter and Four-Quarter Style-Adjusted Returns

Each quarter funds are sorted into 10 rank portfolios based on their previous one- or four-quarter style-adjusted returns, respectively, where style-adjusted returns are raw returns in deviation of the returns on an appropriate style index. Next, average style-adjusted returns over the next one or four quarters are computed for each decile. Using returns from 1994-2000, this produces a time series for each decile of 22 average one-quarter returns and 16 (overlapping) average four-quarter returns. The numbers in the table are the annualized time-series averages and their standard errors are in parenthesis. The standard errors are corrected for autocorrelation based on the Newey-West approach. The corrected figures employ a weighting procedure to eliminate look-ahead bias.

	Average Performance (Style-Adjusted Returns)			
	One-Quarter		Four-Quarter	
Decile	Non-corrected	Corrected	Non-corrected	Corrected
1 (losers)	-0.029	-0.033	-0.007	-0.036
	(0.042)	(0.043)	(0.069)	(0.063)
2	-0.021	-0.018	-0.019	-0.028
	(0.022)	(0.022)	(0.043)	(0.042)
3	-0.034	-0.036	-0.010	-0.010
	(0.015)	(0.016)	(0.029)	(0.029)
4	-0.022	-0.021	-0.014	-0.018
	(0.011)	(0.011)	(0.022)	(0.021)
5	-0.001	-0.003	-0.015	-0.020
	(0.011)	(0.012)	(0.014)	(0.016)
6	-0.002	-0.002	-0.010	-0.012
	(0.014)	(0.014)	(0.011)	(0.011)
7	0.019	0.019	-0.006	-0.007
	(0.013)	(0.013)	(0.014)	(0.014)
8	0.038	0.040	0.016	0.010
	(0.021)	(0.021)	(0.013)	(0.014)
9	0.052	0.047	0.018	0.014
	(0.025)	(0.025)	(0.016)	(0.015)
10 (winners)	0.065	0.067	0.066	0.062
	(0.037)	(0.037)	(0.053)	(0.054)
Winners-Losers	0.094	0.100	0.073	0.099
	(0.067)	(0.068)	(0.090)	(0.083)

[13] I am grateful to Narayan Naik for this suggestion.

to investment, this applies only at the time the data were purchased. To solve this problem, we use money flows during the evaluation period to classify funds as closed or open to investment. In particular, we define funds as being closed to investment if average cash flows during the four quarters before the end of the evaluation period are less than 1% [14].

Figure 5

Annual Persistence of Style-Adjusted Returns

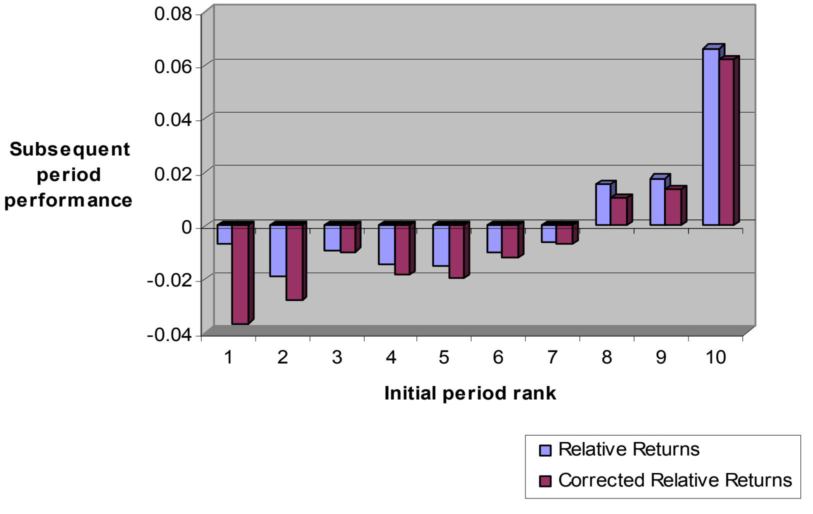


Table XI presents the estimated average returns for the top three deciles when we exclude funds that are classified as closed for investment and contrasts them with the corresponding figures based on the entire sample of funds. In the case of decile 10, the average return increases from 20.4% to 22.2% at the quarterly horizon, while at the annual horizon, the average return increases from 20.2% to 21.7% (corrected returns). From Table XI we conclude that the persistence results are robust for excluding funds that are classified as closed for new investments. Apparently, the persistence is not driven by well performing funds that are closed for new money, suggesting that it might be exploitable for investors.

[14] Experimenting with alternative cut-off rates leads to very similar results.

Table X

Persistence Estimates for Eight-Quarter Style-Adjusted Returns

Each quarter funds are sorted into 10 rank portfolios based on their previous eight-quarter style-adjusted returns. Next, average returns over the next eight quarters are computed for each decile. Using returns from 1994-2000, this produces a time series for each decile of 8 (overlapping) average eight-quarter returns. The numbers in the table are the annualized time-series average returns and their standard errors are in parenthesis. The standard errors are corrected for autocorrelation based on the Newey-West approach. The corrected figures employ a weighting procedure to eliminate look-ahead bias. The robust estimates give zero weight to the 1% lowest and 1% highest returns.

	Average Performance (Style-Adjusted Returns)		
	Eight Quarter		
Decile	Non-corrected	Corrected	Corrected (Robust Estimates)
1 (losers)	-0.039	-0.116	-0.050
	(0.099)	(0.095)	(0.068)
2	0.008	0.004	-0.013
	(0.064)	(0.062)	(0.040)
3	0.001	-0.007	-0.014
	(0.049)	(0.048)	(0.040)
4	-0.005	-0.009	-0.007
	(0.034)	(0.028)	(0.026)
5	-0.009	-0.015	-0.012
	(0.042)	(0.041)	(0.039)
6	-0.016	-0.016	-0.016
	(0.032)	(0.027)	(0.027)
7	0.005	-0.002	-0.004
	(0.051)	(0.050)	(0.025)
8	0.025	0.025	0.017
	(0.037)	(0.038)	(0.019)
9	0.017	0.005	0.002
	(0.030)	(0.041)	(0.036)
10 (winners)	-0.027	-0.047	-0.053
	(0.040)	(0.052)	(0.036)
Winners-Losers	0.012	0.069	-0.003
	(0.136)	(0.138)	(0.102)

Table XI

Persistence Estimates of Top Three Deciles in Raw Returns

Each quarter funds are sorted into 10 rank portfolios based on their previous one- or four-quarter returns, respectively. Next, average returns over the next one or four quarters are computed for each decile. Using returns from 1994-2000, this produces a time series for each decile of 22 average one-quarter returns and 16 (overlapping) average four-quarter returns. The numbers in the table are the annualized time-series averages and their standard errors are in parenthesis. The standard errors are corrected for autocorrelation based on the Newey-West approach. The columns labelled Open Funds are based on average returns across the subset of funds in that decile that are classified as open for investment. The figures employ a weighting procedure to eliminate look-ahead bias.

	Average Performance (raw returns)			
	One-Quarter		Four-Quarter	
Decile	All Funds	Open Funds	All Funds	Open Funds
8	0.168	0.177	0.159	0.154
	(0.034)	(0.036)	(0.035)	(0.038)
9	0.197	0.219	0.191	0.190
	(0.044)	(0.050)	(0.051)	(0.049)
10 (winners)	0.204	0.218	0.203	0.217
	(0.066)	(0.073)	(0.109)	(0.116)
Winners-Losers	0.121	0.135	0.082	0.096
	(0.079)	(0.083)	(0.080)	(0.079)

2.5 Concluding remarks

Empirical studies analyzing the performance of hedge funds are hampered by high attrition rates, due to fund liquidation and the possibility that funds stop reporting to the database vendor. The results in this paper clearly indicate that fund liquidation is driven by historical returns, with attrition rates being higher for funds that perform poorly. Given endogenous liquidation, standard ways of analyzing performance persistence are affected by look-ahead bias, as one implicitly conditions upon the fund having observed returns for a number of consecutive quarters. To eliminate such biases, it is possible to use a weighting procedure, which requires an appropriate model that relates fund survival to fund performance and other observables.

The empirical model for hedge fund liquidation estimated in this paper indicates that historical performance is an important factor explaining fund liquidation, where performance in the more distant past is of less importance. Moreover, if the aggregated return over a previous predetermined period is negative, implying that it is unlikely for the manager to receive the incentive fee, a hedge fund has a much higher probability of liquidation. Other significant factors explaining survival are fund age, net asset value, investment style and the magnitude of the incentive fee. The impact of age is nonlinear, with lower attrition rates for both young and mature funds. Using the empirical liquidation model, we determine fund return persistence with and without correcting for look-ahead bias, using a simple weighting procedure. The results indicate that look-ahead bias is quite severe. While ter Horst, Nijman and Verbeek [2001] find that look-ahead bias is of minor importance for mutual funds, this paper finds that it can be quite important for hedge funds, whose attrition rates are higher. For example, without correcting for look-ahead bias, expected future returns of poorly performing funds may be overestimated by as much as 3.8% per year, a number that is statistically significant and higher than the typical 2% per year that is associated with survivorship bias. This stresses the importance in empirical studies of correcting for look-ahead bias in addition to survivorship bias. The finding that the greater total risk of hedge funds over their mutual fund counterparts exacerbates look-ahead bias confirms the results in Brown et al. [1992] who introduce the idea that look-ahead bias is a theoretical result of the cross-sectional dispersion of volatility across funds.

For the one quarter horizon, the corrected results indicate a clear pattern of positive persistence in raw fund returns. That is, the best performing 20 to 30% of the funds are expected to provide above average returns in the subsequent evaluation period. For the annual horizon, the pattern is also consistent with positive persistence, though statistically insignificantly so. To check whether the presence of cross-sectional variation in expected returns due to style or risk characteristics explains the observed persistence patterns in raw returns, we also examine persistence in style-adjusted returns. By subtracting from the raw hedge fund returns the return of the corresponding style benchmark, and following the same procedure as in case of raw returns, we determine the persistence in relative returns both with and without correcting for look-ahead bias. At the quarterly and annual horizon we show that on average the top deciles outperform their style benchmark. For the top 10% of the hedge funds this outperformance is around a statistically insignificant 6% at the annual horizon, and around 6.7% (annualized) at the a quarterly horizon. At the biannual horizon we mainly find underperformance of the hedge funds with respect to their style benchmarks. Interestingly, persistence in hedge fund performance seems to be located in both the top and bottom parts of the distribution. That is, poorly performing funds tend to underperform during the next 12 months, while the best performing funds tend to outperform.

The average excess returns on a winner-loser strategy at the annual horizon during the period 1994-2000 are 8.2% and 9.9%, based on raw and style-adjusted returns, respectively. Despite a lack of statistical significance, these numbers are potentially economically important. A major explanation for the fact that we observe more persistence in hedge fund returns than what is usually found for mutual fund returns, is that liquidity in the hedge fund industry is severely restricted. While Berk and Green [2004], argue that much of the persistence in mutual fund returns is competed away by mutual fund investors rationally shifting their capital in search of superior investments, hedge funds are characterized by lockup periods and redemption notice periods. Moreover, regulatory restrictions may limit the growth of (onshore) hedge funds. Further, when investment strategies employed by hedge fund managers cannot be scaled up without limit, performance fees and high-water mark contracts provide incentives for the manager to close the fund to new investors or otherwise limit the inflow of new money (see Goetzmann, Ingersoll and Ross [2003]). In a robustness check, where we consider funds with very low or negative cash flows as closed for investment, we find very similar returns for the top three deciles, suggesting that the persistence results are robust, and thus might be exploitable for investors.

"Please note that investing in hedge funds is speculative, not suitable for all clients, and intended only for financially sophisticated investors who are capable of evaluating the merits and risks of such investment, who do not require immediate liquidity for their investment and who have sufficient resources to bear any loss which might result from such investment".

(Common disclaimer of companies managing funds of hedge funds)

Chapter 3

A Portrait of Hedge Fund Investors: Flows, Performance and Smart Money[15]

3.1 Introduction

A number of recent studies have focused on the evaluation of performance persistence of hedge funds (see e.g. Brown, Goetzmann and Ibbotson [1999], Agarwal and Naik [2000], Boyson [2003], Baquero, Ter Horst and Verbeek [2005]). Their results indicate that persistence is particularly strong at quarterly horizons and somewhat less pronounced at annual horizons. This is relevant for investors, as they tend to allocate their money across funds by inferring managerial skill from past performance. However, the issue of the responsiveness of money flows to past performance has been addressed by two conflicting theories. On the one hand, persistence is an indication that past performance plays a role in signalling quality to investors, which supports the hypothesis that past performance influences the market shares of hedge funds (see Ippolito [1992], Lynch and Musto [2003]). On the other hand, it has been recently argued (see Berk and Green [2004]) that persistence is evidence of a lack of competition in the provision of capital and therefore of a weak response of flows to past performance. If this is the case, we should expect a less pronounced flow-performance relation with quarterly data than with annual data in hedge funds. This paper tests this hypothesis by empirically exploring the short-term dynamics of hedge fund flows and performance and their interrelationship.

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[15] This chapter is based on Baquero and Verbeek [2005]. I am grateful to Chester Spatt, Melvyn Teo and Bas Werker for their valuable insights and suggestions.

For the mutual fund industry, Berk and Green's argument is supported by empirical evidence of a positive correlation between flows and past performance (see e.g. Sirri and Tufano [1998]) [16], together with the general finding that performance of mutual funds is to a great extent unpredictable using past relative performance (see e.g. Carhart [1997]). However, little attention has been paid to the responsiveness of flows of capital to past performance of hedge funds. An important issue in the hedge fund industry that might affect the relation between asset flows and performance is that flows of money into and out of hedge funds are restricted. There are typically lock-up periods (i.e. minimum initial investment periods) and redemption notice periods restricting withdrawals. There are also subscription periods limiting inflows. Additionally, if a fund has reached the maximum limit of 500 investors it might be closed to new investors, while it may also be the case that given diminishing returns to scale in this industry, hedge fund managers are unwilling to accept new money before reaching the critical size. Thus, while in the mutual fund industry investors' decisions in supplying capital ultimately drive the flow-performance relationship, in the hedge fund industry liquidity restrictions and other organizational aspects on the demand side for capital are likely to have some influence on the shape of the relation.

Hedge fund investors also face high searching costs along their allocation process. Given advertising restrictions imposed by many countries and the little transparency characterizing the hedge fund industry, investors engage in a long and complex process of information gathering and evaluation, through hedge fund conferences, hedge fund databases, industry newsletters, consultants, prime broker capital introduction groups and direct contact with managers. Hedge fund selection includes quantitative and qualitative screening, followed by a thorough manager due diligence process, where manager attributes are especially taken into consideration. This selection procedure is likely to lengthen the decision of purchasing shares in hedge funds. Furthermore, while the decision to hire a hedge fund manager for the first time may take place at relatively low frequencies compared to other investment pools as mutual funds, the post-investment behaviour of hedge fund investors is instead characterized by a regular monitoring, especially for style drift, on a monthly or a

[16] For mutual funds, the relation between money flows and past performance has been widely documented, using different methodologies, data, flows measures and performance measures. Hendricks, Patel and Zeckhauser [1994], Ippolito [1992], Chevalier and Ellison [1997], and Sirri and Tufano [1998] find that the relationship is highly convex, meaning that money flows tend to go to funds that recently performed well. In addition, Ippolito [1992], Warther [1995], and Chevalier and Ellison [1997] find that managers lose funds under management when they perform poorly. In the hedge fund industry, Goetzmann, Ingersoll and Ross [2003], document that money tends to flow out of the recent top performing funds, while Agarwal, Daniel and Naik [2003] find a positive and convex relationship but cannot identify outflows from top performers. All studies mentioned above have focused their attention on the long-run (i.e. annual flows and one to 5-year aggregate past performance).

quarterly basis[17]. Searching costs and active monitoring are also likely to have an impact on the response of money flows to past performance.[18]

All together these functional aspects of the hedge fund industry motivate the main argument of this paper: the organizational structure of hedge funds creates multiple asymmetries between the decisions to invest and divest of hedge fund investors, most notably concerning the evaluation horizons. First, liquidity restrictions affect differently money inflows and outflows. Further, an extended procedure to select managers slows down the investment decision, while an active post-investment monitoring allows a swift divestment decision. Accordingly, studying the mutual effects between money flows and the performance and persistence of hedge funds requires explicitly separating these two decisions and an understanding of their specific determinants.

Our paper extends the existing literature in several directions and makes a number of empirical contributions. First, our results indicate that the shape of the flow-performance relation depends on the time horizon being analyzed. Specifically, with quarterly data, flows and performance appear to be related in a more or less linear fashion, which contrasts with the convex relation found at annual horizons (see Agarwal, Daniel and Naik [2003]), where investors display a higher sensitivity to good performance and almost no sensitivity to poor performance. Further, the response of flows to quarterly past performance, especially outflows, occurs most significantly during the first quarter and disappears gradually over the subsequent three or four quarters. Our model incorporates the effect of liquidity restrictions upon the flow-performance relationship, which can only be captured at short horizons since most restrictions are defined on a monthly or quarterly basis.

Second, unlike previous papers, we separately model positive and negative cash flows, using a switching regression model that allows for a differential impact of past performance measures and other characteristics. Our model provides a likely

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[17] The limited regulation of the hedge fund industry gives a great flexibility to hedge fund managers to employ a variety of trading strategies, which raises the need of a permanent monitoring to reduce the incentives for managers to deviate from their stated investment style. According to Bekier [1996]'s survey and L'Habitant [2002], style drift is the most important reason for investors to terminate a hedge fund manager.

[18] In this respect, investing in hedge funds has some of the features documented by Del Guercio and Tkac [2002] for the pension fund industry, although the underlying motives are different. Del Guercio and Tkac document that pension fund investors engage in screening procedures that evaluate first quantitative performance and subsequently non-performance characteristics such as manager's reputation and credibility. The process involves often face-to-face meetings, written questionnaires and hiring of consultants. They interpret these evaluation procedures as the result of agency problems faced by pension fund sponsors as argued by Lakonishok, Shleifer and Vishny [1992]. They also document that pension fund investors perform high levels of monitoring of hired managers. Del Guercio and Tkac suggest that these features determine the linear shape of the flow-performance relation they find for pension funds.

explanation for the different shape of the flow-performance relation between time horizons, by revealing that the purchasing decision is more sensitive to a consistent long-term good performance, while the decision to divest or not is highly sensitive to short-term poor performance and cannot be captured at annual horizons. Our results support Berk and Green [2004]'s argument by showing that capital inflows are slow in chasing short-term performance and thus would be unable to compete away the patterns of short-run persistence. Further, we show that if the investment and divestment decisions are not modelled separately, important asymmetries between both regimes remain hidden due to an improper estimation of the impact of size, age, incentive fees and other variables upon cash flows.

Third, in light of our previous results, our paper explores several implications of Berk and Green's intuition concerning the mutual effects between money flows and performance. Specifically, by looking into detail at the actual investment and divestment allocations of money flows across hedge funds, we provide an assessment of the performance of the investors' portfolio and the extent of investors' ability to exploit persistence patterns. Our evidence indicates that investors are indeed limited in identifying and directing their capital towards the best performers in the short run. Consequently, most investors are unable to exploit the persistence of the winners. In fact, they fail in their investment allocation by investing mostly in funds that subsequently perform poorly, especially large funds experiencing limits to scale. But they also fail to discriminate expected performance among small and young funds growing at fast rates. On the other hand, hedge fund investors appear to be successful in their divestment strategies, responding fast and appropriately by de-allocating from the persistent losers. In terms of Ippolito [1992], this immediate response has the effect of a disciplining mechanism for low-quality funds, characterized by high liquidation rates subsequently. Our results do not support the existence of smart money as defined by Gruber [1996] and Zheng [1999] for mutual funds.

The remainder of this paper is organized as follows. The next section describes our sample of hedge funds, variables and hypotheses. The first part of our investigation consists of two sections exploring the determinants of money flows to hedge funds. Section 3.3 presents the base specification of our model of flows and demonstrates the existence of a linear short-run flow-performance relation, while Section 3.4 provides a switching-regression model to explain positive and negative cash flows that also incorporates liquidity restrictions. The second part of our study corresponds to Section 3.5 and is devoted to the implications of our previous findings for investors' wealth and for the persistence and survival of hedge funds. Finally, Section 3.6 concludes.

3.2 Data, variables and hypotheses

We use hedge fund data from TASS Management Limited, a private advisory company and provider of information services. The TASS database goes back to 1979 and is primarily created to help potential investors to evaluate, select and monitor hedge funds. Hedge-fund participation in any database is voluntary, given the lack of disclosure requirements and restrictions that are in place for public advertising. Therefore, a self-selection bias might arise either because poor performers do not wish to make their performance known, because funds that performed well and reached a critical size have less incentive to report to data vendors to attract additional investors, or because funds fear intervention in case reporting is interpreted as illegal advertising. Also, different databases have different criteria for including or maintaining funds, which can lead to a further selection bias. On the other hand, active monitoring of managers by database vendors gives an incentive to hedge funds to provide complete and accurate data to avoid being deleted from a database.

For each individual fund, our dataset provides raw returns and total net assets under management (TNA) on a monthly basis until September 2004. Returns are net of all management and incentive fees, but do not reflect front-end and back-end loads (i.e. sales commissions, subscription and redemption fees)[19]. We concentrate on the period between the fourth quarter of 1994 and the third quarter of 2004 since asset information prior to 1994 is too sporadic. Moreover, information on defunct funds is available only from 1994 onwards, although several studies suggest that estimation of the flow-performance relationship is not affected by survivorship biases.[20] We focus on hedge funds reporting returns in $. We exclude 1352 closed-end funds that are present in our database, since subscriptions in these funds are only possible during the initial issuing period, although rare exceptions allow for additional subscriptions at a premium. Further, we exclude 836 fund-of-funds, which have a different treatment of incentive fees and may have different performance characteristics. Clients of funds-of-funds may follow a different decision making process than investors allocating their money to individual hedge funds. While a single-manager selection process may

[19] Investing in hedge funds is costly. There are multiple and varied fees and costs involved when subscribing and redeeming shares, as well as along the period of shareholding. Performance fees are deducted from the fund's asset value before a monthly rate of return is reported. This is usually a time consuming procedure since incentive fees are client specific which implies that almost every share has a different value and requires a separate accounting. Moreover, incentive fee periods do not necessarily correspond to subscription and redemption periods. There are several methods accepted in the non-traditional sector to deduct fees and calculate total net assets (TNA) and rates of returns. Given the complexity of this process, many funds report returns and TNA with some delay after the end of the month or report some estimates that may be revised and adapted subsequently.

[20] See Sirri and Tufano [1998], Chevalier and Ellison [1997], Goetzmann and Peles [1997], Del Guercio and Tkac [2002]. We also performed robustness checks estimating our model only for a sub-sample of survivors.

be time consuming and costly, requiring both quantitative and qualitative evaluation and personal contacts with managers, an investment in a fund-of-funds does not require the same amount of expertise and time, since funds-of-funds already provide investors with a number of benefits, including diversification across several types of hedge funds.

We use quarterly data, which allows us to explore the short-term dynamics of investment and redemption behaviour. Previous studies typically make use of annual data (e.g. Agarwal, Daniel and Naik [2003]). However, in the case of hedge funds, liquidity restrictions are likely to affect the relationship between asset flows and performance. Most subscription and redemption restrictions are defined on a monthly or quarterly basis, and only few on an annual basis. Furthermore, quarterly and monthly horizons seem to be the typical monitoring frequencies among hedge fund investors[21]. These facts together with the findings of patterns of quarterly performance persistence (see for example Agarwal and Naik [2000], Baquero, Ter Horst and Verbeek [2005]), suggest we can expect an important amount of buying and selling transactions of hedge fund shares taking place within a year.[22]

Since we consider quarterly horizons, we take into account the most recently available value of total net assets (TNA) in each quarter.[23] We only consider funds with an uninterrupted series of quarterly TNA to be able to compute flows of money as the difference between consecutive TNA correcting for reinvestments. Further, we restrict attention to funds with a minimum of 6 quarters of return history and with quarterly cash flows available at least for one year. While the last two selections impose a survival condition, they ensure that a sufficient number of lagged returns and lagged cash flows is available to estimate our model and reduce at the same time the effect of a potential instant-history bias.[24] Moreover, in this way we do not take into account extreme cash inflow rates commonly observed during the first quarters after a fund has started operations. Our final sample contains 1543 funds and a total of 21841 fund-period observations. The graveyard consists of 714 funds, from which 425

[21] In his study about marketing of hedge funds, Bekier [1996] conducted a survey among institutional investors and found that 50% of them prefer to receive quarterly monitoring information about their non traditional investments, around 30% prefer monthly (or between quarterly and monthly) monitoring information, and only 15% monitor less frequently than quarterly.

[22] A further advantage of using quarterly data is the reduction of the impact on the flow-performance relation of a potential return smoothing in a monthly basis. Getmansky, Lo and Makarov [2004], argue that the patterns of serial correlation found in hedge fund data are induced by return smoothing, which results from a number of sources, most importantly hedge funds' exposure to illiquid securities.

[23] When TNA is not available at the end of a quarter, we take the most recent value of TNA, up to two months ago.

[24] Instant-history bias (or backfilling bias) has been documented by Park [1995], Ackermann et al. [1999] and Fung and Hsieh [2002], and refers to the possibility that hedge funds participate in a database conditional on having performed well over a number of periods prior to inception.

actually liquidated, while the remaining 289 funds self-selected out of the database for different reasons (e.g. at the fund manager's request or closed to new investors).

Table I provides an overview of the number of funds in our dataset per quarter, aggregate growth rates and aggregate net assets under management. Our sample contains 231 funds at the end of the fourth quarter of 1994, accounting for about $ 18 billion in net assets, and 692 funds at the end of the third quarter of 2004, accounting for about $ 165 billion. This represents around 15% of the total for the entire industry estimated by TASS of about $ 1 trillion of assets under management by the end of 2004.

Flows are measured as the growth rate in total net assets under management (TNA) of a fund between the start and end of quarter $t+1$ in excess of internal growth r_{t+1} of the quarter, had all dividends been reinvested. Alternatively, a measure of cash flows in dollars is computed as a net change in assets minus internal growth. These definitions assume that flows take place at the end of period $t+1$. [25]

$$CashFlow_{t+1} = \frac{TNA_{t+1} - TNA_t}{TNA_t} - r_{t+1} \tag{1}$$

$$DollarFlow_{t+1} = TNA_{t+1} - TNA_t(1 + r_{t+1}) \tag{2}$$

We refer to the first definition as *normalized cash flows* or *growth rates* and to the second as *absolute* or *dollar cash flows*. The definition of flows in dollar terms presents a drawback in case inflows or outflows are proportional to the size of the fund, irrespective of performance. This concern has made the first definition of normalized cash flows the preferred one in several studies about mutual funds (see e.g. Gruber [1996] and Chevalier and Ellison [1997]). For the pension fund industry, however, Del Guercio and Tkac [2002] document that size and flows are not positively correlated, and they use both definitions of cash flows in their study. Similarly, in the case of hedge funds we might expect outflows from large funds because of decreasing returns to scale. On the other hand, the use of normalized cash flows tends to magnify inflow rates of small funds while minimizing outflow rates of large funds, as this measure is constructed as a growth rate with respect to total net assets (TNA) at the start of a period (see, e.g., Gruber [1996] and Zheng [1999]). Therefore, we use the two definitions of flows, while controlling for any size effect. As will become clear below, especially in Section 3.5, both definitions contribute with different information regarding the investments in hedge funds.

[25] See Ippolito [1992] for a discussion about the assumptions underlying these definitions of flows.

Table I

Aggregate Cash Flows and Total Net Assets from a Sample of Hedge Funds from TASS Database

This table gives the total number of hedge funds in the sample per quarter, aggregate cash flows, total net assets under management and average return. The sample consists of 1543 open-end hedge funds from TASS database, with a minimum of 6 quarters of quarterly returns history and with quarterly cash flows available at least for one year. Funds of funds are not included. The sample period has 40 quarters from 1994Q4 till 2004Q3. Cash flows are computed as the change in total net assets between consecutive quarters corrected for reinvestments. A growth rate is calculated as relative cash flows with respect to TNA of previous period.

	Number of funds	Aggregate Cash Flows (million dollars)	Cash flows (growth rate)	Aggregate TNA (million dollars)	Average Return
1994 Q4	231	-437.44	-0.0235	17861.15	-0.0077
1995 Q1	258	-1312.14	-0.0646	19387.67	0.0524
1995 Q2	279	-461.56	-0.0228	20469.12	0.0370
1995 Q3	315	-317.83	-0.0146	22972.14	0.0459
1995 Q4	326	-757.99	-0.0327	23215.81	0.0345
1996 Q1	348	148.85	0.0050	30969.63	0.0244
1996 Q2	360	-334.21	-0.0107	33047.34	0.0596
1996 Q3	364	377.79	0.0112	34275.64	0.0164
1996 Q4	371	945.09	0.0260	40431.19	0.0603
1997 Q1	379	2277.90	0.0561	45255.20	0.0427
1997 Q2	392	301.99	0.0066	48434.29	0.0467
1997 Q3	414	2353.93	0.0471	56745.53	0.0742
1997 Q4	438	675.00	0.0115	59948.61	-0.0136
1998 Q1	470	1821.63	0.0295	66989.86	0.0484
1998 Q2	482	1107.31	0.0167	68556.61	-0.0240
1998 Q3	496	-268.07	-0.0041	60234.29	-0.0502
1998 Q4	528	-3822.72	-0.0615	56650.24	0.0518
1999 Q1	571	-2845.61	-0.0490	55262.50	0.0324
1999 Q2	582	-850.49	-0.0152	58979.19	0.0832
1999 Q3	598	-1289.20	-0.0219	56682.70	-0.0006
1999 Q4	597	-703.00	-0.0124	63413.15	0.1177
2000 Q1	626	670.00	0.0101	69948.90	0.0607
2000 Q2	629	-2299.42	-0.0336	63643.12	-0.0139
2000 Q3	658	697.77	0.0108	67016.20	0.0185
2000 Q4	667	734.74	0.0109	68463.32	-0.0020
2001 Q1	670	3382.16	0.0456	78678.59	0.0086
2001 Q2	697	3380.75	0.0403	89049.14	0.0257
2001 Q3	699	3145.77	0.0355	89959.58	-0.0250
2001 Q4	702	-5713.63	-0.0574	97069.95	0.0482
2002 Q1	702	1533.24	0.0157	100359.61	0.0184
2002 Q2	700	2279.75	0.0222	105192.95	0.0057
2002 Q3	702	67.69	0.0006	104609.51	-0.0212
2002 Q4	697	-1099.04	-0.0104	106726.81	0.0219
2003 Q1	685	2431.55	0.0255	99383.00	0.0116
2003 Q2	687	5628.85	0.0560	112169.77	0.0775
2003 Q3	703	6970.84	0.0607	124438.64	0.0376
2003 Q4	711	6722.30	0.0539	137685.21	0.0541
2004 Q1	703	16056.57	0.1207	154496.43	0.0409
2004 Q2	712	10330.84	0.0659	163689.45	-0.0244
2004 Q3	692	2730.60	0.0170	164632.56	0.0090

Table II shows some descriptive statistics for assets under management and the two alternative measures of cash flows. Interestingly, the distribution appears to be relatively symmetric, similar to findings in the pension fund industry and in sharp contrast with the distributions found for mutual funds. For example, Del Guercio and Tkac [2002] find that the top 5% of dollar inflows in mutual funds are nearly three times larger than the outflows at the bottom 5%. This suggests that the flow-performance relationship in mutual funds and hedge funds may also have different characteristics.

Table II

Distributions of Flows and Assets under Management in the Hedge Fund Industry

This table shows the cross-sectional distribution of cash flows and total net assets under management in our sample of 1543 open-end hedge funds from 1994Q4 till 2004Q3. Cash flows are computed as the change in total net assets between consecutive quarters corrected for reinvestments. A growth rate is calculated as relative cash flows with respect to the fund's TNA of the previous quarter.

Percentile	Cash Flows (growth rate)	Cash Flows (dollars)	Total Net Assets (million dollars)
99%	1.0389	134000000	1680.0000
95%	0.3904	38600000	543.0000
90%	0.2217	16400000	296.0000
75%	0.0689	2541022	106.0000
50%	0.0000	130.3989	32.0000
25%	-0.0503	-1225081	8.5138
10%	-0.1701	-9006655	2.4467
5%	-0.2870	-21600000	1.2000
1%	-0.5758	-79000000	0.2801

In selecting which performance measure to use, we look at the information that is available to investors through different channels. Although some of these risk and performance metrics might not be the most appropriate to characterize hedge funds from a theoretical perspective, they might be underlying investor's decisions. We use the simple performance measures offered by most databases, that is raw returns, return rankings relative to other funds and Sharpe ratios. In a similar way, a fund's riskiness is usually reported in terms of its total risk (standard deviation of historical returns) and measures of downside risk.[26] Measures of downside and upside variation with respect to a target have gained popularity among investors given that hedge fund return distributions are not normal and are often multi-modal. Professionals in the hedge fund and pension fund industries advocate the use of such risk measures while they discourage the use of standard deviation. The reason is that a higher standard deviation might be desirable if the entire distribution is shifted upwards in a way that

[26] Downside risk is a popular term for what is referred to as lower partial moment, a probability weighted function of deviations below a specified target return, as developed by Fishburn [1977]. Among pension fund managers, the term "target return" is rather known as "minimal accepted return" (MAR). Upside potential is instead the probability-weighted function of returns in excess of the MAR.

guarantees a minimum target return. Implicit in this argument is the assumption that investors prefer a variation above a minimum target return while minimizing variation below.[27] A popular measure that captures aversion for negative skewness is the downside-upside potential ratio, which combines downward variation as the numerator and upside potential as the denominator.[28] We measure downside deviations and upside potential with respect to the return of 3-month Treasury bills over the entire past history of the fund.

Besides monthly raw returns and total net assets, the TASS database provides fund specific characteristics that may be important determinants of money flows. Table III shows descriptive statistics for fees, ownership structure, styles and several other variables. Below we give a brief explanation of each of these variables and hypothesize their impact on flows of money.

Incentive fees constitute one of the mechanisms in place in the hedge fund industry to mitigate principal-agent problems and align investors' goals with fund managers' incentives.[29] The typical incentive contract aims at enhancing managerial effort by paying hedge fund managers a percentage of annual profits if returns surpass some benchmark and in case past losses have been recovered. According to Table III, managers receive on average an incentive fee of about 18% of profits, a bonus that varies substantially across funds with a range between zero and 50%. A higher fee would be more attractive for an investor since it should translate into higher performance, but possibly with the trade-off of inducing greater risk.[30] Additionally, an investor pays an annual management fee, defined as a percentage of total assets under management. In our dataset the average management fee is around 1.5% and varies between zero and 8%. Management fees may imply an indirect performance incentive in case an increase on size is related to an increase in performance.

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[27] The idea that investors favor variation in the upside but not in the downside has been supported empirically and theoretically (as recently documented by Harvey and Siddique [2000] and first analyzed theoretically by Bawa and Lindenberg [1977] and Fishburn [1977]). Preference for positive skewness has also been stressed in the behavioral finance literature (e.g. Olsen [1998], Shefrin [1999]) and by practitioners (e.g. Sortino and van der Meer [1991], Sortino et al [1999]).

[28] We use the following definition of downside-upside potential ratio:

$$DUPR = \frac{\sqrt{\frac{1}{T}\sum_{1}^{T} \iota^{-}(R_{i,t} - R_{mar})^2}}{\frac{1}{T}\sum_{1}^{T} \iota^{+}(R_{i,t} - R_{mar})}$$

where $\iota^{-} = 1$ if $R_{i,t} \leq R_{mar}$, otherwise $\iota^{-} = 0$

and $\iota^{+} = 1$ if $R_{i,t} > R_{mar}$, otherwise $\iota^{+} = 0$

($R_{i,t}$ is the return of a fund *i* at time *t* while R_{mar} refers to the minimal acceptable rate of return or the investor's target return)

[29] See Ackermann et al [1999] for a discussion of principal-agent issues in the hedge fund industry

[30] See Starks [1987] for a theoretical approach of incentive fees.

However, Goetzmann et al [2003] find evidence of diminishing returns to scale in this industry, in contrast to mutual funds.

A joint ownership structure is a second mechanism in place to mitigate principal-agent problems in the hedge fund industry. Intuitively, a fund that requires a substantial managerial investment should enhance manager effort but possibly at the cost that managers take-on less risk compared to the investor's preferred risk level. Therefore, as noted by Ackermann et al [1999], a fund that combines substantial investment of a manager's personal capital together with high incentive fees might be the most attractive option from an investor's perspective, as managerial effort is greatly enhanced while managerial risk-taking of both approaches counterbalance. Nearly 62% of managers in our sample are required to invest their own capital.

We define age of a fund as the number of months the fund has been in existence from the time of its inception. From Table III, the mean is 55 months (ln(Age) = 4.007). As indicated above, age is truncated at 18 months (6 quarters). Investors might perceive older funds as more experienced in identifying and exploiting mispricing opportunities. However, the effect of age on money flows is difficult to predict in case age is correlated with size and in case diseconomies of scale are present.

The TASS database distinguishes between onshore and offshore funds. Offshore hedge funds are typically corporations. The number of investors is not limited and therefore offshore funds tend to be larger. They represent 62% of all funds in our dataset. Onshore funds are generally limited partnerships with less than 500 investors and therefore more restricted to new investors, while imposing more extended redemption periods than offshore funds.

Hedge funds invest in different asset classes, with different geographical focus and using a variety of investment techniques and trading strategies. Brown and Goetzmann [2003] find that differences in style account for 20% of the cross-sectional variation in performance as well as for a significant proportion of cross-sectional differences in risk. This suggests that, from an investor's perspective, a careful assessment of style is crucial. There is no consensus in the hedge fund industry, however, on the use of a unique style classification. TASS provides a style classification of mutually exclusive styles based on manager survey responses and information from fund disclosure documents. Although self-reported styles may suffer from a self-selection bias, they constitute the most readily available source of information concerning styles for any investor. Therefore, we expect they are an important determinant of hedge fund investors' preferences, which is the focus of our study. Furthermore the TASS classification closely matches the definitions of

CSFB/Tremont Hedge Fund Indices, a set of 10 indices increasingly used as a point of reference to track fund performance and to compare funds. Based on this TASS classification, we assigned each fund to one only index category. The more general “hedge fund index” category includes funds without a clear investment style (for further details, see Baquero, Ter Horst and Verbeek [2005]).

Table III

Cross-Sectional Characteristics of the Hedge Fund Sample

This table presents summary statistics on cross-sectional characteristics of our sample of 1543 hedge funds for the period 1994Q4 till 2004Q3. Cash flows are the change in total net assets between consecutive quarters corrected for reinvestments. Returns are net of all management and incentive fees. Age is the number of months a fund has been in operation since its inception. In each quarter, the historical standard deviation of monthly returns, semi deviation and upside potential have been computed based on the entire past history of the fund. Semi deviation and upside potential are calculated with respect to the return on the U.S. Treasury bill taken as the minimum investor’s target. Offshore is a dummy variable with value one for non U.S. domiciled funds. Incentive fee is a percentage of profits above a hurdle rate that is given as a reward to managers. Management fee is a percentage of the fund’s net assets under management that is paid annually to managers for administering a fund. Personal capital is a dummy variable indicating that the manager invests from her own wealth in the fund. We include 10 dummies for investment styles defined on the basis of the CSFB/Tremont indices.

Variable	Mean	Std. Dev.	Min	Max
Cash Flows (growth rate)	0.0287	0.2734	-0.9107	4.3656
Cash Flows>0 (10876 obs)	0.1639	0.3052	0.0001	4.3656
Cash Flows<0 (10367 obs)	-0.1115	0.1444	-0.9107	-0.0001
Cash Flows=0 (598 obs)				
Cash Flows (dollars)	2484343	6.80E+07	-7.23E+09	1.12E+09
Ln(TNA)	17.1746	1.8491	8.1050	23.2959
Ln(AGE)	4.0070	0.6189	2.8904	5.8171
Quarterly Returns	0.0255	0.1175	-0.9763	1.7449
Historical St.Dev.	0.0513	0.0407	0.0004	0.8318
Semi Deviation	0.0299	0.0245	0	0.3326
Upside Potential	0.0236	0.0169	0.0002	0.2797
Downside-Upside Potential Ratio	1.2862	0.8600	0	19.2076
Offshore	0.6236	0.4845	0	1
Incentive Fee	18.4599	5.8253	0	50
Management Fees	1.4632	0.8832	0	8
Personal Capital	0.6197	0.4855	0	1
Leverage	0.7579	0.4283	0	1
Convertible Arbitrage	0.0525	0.2231	0	1
Dedicated Short Bias	0.0160	0.1256	0	1
Emerging Markets	0.1036	0.3047	0	1
Equity Market Neutral	0.0463	0.2102	0	1
Event Driven	0.1222	0.3275	0	1
Fixed Income Arbitrage	0.0490	0.2159	0	1
Global Macro	0.0691	0.2536	0	1
Long/Short Equity	0.3468	0.4760	0	1
Managed Futures	0.1576	0.3644	0	1
Hedge Fund Index	0.0368	0.1883	0	1

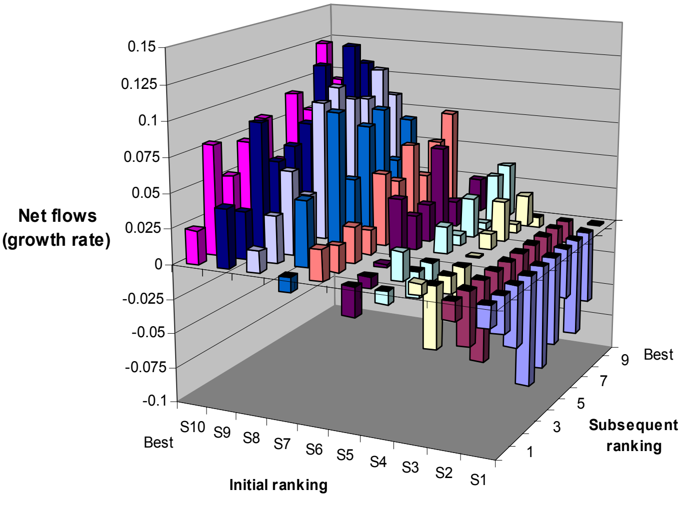
3.3 The flow-performance relationship for hedge funds

Figure 1 illustrates the structure of the interrelationship between flows and performance in the hedge fund industry, based on our sample of funds for the period 1994Q4 – 2004Q3. Flows are measured as the quarterly growth rate in total assets under management of a fund, corrected for the return realized during the quarter.

Figure 1

Flow-Performance Interrelation for Hedge Funds (Decile 10: best performers)

Hedge funds are sorted every quarter from 1994Q4 to 2004Q3 into ten rank portfolios based on their raw returns in previous quarter. This initial ranking is compared to the fund's ranking in the subsequent quarter. The bar in cell *(i,j)* represents the average growth rate (net of reinvestments) of all funds achieving a subsequent ranking of decile *j* given an initial ranking of decile *i*.



In each quarter, funds are ranked on the basis of raw returns and divided into 10 deciles. If a fund is ranked in decile S10, this indicates that the fund performed in the top 10 percent of all existing funds in that quarter. This initial ranking is compared to the ranking in the subsequent quarter. Each bar in Figure 1 represents the average growth in the subsequent quarter. It is clear from the graph that the funds that performed relatively well (decile S6 to S10) attracted high inflows, while hedge funds that performed worse in the past experienced negative or small positive cash flows (deciles S1 to S5). This suggests that, to some extent, investors consider historical performance as an argument for determining their hedge fund investments. Interestingly, we also observe a positive relationship between inflows and contemporaneous performance. Apparently, most of the net cash flows are directed to those funds that perform well in the same quarter (deciles 6 to 10). This may indicate that larger cash flows experienced in a given quarter actually enhance performance towards the end of the quarter, while for those funds that experienced few flows or even outflows it was more difficult to make up for their bad performance. It may also indicate that performance persists and is not competed away by investors rationally shifting their investments in search of superior performance. An intriguing question is why some good performers in the initial period experiencing huge inflows perform very poorly in the subsequent period. For example, funds ranked in decile S10 that subsequently reached decile 2, had a growth of 7.5% in assets under management. A likely explanation for this finding is that funds in the extreme deciles are more risky than those in the other deciles. More risk is associated with higher average returns, but also with bigger chances of extremely good and extremely poor outcomes. Such funds are more likely to move from the winner to the loser decile or vice versa.

To further examine the dynamics of the relationship between past performance and cash flows, we use a linear regression model, controlling for other factors like fund age, size, incentive fees and investment styles. Consider the following model:

$$Flow_{i,t} = \alpha + \sum_{j=1}^{6} \beta_{1,j}.(rnk_{i,t-j}) + \beta_2.\ln(NAV_{i,t-1}) + \beta_3.\ln(AGE_{i,t-1}) + \sum_{j=1}^{4} \beta_{4,j}.(Flow_{i,t-j}) + \gamma'.X_{i,t} + \lambda_t + \varepsilon_{i,t} \quad (3)$$

where $Flow_{i,t}$ represents the net percentage growth in fund i in period t, and $rnk_{i,t-j}$ is the jth lagged relative performance as measured by a fund's cross-sectional rank. We include the size and age of the fund in the previous period, $ln(TNA_{i,t-1})$ and $ln(AGE_{i,t-1})$. $Flow_{i,t-j}$ is the jth lagged flow. $X_{i,t}$ is a vector of fund specific characteristics like management fees, incentive fees, managerial ownership and style. The style dummies capture the possibility that funds in a particular style may experience average flows significantly different from other styles. We control for time effects by including time dummies, denoted by λ_t, to capture economy wide shocks conducing to different average flows across quarters, as suggested by Table I.

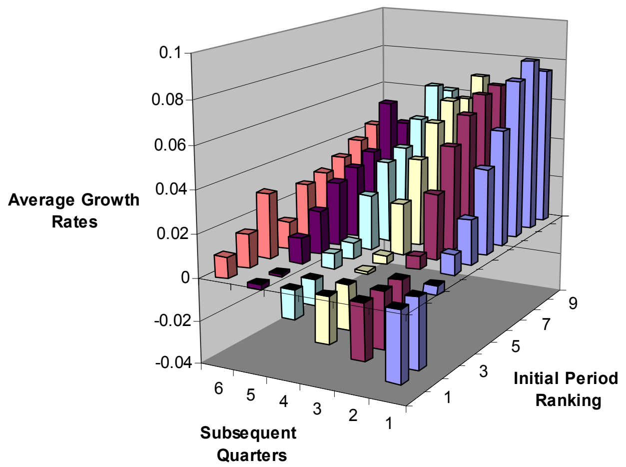
Previous research on the flow-performance relationship uses annual data and studies the impact of previous year performance upon current year flows. Here we use quarterly data and we should determine the (maximum) time horizon over which historical performance has an impact on quarterly flows of money. To obtain an insight into this question, we compute the average cash flows over several subsequent quarters after the ranking period, for each initial decile in Figure 1. The results are shown in Figure 2. The top panel presents averages for growth rates; the bottom panel presents averages for dollar flows. In both panels, a clear flow-performance relationship exists for the first four quarters or so after the ranking period, while average flows seem to be unrelated to initial rank after six quarters. This suggests that

Figure 2

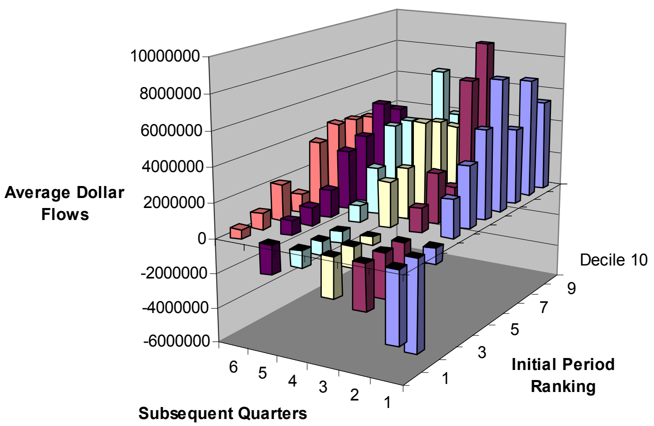
Average Flows across Deciles Over Subsequent Quarters after Ranking

In each quarter from 1994Q4 to 2004Q3 funds are ranked into decile portfolios based on their past quarter raw returns. For the quarter subsequent to initial ranking and for each of the next 6 quarters after formation, we compute the average growth rate (Panel A) and the average dollar flows (Panel B) of all funds in each decile portfolio. Thus, the bar in cell *(i,j)* represents average flows (net of reinvestments) in the j[th] quarter after initial ranking of funds ranked in decile *i*. Decile 10 corresponds to the best performers.

Panel A



Panel B



historical performance may be an important determinant of money flows over a horizon of six quarters or less. Notice in Panel B that poor performers experience important dollar outflows, comparable in magnitude to the level of inflows experienced by the top deciles. In Panel A, these same cash outflows averaged in terms of growth rates appear smaller in magnitude compared to the large growth rates enjoyed by the best performers. This indicates that poor performers might be over-represented among funds managing large amounts of assets. Obviously, size is a necessary control variable to take into account. Figure 2 also highlights the importance of considering both measures of cash flows in the analysis, as each of them may reveal distinctive features of flows behaviour.

We estimate our model by pooling the entire dataset, considering each fund-period observation as an independent observation (as in e.g. Gruber [1996], Del Guercio and Tkac [2002]).[31] Results, explaining both normalized and absolute flows, are presented in Table IV. All t-statistics reported are based on robust standard errors. Our estimates confirm that hedge fund flows are sensitive to historical relative performance and the relation appears to be linear. If a fund's ranking improves from the 25th to the 75th percentile in the previous quarter, this is associated with an economically and statistically significant 6.2% quarterly growth (column A). This accounts for nearly 31% of the total long-run impact. The effect gradually disappears but is an important determinant of growth rates even up to 6 lagged quarters. In the long-run, an improvement in relative performance from the 25th to the 75th percentile corresponds to a growth rate of about 23% over the next 6 quarters. The effect of past performance is also confirmed when we use absolute flows as the dependent variable (column B). The significant impact on dollar flows also decreases over time and is mostly concentrated over the next 3 quarters. Our results clearly indicate that investors respond most strongly to the most recent quarterly fund history.

We tested for non-linearities in the response of flows to performance in the previous quarter using different alternative specifications. We divided the first lagged rank in ten deciles and we estimated our model allowing for kinks at each decile. We found no evidence of significant differences between the slopes in the 10 segments. We also allowed for kinks in the top 10% and 20% of funds and 10% bottom, isolating the middle deciles, and again linearity was not rejected. When we divide lagged rank between winners and losers and we test a two segment piecewise linear regression, we do not reject linearity either. Finally, we added the square of each lagged rank to our base specification, but we did not find significant coefficients for the additional

[31] Our results are robust to a different estimation procedure based on Fama-McBeth [1973] as implemented by Sirri and Tufano [1998] and Agarwal, Daniel and Naik [2003]. Estimates of these regressions are available upon request.

Table IV

The Effect of Relative Performance and Fund Specific Characteristics Upon Money Flows in Open-End Hedge Funds

The table reports OLS coefficients estimates using cash flows as the dependent variable. The sample includes 1543 open-end hedge funds for the period 1994 Q4 till 2004 Q3. In column B we measure cash flows in dollar terms as the change in total net assets between consecutive quarters corrected for reinvestments. In column A we measure cash flows as a growth rate relative to the fund's total net assets of previous quarter. The independent variables that account for relative performance include six lagged fractional ranks. The fractional rank ranges from 0 to 1 and is defined as the fund's percentile performance relative to all the funds existing in the sample in a given period, based on the fund's raw return at the end of the period. Independent variables accounting for fund specific characteristics include the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows, downside-upside potential ratio based on the entire past history of the fund and calculated with respect to the return on the U.S. Treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund and 7 dummies for investment styles defined on the basis of CSFB/Tremont indices. The general hedge fund index is taken as reference category. The model also includes 39 time dummies (estimates not reported). We estimate our model by pooling all fund-period observations. T-statistics based on robust standard errors are provided in parentheses.

Parameters	OLS estimates, model of cash flows as growth rates (A)		OLS estimates, model of dollar flows (B)	
Intercept	0.1221	(3.85)	-27400000	(-1.77)
Rank lag 1	0.1240	(19.42)	13400000	(7.58)
Rank lag 2	0.0945	(14.55)	11300000	(3.04)
Rank lag 3	0.0800	(12.07)	6736293	(2.28)
Rank lag 4	0.0571	(8.54)	4506515	(2.43)
Rank lag 5	0.0288	(4.52)	2277394	(1.41)
Rank lag 6	0.0154	(2.37)	-97838.64	(-0.08)
ln(TNA)	-0.0135	(-9.32)	942539.4	(1.08)
ln(AGE)	-0.0157	(-4.56)	-2353853	(-1.50)
Flows lag 1	0.0507	(4.44)	-0.2349	(-0.77)
Flows lag 2	0.0472	(5.70)	0.0477	(0.38)
Flows lag 3	0.0106	(1.60)	0.0957	(1.78)
Flows lag 4	0.0133	(2.18)	0.0626	(1.57)
Offshore	0.0091	(2.20)	298604.4	(0.49)
Incentive Fees	-0.0006	(-2.32)	-141126.4	(-1.41)
Management Fees	-0.0047	(-1.83)	1339276	(1.82)
Personal Capital	-0.0070	(-1.71)	-1577176	(-2.42)
Leverage	0.0131	(3.34)	43903.05	(0.07)
Downside-Upside Pot. Ratio	-0.0139	(-5.85)	-434606.4	(-1.09)
Emerging Markets	-0.0223	(-2.98)	-774879.8	(-0.34)
Equity Market Neutral	0.0068	(0.61)	349546.5	(0.13)
Event Driven	-0.0033	(-0.48)	841935.4	(0.32)
Fixed Income Arbitrage.	0.0116	(1.17)	1078473	(0.37)
Global Macro	-0.0092	(-0.95)	-2813528	(-0.80)
Long/Short Equity	-0.0248	(-4.21)	-1302199	(-0.62)
Managed Futures	-0.0190	(-2.17)	3902279	(1.09)
R^2	0.0937		0.1122	
Number of observations	21841		21841	

variables.[32] In conclusion, all of our specifications show a robust linear relationship between quarterly cash flows and past relative performance, in contrast to the more convex relationship found in previous studies for mutual funds, or as documented by Agarwal et al [2003] for hedge funds using annual data.

It is unclear, however, what particular measure of performance is pre-eminent for hedge fund investors. This issue has not been addressed in previous studies.[33] In an alternative specification we use raw returns instead of ranks as a measure of performance. Both absolute and relative performance are measures available to investors. Given the structure of incentives in the industry and the high watermarks in place, managers seek for absolute returns and their investors expect managers to depart from benchmarks to the upside. Our regressions (not reported) show a similar pattern as with relative performance, that is, historical returns have a positive and linear impact on flows up to five lags and investors' responses are stronger for the most recent quarterly raw returns. A difference of 1% in raw returns in the previous quarter represents 0.23% difference in expected growth rates. Interestingly, however, when we include both raw returns and ranks in our model, ranks appear to capture all the effect of performance on flows. Individually, the coefficients for raw returns are not significant, while the impact of ranks on cash flows remains economically and statistically significant.[34]

Several of the control variables in our model have a statistically significant impact. First, investors appear to prefer funds with lower fees, ceteris paribus. Incentive fee differences of 1% between funds are associated with differences in flows rates of 0.06% per quarter. It is evident that in spite of the presumably higher managerial

[32] Results of our tests for non-linearities are available upon request.
[33] For the mutual fund industry, Gruber [1996] analysed the impact of different predictors of performance on cash flows, specifically the alphas from one- and four-index models and the excess returns over the S&P500 index. He finds that both the individual and the joint impact of these performance measures are significant. Sirri and Tufano [1998] find that ranks based on simple measures like one to five year raw returns have a significant effect on flows besides that of more sophisticated rankings based on excess returns of a market model or Jensen's alpha. For the pension fund industry, Del Guercio and Tkac [2002] also test the impact of excess raw returns relative to the S&P500, style adjusted performance, tracking error and Jensen's alpha from a one-factor model. They find that flows are strongly positively related to Jensen's alpha and negatively related to tracking error. For the hedge fund industry, Goetzmann et al. [2001] analyze separately the impact of raw returns and ranks, but not their joint effect.
[34] An F-test on the inclusion of the six lagged raw returns in our model gives the value of 3.60 (the 1% critical value being 2.80 for an F-distribution with 6 and 21770 degrees of freedom), leading to a marginal rejection of the joint hypothesis that the six additional variables have zero coefficients. Although the inclusion of lagged raw returns slightly improves the explanatory power of the model, it leads to an erratic pattern of the coefficients on returns, which is difficult to interpret economically. In addition, we also tried other specifications using more sophisticated performance measures popular in the industry, like Sharpe ratios, and style adjusted returns scaled by the standard deviation of historical returns. The patterns remain the same, i.e. flows are related in a linear way to past performance. However, performance relative to the peers appears to have the strongest explanatory power for money flows.

effort due to higher fees and a possible increase in return, as a consequence, investors are more sensitive to the level of costs involved and the concomitant increase in risk. Several investment styles have a significant and negative effect on cash flow rates. Funds with style “emerging markets”, “long short equity” and “managed futures” tend to experience, ceteris paribus, lower growth rates than the other styles. Smaller and younger funds enjoy larger percentage flows than larger and older funds, in line with the findings of Agarwal, Daniel and Naik [2003]. The coefficients on asset size are negative, significant and highly robust to alternative specifications. This indicates that hedge funds managing large amounts of assets grow less quickly. One explanation might be that hedge fund strategies seeking mispricing opportunities are not scalable, as pointed out by Goetzmann et al [2003]. Interestingly, however, the size effect disappears when our model explains dollar flows. This is an important point that will be discussed in Section 3.4, where we show that the impact of size cannot be appropriately captured if the investment and divestment decisions are not modelled separately. The size effect is probably more apparent with growth rates due to the fact that flows are magnified for small funds compared to large funds.

Persistence in money flows appears to be economically significant and highly robust to the alternative specifications discussed above. Funds that have experienced increased levels of inflows (outflows) will, ceteris paribus, continue growing (shrinking) over the next two or three quarters. The effect dies out at longer time horizons, suggesting once again the existence of short-run factors conditioning money flows. We defer the discussion of this issue to Section 3.4, which provides further insights into the impact of lagged flows.

There is strong evidence that investors in hedge funds look for upside potential with minimum downside risk, given the highly significant coefficient for the downside-upside potential ratio. In alternative specifications we experimented with other risk metrics that are popular in the industry, like downside deviation, upside potential, standard deviation, either based on the entire past history of the fund or based on the preceding six months. Downside deviations and upside potential with respect to the return of 3-month Treasury bill and with respect to the return on the S&P 500 were not significant. In the current model, however, the ratio of downside deviation to upside potential measured with respect to Treasury bills has a highly significant impact on flows.

Our main results appear to be robust when we estimate our model separately for the sub-samples of survivors and dead funds. Although by not including funds that disappeared, the impact of last quarter performance upon flows reduces slightly by 3% and the total long-run impact of historical performance reduces by 2%, linearity is still not rejected, while the coefficients remain significant and follow the same previously identified patterns. Thus, also at short horizons, the shape of the flow-performance relation does not seem to be affected by survivorship biases.[35] Summarizing, in all of our regressions, we find a strong quarterly relationship among poor performers as much as among good performers. This result is in sharp contrast with the relatively weak relationship found among poor performers at annual horizons in the mutual fund industry or as found by Agarwal et al. [2003] for hedge funds. Furthermore, unlike previous papers (see e.g. Goetzmann and Peles [1997], Sirri and Tufano [1998], Goetzmann et al. [2003], Agarwal et al. [2003]) we did not assign a flow rate of –100% when a fund drops out from the database, which might be justified in studies of mutual funds and horizons of one year or more. However, for hedge funds this is a perilous exercise particularly at short horizons, as the date at which a fund stops reporting is not necessarily the date of liquidation (see Ackermann et al. [1999]). Further, a flow rate of –100% does not reflect a conscious decision of investors but the decision of a manager to liquidate the fund.

In conclusion, hedge fund investors appear to make their investment and divestment decisions based on the most recent quarterly performance information. This evidence suggests that investors are frequently monitoring hedge funds. Interestingly, their allocation is proportional among bad and good performers. This result differs from the general findings at annual horizons for both the hedge fund and mutual fund industries, where flows of money are directed mostly to the best performers the prior year. Instead, in short horizons hedge fund investors are equally sensitive to good performance and poor performance. We interpret our findings partly as a result of active monitoring, mostly through audited reports and personal interviews, which makes investors better able to assess poor performers on time. But hedge fund investors also face high searching costs along their allocation process, which creates conditions that may weaken the sensitivity of inflows of money to funds that performed well in the past, as argued by Sirri and Tufano [1998].[36] Hedge funds face advertising restrictions and furthermore their activities lack transparency. As a consequence, hedge fund investors, both private and institutional, engage in a time-consuming process of gathering and evaluating information, which implies substantial costs.[37] The result might be a slow reaction of hedge fund investors to hire managers

[35] Using annual data, Goetzmann and Peles [1997], Chevalier and Ellison [1997] and Sirri and Tufano [1998] all document that the convexity of the flow-performance relation in mutual funds is not affected by survivorship biases. Del Guercio and Tkac [2002] and Agarwal, Daniel and Naik [2003] find the same result for pension funds and hedge funds, respectively.

[36] One of the main results from Sirri and Tufano [1998] is that marketing effort of mutual funds emphasizes good performance and by this means reduces searching costs for investors. These are conditions that enhance the sensitivity of investors to good past performance.

[37] See Bekier [1996] for evidence and for a detailed description of the buying process and the post-investment behaviour of hedge fund investors. Bekier quotes a hedge fund institutional investor who acknowledges that

that performed well in the recent past. However, this also suggests that inflows of money from new investors are likely to be more sensitive to measures of long-run performance (i.e. annual horizons), while outflows of money, which are the result of frequent monitoring, are therefore more sensitive to short-run performance. This explanation is consistent with the results of Agarwal, Daniel and Naik [2003], who find a high sensitivity of flows to good performance in the previous year, while they fail to capture the response of outflows to bad performance. In light of our interpretation, we study in the next section inflows and outflows separately and look into more detail at potential differences in their sensitivity to past performance.

3.4 Money inflows and outflows and the effect of liquidity restrictions

Hedge funds present several of the distinctive features that characterize any alternative investment. One of them is illiquidity. Lock-up periods are common and redemptions and subscriptions are limited to certain dates, typically the end of a month or a quarter. In rare exceptions, investors may obtain more frequent redemptions at a premium. Additionally, as limited partnerships, U.S. domiciled hedge funds are generally not registered with the Securities and Exchange Commission and therefore cannot freely trade their shares in the public market.

Restricted flows enable a hedge fund to minimize cash holdings and reduce administrative work. Subscription periods generally match the redemption periods of a fund or are somewhat shorter, depending on the trading strategies, i.e. the liquidity of the markets and instruments traded. Nearly 75% of the funds in our dataset have monthly subscription periods and 15% have subscription periods of 90 days. Figure 3 shows the distribution of redemption frequencies for our sample. Nearly 40% of funds have redemption periods of one quarter or more, of which onshore funds account for almost 60%.

A written notice to the manager of the fund is often required prior to redemption in order to simplify cash flow management. The combination of redemption periods and notice periods may have an adverse effect on investor's liquidity. For example, consider a fund with quarterly redemptions and 90 days of notice period. If an investor decides to redeem her shares on July 2nd based on last quarter performance,

their standard process of investment may take up to 18 months, from the identification of potential alternatives until the final decision to hire a manager. Also several alternative investment advisors acknowledge often in hedge fund conferences that the manager due diligence process may take from two to six months to be completed.

the earliest possible redemption date is only at the end of December. Most typically, funds have monthly or quarterly redemption periods with minimum notice periods of 15 to 90 days. The possible combinations found in our sample are shown in Table V.

Figure 3

Hedge Funds Redemption Frequencies

Redemptions in hedge funds are limited to certain dates. The figure represents the distribution of redemption frequencies for the cross-section of funds from TASS database.

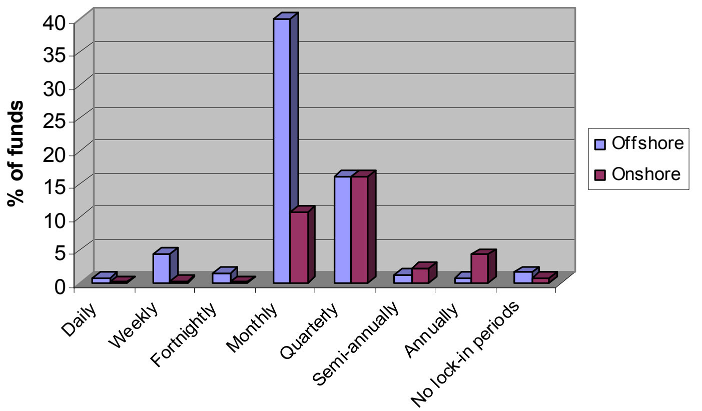


Table V

Percentage of Funds for Different Combinations of Redemption Periods and Notice Periods in TASS database

	Redemption Notice Periods						
Redemption periods	No notice Period	1day	2 to 7 days	8 to 15 days	16 to 30 days	31 to 90 days	91 to 180 days
1	0.13	0.19	0.39		0.06	0.06	
7	2.33	0.19	1.69	0.13	0.19		
15	0.39	0.13	0.65	0.19	0.13		
30	10.69	0.52	4.54	10.82	18.54	5.38	0.19
90	4.21	0.13	0.19	1.62	13.87	11.86	0.13
183	0.52				0.45	2.33	
365	0.58		0.06		1.69	2.33	0.19

Put differently, the decision of an investor to subscribe or redeem in response to past performance may not become effective immediately, but with a substantial delay. News about fund performance released at the end of a quarter may not necessarily have an impact on flows during the next quarter, depending on redemption, subscription and notice periods. Therefore, we explore the response of flows to past performance subject to liquidity restrictions. We focus for the moment on restrictions to withdrawals, since subscription periods are shorter and their effects are difficult to capture at a quarterly horizon. For each fund and each quarter we compute the maximum delay that an investor responding to past monthly performance would have to face to see her decision of withdrawing her money made effective. For 10% of funds, the maximum delay is 2 quarters or more. In a few cases it is as long as five quarters. Given this delay, we can identify in our model those lags that could have an effective impact on flows. For each quarter and for every fund, we construct five dummy variables corresponding to each of the five lagged quarters, taking the value 1 if liquidity restrictions do not prevent outflows in response to the lagged performance measure.

We modify our model of flows to allow for interactions between lagged ranks and dummies accounting for limits to liquidity.[38] Estimates of our modified model are shown in Table VI. Unrestricted ranks have an impact on growth rates with higher levels of significance than restricted ranks (column A). The impact of the first lag is 18% higher for unrestricted ranks while the effects of the control variables remain basically unchanged. Nearly 75% of the long-run impact is still concentrated over the next three quarters. This effect is enhanced when our model explains dollar flows (column B). In this case, when restrictions are present, almost all coefficients for lagged ranks are even insignificant. Thus, our estimates provide conclusive evidence that quarterly net cash flows are less sensitive to past performance for funds imposing extended redemption periods compared to less restricted funds.

However, given differences between redemption and subscription periods, it is not clear whether inflows and outflows respond with equal sensitivity to good and bad performance, respectively.[39] Also the sensitivity of inflows and outflows might be

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[38] In each quarter t, we define for each j-lagged rank and for each fund i :

$$Rank\ Unrestricted_{i,t-j} = Rank_{i,t-j}\ (REDR_{i,t-j})$$
$$\text{and}\quad Rank\ Restricted_{i,t-j} = Rank_{i,t-j}\ (1\text{-}REDR_{i,t-j})$$

where $REDR_{i,t-j}$ is a dummy variable that takes value 1 if redemption restrictions do not prevent outflows in quarter t in response to j-lagged performance given by $Rank_{i,t-j}$.

[39] From our dataset we cannot extract information relative to outflows and inflows per fund and per period. For each fund, we can only distinguish between periods in which outflows outweigh inflows (negative net cash flows) and periods in which inflows outweigh outflows (positive net cash flows).

Table VI

The Effect of Relative Performance Subject to Liquidity Restrictions Upon Money Flows in Open-End Hedge Funds

The table reports OLS estimates of a model of flows subject to liquidity restrictions. The sample includes 1543 open-end hedge funds for the period 1994 Q4 till 2004 Q3. We measure dollar cash flows as the change in total net assets between consecutive quarters corrected for reinvestments. Alternatively, we measure cash flows as a growth rate relative to the fund's total net assets of previous quarter. The independent variables that account for relative performance include six lagged fractional ranks interacting with dummies accounting for limits to liquidity. The fractional rank ranges from 0 to 1 and is defined as the fund's percentile performance relative to all the funds existing in the sample in the same period, based on the fund's raw return in previous quarter. Independent variables accounting for fund specific characteristics include the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows, downside-upside potential ratio based on the entire past history of the fund and calculated with respect to the return on the U.S. Treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund and 7 dummies for investment styles defined on the basis of CSFB/Tremont indices. The model also includes 39 time dummies (estimates not reported). We estimate our model by pooling all fund-period observations.
T-statistics based on robust standard errors are provided in parentheses.

Parameters	OLS estimates Modelling growth rates (A)		OLS estimates Modelling dollar flows (B)	
Intercept	0.1180	(3.72)	-2.82E+07	(-1.81)
Rank lag 1 Unrestricted	0.1255	(19.00)	1.31E+07	(7.58)
Rank lag 2 Unrestricted	0.0952	(14.09)	1.11E+07	(2.96)
Rank lag 3 Unrestricted	0.0811	(11.76)	7044145	(2.37)
Rank lag 4 Unrestricted	0.0570	(8.20)	4389959	(2.41)
Rank lag 5 Unrestricted	0.0276	(4.18)	3159295	(1.79)
Rank lag 6	0.0157	(2.41)	-167517.2	(-0.13)
Rank lag 1 Restricted	0.1061	(6.60)	1.97E+07	(2.29)
Rank lag 2 Restricted	0.0846	(4.42)	1.49E+07	(2.73)
Rank lag 3 Restricted	0.0661	(4.28)	2613660	(0.32)
Rank lag 4 Restricted	0.0579	(3.52)	7531471	(1.69)
Rank lag 5 Restricted	0.0499	(2.95)	-1.08E+07	(-1.22)
ln(TNA)	-0.0134	(-9.21)	968341.2	(1.10)
ln(AGE)	-0.0156	(-4.55)	-2351888	(-1.50)
Flows lag 1	0.0506	(4.44)	-0.2351	(-0.78)
Flows lag 2	0.0471	(5.70)	0.0475	(0.38)
Flows lag 3	0.0106	(1.60)	0.0956	(1.78)
Flows lag 4	0.0133	(2.18)	0.0626	(1.57)
Offshore	0.0075	(1.74)	-45133.74	(-0.06)
Incentive Fees	-0.0006	(-2.29)	-141537.6	(-1.42)
Management Fees	-0.0047	(-1.82)	1346796	(1.82)
Personal Capital	-0.0070	(-1.73)	-1566741	(-2.41)
Leverage	0.0136	(3.44)	103305.8	(0.16)
Downside-Upside Potential Ratio	-0.0136	(-5.74)	-374809.2	(-0.98)
Emerging Markets	-0.0220	(-2.94)	-681122.1	(-0.29)
Equity Market Neutral	0.0072	(0.64)	289951.3	(0.11)
Event Driven	-0.0022	(-0.33)	1005455	(0.38)
Fixed Income Arbitrage.	0.0117	(1.18)	1085233	(0.37)
Global Macro	-0.0092	(-0.95)	-2780232	(-0.79)
Long/Short Equity	-0.0241	(-4.07)	-1115327	(-0.52)
Managed Futures	-0.0194	(-2.21)	3819735	(1.07)
R2	0.0939		0.1125	
Number of observations	21841		21841	

related to different time horizons, as discussed at the end of the previous section. Thus, it might be the case that the flow-performance relationship displays two different regimes, depending on whether outflows are more important than inflows (in which case we observe negative net cash flows) or vice versa. To investigate to what extent the flow-performance relationship is distinct for positive and negative net cash flows we extend our model to allow for a differential impact of the explanatory variables depending upon the sign of the cash flows.[40] The resulting model consists of three equations. A first equation explains the sign of aggregate cash flows and reflects the decision of investors either to invest or divest in a particular fund. The two remaining equations describe the relation of positive cash flows to past performance and negative cash flows to past performance, respectively, controlling for other characteristics like fund age, size and style. The easiest way to interpret the model is by considering the last two equations as truncated regression models (truncated at zero), where a common binary choice model explains the appropriate regime. As a result, the two flow equations contain an additional term that captures the truncation. This term is based on the generalized residual of the binary choice model, while its coefficients depend upon the covariances between the equations' error terms (see Maddala [1983] for an extensive treatment of such models).

Let $Flows_{n,it}$ and $Flows_{d,it}$ be the observed rates of cash flows for an individual fund i, conditional upon an aggregate decision of investors either to invest or divest in the fund, respectively. Let S_{it} be a dummy variable capturing the aggregate investors' decision, taking the value 1 if the observed sign of net cash flows is positive and 0 otherwise. Thus, we observe either

$$\begin{array}{lll} & Flows_{n,it} \text{ when} & S_{it} = 1, \\ \text{or} & Flows_{d,it} \text{ when} & S_{it} = 0, \text{ but never both.} \end{array}$$

The first stage consists of estimating a probit model explaining the sign of flows:

$$S_{i,t}^{*} = \alpha + \sum_{j=1}^{6} \beta_{1,j}.(rnk_{i,t-j}) + \beta_2.\ln(TNA_{i,t-1}) + \beta_3.\ln(AGE_{i,t-1}) + \sum_{j=1}^{4} \beta_{4,j}.(Flow_{i,t-j}) + \gamma'.X_{i,t} + \lambda_t + \mu_{i,t} \quad (4)$$

where $S_{it} = 1$ if $S^{*}_{it} > 0$, and $S_{it} = 0$ otherwise.

The second stage is estimation by ordinary least squares of the truncated variables $Flows_{n,i}$ and $Flows_{d,i}$, modelled as in equation (3) but incorporating the generalized

[40] To the best of our knowledge, only Bergstresser and Poterba [2002] study separately inflows and outflows in mutual funds, and look at the impact of after-tax returns compared to pre-tax returns upon flows. However, contrary to our study, they could obtain data on gross outflows and inflows and therefore could treat both datasets separately.

residual from the probit model as an additional explanatory variable. This additional variable, captures $E[\varepsilon_{i,t} \mid S_{it}=1]$ and $E[\varepsilon_{i,t} \mid S_{it}=0]$, respectively, where

$$E\,[\varepsilon_{i,t} \mid S_{it}=1] = \mathrm{cov}(\mu_{i,t}, \varepsilon_{i,t}).E[\mu_{i,t} \mid S_{it}=1].$$

The latter expectation reflects the generalized residual of equation (4) (see e.g. Verbeek [2004], Chapter 7).[41] We do not impose that the coefficients in any of the three equations are identical.

Table VII provides the estimates of the probit model explaining the regime of cash flows (column A). For these results we do not take into account cash flows having value zero. The results show that the impact of historical relative performance upon the direction of the investment decision is positive and highly significant, both economically and statistically. Funds with a good track performance relative to their peers are very likely to experience positive net cash flows, while a bad past performance is more likely to determine a divestment decision. Moreover, for funds imposing lower restrictions to liquidity, the investors' decision to invest or divest is strongly driven by the most recent quarterly performance. The effect attenuates progressively with each lag and dies away after the fifth lag. Instead, for more restricted funds the impact of historical performance on the investment decision is considerably reduced, particularly for the most recent quarter. This results in less dispersion of the impact across lagged ranks, although coefficients are highly significant up to the fourth lag. The control variables also capture some interesting and significant effects. Younger funds are, ceteris paribus, more likely to attract flows of money than older funds do. Offshore funds operating in tax heavens are, ceteris paribus, more likely to trigger a divestment decision from its investors compared to onshore funds. Also the dynamics of flows appear to be an important determinant of the regime of flows. Funds that experienced inflows in the past are, ceteris paribus, more likely to continue experiencing inflows over the next four quarters. Finally, several investment style dummies also have a significant impact. Long/short equity funds and funds operating in emerging markets have, ceteris paribus, the highest probability to induce a divestment decision from investors.

Columns B and C in Table VII show the results of estimating the two equations for negative and positive cash flows respectively. The differences between both regimes are apparent. Surprisingly, the coefficients for the model of positive cash flows become statistically en economically insignificant in comparison with our previous results using the pooled model. The impact of past relative performance upon the rates

[41] This analysis assumes joint normality of all unobservable error terms.

Table VII

Switching Regression Model Explaining Positive and Negative Cash Flows Subject to Liquidity Restrictions in Open-End Hedge Funds

The table reports estimates of a switching regression model explaining positive and negative flows. Columns B and C report OLS coefficients estimates using cash flows as the dependent variable. The sample includes 1543 open-end hedge funds for the period 1994 Q4 till 2004 Q3. We measure cash flows as a quarterly growth rate corrected for reinvestments. The independent variables that account for relative performance include six lagged fractional ranks interacting with dummies for liquidity restrictions. The fractional rank ranges from 0 to 1 and is defined as the fund's percentile performance relative to all the funds existing in the sample in the same period, based on the fund's raw return in previous quarter. Independent variables accounting for fund specific characteristics include the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows, downside-upside potential ratio based on the entire past history of the fund and calculated with respect to the return on the U.S. Treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund and seven dummies for investment styles defined on the basis of CSFB/Tremont indices. The model also includes 39 time dummies (estimates not reported). The two models using the truncated samples also incorporate as explanatory variable the generalized residual obtained from a probit model explaining the regime of flows (loglikelihood estimates reported in column A. The dependent variable takes the value 1 if net cash flows are strictly positive). We estimate each model by pooling all fund-period observations. T-statistics based on robust standard errors as well as z-statistics for probit estimates are provided in parentheses.

Parameters	Probit model explaining positive and negative cash flows (A)	Truncated sample for CFlows <0 (B)	Truncated sample for CFlows > 0 (C)
Intercept	-0.8208 (-5.37)	-0.1519 (-4.78)	0.7944 (6.87)
Rank lag 1 Unrestricted	0.7317 (22.06)	0.1885 (6.72)	0.0375 (0.97)
Rank lag 2 Unrestricted	0.5720 (16.66)	0.1506 (6.73)	0.0179 (0.59)
Rank lag 3 Unrestricted	0.4766 (13.76)	0.1124 (5.99)	0.0266 (1.02)
Rank lag 4 Unrestricted	0.3287 (9.66)	0.0795 (5.92)	0.0149 (0.69)
Rank lag 5 Unrestricted	0.1796 (5.29)	0.0457 (5.52)	-0.0004 (-0.03)
Rank lag 6	0.0720 (2.17)	0.0258 (4.53)	-0.0015 (-0.13)
Rank lag 1 Restricted	0.6762 (6.16)	0.1772 (5.87)	0.0371 (0.97)
Rank lag 2 Restricted	0.5676 (4.75)	0.1778 (6.39)	-0.0071 (-0.18)
Rank lag 3 Restricted	0.4580 (3.79)	0.1211 (4.98)	0.0061 (0.21)
Rank lag 4 Restricted	0.5511 (4.52)	0.1119 (3.86)	-0.0164 (-0.48)
Rank lag 5 Restricted	0.2734 (2.23)	0.0501 (2.70)	0.0368 (1.45)
Ln(TNA)	0.0167 (2.67)	0.0033 (3.17)	-0.0333 (-11.63)
Ln(AGE)	-0.1606 (-9.18)	-0.0043 (-0.66)	-0.0122 (-1.12)
Flows lag 1	0.3920 (4.75)	0.1055 (6.92)	0.0201 (1.48)
Flows lag 2	0.2146 (4.65)	0.0684 (6.31)	0.0252 (2.02)
Flows lag 3	0.0758 (2.57)	0.0103 (1.62)	0.0076 (1.03)
Flows lag 4	0.0640 (2.90)	0.0234 (5.75)	0.0084 (0.98)
Offshore	-0.0980 (-4.58)	-0.0471 (-9.36)	0.0686 (8.06)
Incentive Fees	-0.0023 (-1.36)	-0.0013 (-5.23)	0.0001 (0.13)
Management Fees	-0.0200 (-1.57)	-0.0047 (-2.25)	0.0014 (0.31)
Personal Capital	-0.0553 (-2.82)	-0.0055 (-1.46)	-0.0138 (-2.01)
Downside-Upside Potential Ratio	-0.0504 (-3.91)	-0.0054 (-2.06)	-0.0188 (-3.36)
Emerging Markets	-0.1428 (-3.42)	-0.0032 (-0.41)	-0.0254 (-1.92)
Event Driven	-0.0118 (-0.31)	-0.0004 (-0.07)	-0.0039 (-0.41)
Fixed Income Arbitrage.	-0.0010 (-0.02)	0.0061 (0.75)	0.0136 (0.96)
Long/Short Equity	-0.1416 (-4.44)	-0.0187 (-2.70)	-0.0200 (-1.81)
Managed Futures	-0.0908 (-2.17)	-0.0192 (-2.54)	-0.0088 (-0.61)
Gen.Residual from Probit Model		0.3340 (5.34)	-0.1065 (-1.28)
Chi^2 (69)	2250.36		
Pseudo R^2	0.1022	0.0700	0.0791
Number of observations	21243	10367	10876

of cash flows is entirely captured by outflows of money in response to bad performance. The most recent quarterly performance has the strongest effect in less restricted funds, accounting for nearly 31% of the total long run impact. It gradually disappears with lags. Also for these funds, the response to previous quarter performance is more sensitive, implying 6% more outflows than restricted funds.

The control variables also capture several significant asymmetries between the two regimes. Size has a significant impact in both regimes, but with opposite sign. On the one hand, smaller funds experience, ceteris paribus, larger outflows (i.e. lower negative growth rates) than bigger funds; on the other hand, smaller funds also experience larger inflows, conditional to the regime of positive money flows. In other words, small funds are subject to more extreme growth rates than large funds, a result that will be discussed more extensively in Section 3.5. In contrast, the impacts of the dynamics of flows, incentive fees and the offshore dummy variable are almost entirely captured by the regime of negative cash flows. In other words, only outflows tend to persist – over the next four quarters – while it is clear that investors penalize more heavily offshore funds as well as funds with higher levels of incentive fees by withdrawing their money[42]. It is noteworthy that in the pooled model, the offshore dummy is insignificant, while it is highly significant in the regime-specification model, with opposite signs. Clearly, more extreme rates of cash flows characterize offshore funds. Conditional to experiencing positive flows of money, these funds are more likely to have substantially higher growth rates than onshore funds. On the contrary, given a regime of negative flows, offshore funds are more likely to experience substantially larger withdrawals compared to onshore funds. This is consistent with the more extended redemption periods imposed by onshore funds, as indicated in Figure 3. Regarding the style dummies, it is interesting to notice the coefficient for style "emerging markets", which becomes marginally significant but only for positive cash flows, while the impact of funds with styles "managed futures" and "long short equity" remains significant only for negative growth rates. Finally, the downside-upside potential ratio appears to affect both regimes negatively and significantly, although the impact upon positive cash flows is substantially larger.

[42] An explanation for the momentum in outflows captured by our model lies in the fact that investors in a given hedge fund are few and large. As pointed out by Brown, Goetzmann and Park [2001], this poses a serious threat of withdrawals, not only because only one investor redeeming might represent a large money outflow, but also communication among few large investors might result in massive withdrawals. The sustained response of outflows over several quarters in our model could be the reflection of certain herd behavior among investors triggered by poor performance. Conversely, the lack of momentum in inflows over the short run is a further indication of the slow reaction of investors to past good performance, which contrasts with the momentum in flows found at annual horizons for mutual funds and hedge funds (see, e.g., Del Guercio and Tkac [2002] and Agarwal, Daniel and Naik [2003]).

Estimating our truncated regression models with dollar flows as the dependent variable gives some additional insights (Table A1, appendix). The pattern of coefficients for ranks remains the same as with growth rates. However, the magnitudes of the coefficients for negative dollar flows are substantially larger than for positive dollar flows. In dollar terms, outflows are highly sensitive to changes in short-run relative performance but inflows change only slightly, as is also suggested by Panel B of Figure 2. On the other hand, it is remarkable that the coefficient for size becomes highly significant, while the sign is opposite in both regimes. Conditional to receiving inflows of money, large funds experience more important amounts of dollar flows compared to small funds. But also they experience considerably larger dollar outflows than small funds conditional to the regime of negative flows. In sum, large funds are subject to more extreme variations of flows of money in dollar terms. This important result remains hidden in Tables IV and VI, while Goetzmann et al. [2003] also did not find evidence that large funds experienced dollar flows as high as small funds. This emphasizes the need of separately modelling money inflows and outflows. Summing up, while our model explaining growth rates shows that large funds grow or shrink at lower rates than small funds, we also show that large funds may face important withdrawals in dollar terms, which gives further evidence in favour of diseconomies of scale playing a role. Section 3.5 will provide additional insights into the size issues.

So far we have shown a clear response of negative flows to past performance in the short run, consistent with our interpretation that outflows of money are the result of frequent monitoring at a monthly or quarterly basis. At the same time, we cannot identify a clear response of positive flows at short horizons, while at annual horizons Agarwal, Daniel and Naik [2003] find a positive and convex response of inflows towards the best performers. Therefore, we perform an additional estimation by aggregating both flows and relative performance over different time horizons. Table VIII shows estimates from a switching regression model explaining positive and negative cash flows, similar to (4). However, in Panel 1 we regress quarterly cash flows upon yearly ranks constructed on the basis of the previous one-year raw return. We only report the coefficient estimates for past performance and size.

Aggregating relative performance over longer horizons does not change our previous results; quarterly outflows remain strongly sensitive to past year performance, in contrast to quarterly inflows. In Panel 2 we regress annual cash flows upon yearly ranks of the previous year. In this case, observations of four-quarter cash flows are overlapping, which introduces an autocorrelation problem and we report t-statistics based on Newey-West standard errors. Our results are remarkably different from previous ones. The response of annual inflows to past year performance becomes marginally significant while the estimated coefficient is substantially larger than the coefficient for outflows, suggesting a convex flow-performance relation. In Panel 3 we regress annual cash flows upon quarterly ranks in previous year. The response of annual outflows to previous quarter performance turns out to be insignificant, while inflows appear to be highly sensitive.

Table VIII

Switching Regression Model Explaining Positive and Negative Cash Flows to Open-End Hedge Funds over Different Time Horizons

The table reports estimates of a switching regression model explaining positive and negative flows. Columns B and C report OLS coefficients estimates using cash flows as the dependent variable. We measure cash flows as a growth rate corrected for reinvestments. In panel 1 we consider quarterly cash flows. In panel 2 and 3 we aggregate cash flows into annual horizons, while moving forward one quarter at the time. The sample includes 1543 open-end hedge funds for the period 1994 Q4 till 2004Q3. The independent variables that account for relative performance are either the previous one-year rank, in Panels 1 and 2, or the lagged one-quarter rank, in Panel 3. The fractional rank ranges from 0 to 1 and is defined as the fund's percentile performance relative to all the funds existing in the sample in the same period, based on the fund's raw return in previous year or in previous quarter. Independent variables accounting for fund specific characteristics include the log of fund's total net assets in the prior period, the log of fund's age in months since inception, lagged measures of flows, downside-upside potential ratio based on the entire past history of the fund and calculated with respect to the return on the U.S. Treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund and 7 dummies for investment styles defined on the basis of CSFB/Tremont indices. The model also includes 39 time dummies. The two models using the truncated samples also incorporate as explanatory variable the generalized residual obtained from a probit model explaining the regime of flows (loglikelihood estimates reported in column A. The dependent variable takes value 1 if net cash flows are strictly positive). We estimate our models by pooling all fund-period observations. We only report estimates for past relative performance and size. T-statistics based on Newey-West standard errors as well as *z*-statistics for probit estimates are provided in parentheses.

Parameters	Probit model explaining positive and negative cash flows (A)	Estimation using a truncated sample for CFlows <0 (B)	Estimation using a truncated sample for CFlows > 0 (C)
Panel 1 : Quarterly Flows (N=22265 obs., from which 10734 are negative cash flows)			
Previous one-year rank	1.1209 (31.97)	0.3302 (6.00)	-0.0332 (-0.65)
Ln(TNA)	0.0217 (3.57)	0.0050 (3.97)	-0.0371 (-12.84)
Panel 2 : Annual Flows (N=20106 obs., from which 9906 are negative cash flows)			
Previous one-year rank	1.2256 (34.87)	0.3174 (4.39)	1.3564 (1.92)
Ln(TNA)	-0.0424 (-6.76)	-0.0147 (-4.92)	-0.2778 (-9.04)
Panel 3 : Annual Flows (N=20106 obs., from which 9906 are negative cash flows)			
One-quarter rank lag 1	0.8774 (26.23)	0.0504 (1.29)	1.0657 (2.08)
One-quarter rank lag 2	0.7282 (21.71)	0.0434 (1.33)	0.9281 (2.21)
One-quarter rank lag 3	0.5137 (15.23)	0.0345 (1.46)	0.7883 (2.58)
Ln(TNA)	-0.0367 (-5.81)	-0.0063 (-2.78)	-0.2777 (-9.74)

These results confirm previous findings of a convex flow-performance relationship when the aggregate of flows over the year are considered. However, we have shown that looking at shorter horizons unmasks an immediate and sustained response of major withdrawals of money when funds perform poorly. Our results also reveal a slow reaction of inflows to short-term past performance of hedge funds, which can be attributable to both high searching costs for investors and infrequent subscription periods. Our claim that investors face different kinds of decisions that operate in different time horizons is clearly supported by our empirical results.

Further, our findings are in line with the main argument of Berk and Green [2004] by showing that capital inflows are slow in chasing short-term performance and thus would be unable to compete away the predictability patterns in hedge fund returns found at quarterly horizons. This argument explicitly addresses the mutual effects between money flows and performance. Two questions arise. First, to what extent are investors able to exploit the predictability patterns of hedge funds returns as a result of their investment and divestment decisions? Second, to what extent do money flows have an impact upon performance? The next section explores the implications of our findings for both hedge funds and their investors.

3.5 Economic implications: is money to hedge funds smart?

This section relates money flows to subsequent performance. The recent literature on smart money has investigated the performance of the portfolios of mutual fund investors (see Gruber [1996], Zheng [1999] and Wermers [2003]). In the same line, we first provide an assessment of how successful hedge fund investors actually are in selecting funds as a result of their asymmetric response to good and bad performance. Second, given the slow response of inflows to past performance, a pertinent question is to what extent investors are able to exploit short-run predictability patterns in hedge fund returns. Finally, the swift response of outflows to bad performance suggests an effective punishing mechanism in place. Therefore, the last part of this section explores what the implications are for hedge funds and their survival. The analysis that follows looks into detail at the actual investors' allocations across funds, providing in turn further insights into our previous results.

A. The Performance of Investors' Allocations

We intend to compare the performance of investors' allocations, measured as a cash flow weighted return, to an equally weighted allocation as a benchmark. We first separate the investment from the divestment decision by ranking funds based on the cash flows they experienced in a given quarter. Then we separate funds with positive and negative money flows into two portfolios. We refer to them as the *investment portfolio* and the *divestment portfolio,* respectively [43]. Following Zheng [1999]'s approach, we look at the performance of both portfolios subsequent to ranking, by compounding funds' returns over different holding periods, from one to eight quarters after the ranking period. We compute both an equally weighted average and a cash flow weighted average of compounded returns for the two portfolios. We repeat this procedure in each quarter. Finally we average the portfolios' returns over time.[44] Table IX summarizes our results when we consider style-adjusted returns. Figure 4 presents the results for both raw returns and style-adjusted returns. For comparison, we also include the time average of returns in the ranking period (averaged across 40 quarters). Ranks are based upon growth rates, but our results differ only slightly when ranks are based upon dollar flows.

In the ranking period, the cash flow weighted style-adjusted return significantly outperforms the equally weighted return for the investment portfolio by 0.67% (Panel A, in Table IX and Figure 4). Surprisingly, the situation reverses in the subsequent quarters. While the equally weighted return reduces by 0.40% in the quarter following the initial ranking, the cash flow weighted style-adjusted return on the investment portfolio falls by 1.5%, significantly underperforming the equally weighted return by nearly 46 basis points per quarter. We obtain comparable differences in terms of raw returns (as shown in Panel A of Figure 4). These differences are far greater than the nearly 0.07% per quarter, as reported by Zheng [1999], by which the equally weighted portfolio of mutual funds with positive cash flows outperforms the cash flow weighted portfolio, in terms of excess returns over the market.

[43] Alternatively, we could use the above median and below median portfolios as a good approximation for the sets of investment and divestment targets, since the median of money flows, either in terms of growth rates or dollar flows, is very close to zero (see Table II).

[44] Recall that our sample period contains 40 quarters. Thus, for a holding period of one quarter, we can conduct this procedure (i.e. ranking in one period and evaluating holding periods over subsequent quarters) only for 39 quarters, until 2004 Q2. Similarly, for a holding period of eight quarters, we can conduct this procedure along 32 quarters only. We adjust for autocorrelation using Newey-West standard errors. We implement a "follow the money" approach to control for a potential survival bias by assuming that investors place the money in the style index whenever a fund disappears from the dataset.

Table IX

The Performance of Investors' Portfolios

Hedge funds are ranked every quarter from 1994Q4 to 2004Q3 based on the net cash flows they experienced during that quarter. Cash flows are measured as growth rates (i.e. normalized cash flows). We assume that flows take place at the end of the period, although in reality they may take place along the quarter. We evaluate the compounded style-adjusted returns of each fund for different holding periods, from one to eight quarters after ranking. The table shows in Panels A and B the time-series averages of cross-sectional average returns for all funds with positive cash flows (the "investment portfolio") and negative cash flows (the "divestment portfolio"). We adjust for autocorrelation using Newey-West standard errors. Whenever a fund disappears from the dataset, we implement a "follow the money" approach by assuming that investors place the money in the style index. We obtain the cross-sectional average of compounded returns in each quarter either as an equally weighted return or as a cash flow weighted return that takes into account investors' allocations. We also report the difference between both weighted averages. Panel C compares the return of the investment portfolio against the return of the divestment portfolio. Standard errors of the differences are reported in parentheses. We include the performance in the ranking period for comparison.

Panel A : Weighted average quarterly returns of the above-median portfolio (the "investment" set)

	Ranking period	Holding period (quarters)							
	0	1	2	3	4	5	6	7	8
CashFlowWeighted	0.0132	-0.0021	-0.0032	-0.0023	-0.0018	-0.0015	-0.0019	-0.0022	-0.0023
Equally Weighted	0.0065	0.0025	0.0011	0.0007	0.0011	0.0012	0.0012	0.0010	0.0009
Difference	0.0067	-0.0046	-0.0043	-0.0030	-0.0029	-0.0028	-0.0031	-0.0032	-0.0032
Standard error	(0.0033)	(0.0023)	(0.0031)	(0.0031)	(0.0033)	(0.0032)	(0.0027)	(0.0025)	(0.0028)

Panel B : Weighted average quarterly returns of the below- median portfolio (the "divestment" set)

	Ranking period	Holding period (quarters)							
	0	1	2	3	4	5	6	7	8
CashFlowWeighted	-0.0045	-0.0052	-0.0042	-0.0041	-0.0034	-0.002	-0.0003	-0.0013	-0.0014
Equally Weighted	-0.0037	-0.0002	0.0006	0.0016	0.0023	0.0030	0.0033	0.0035	0.0039
Difference	-0.0008	-0.0051	-0.0048	-0.0057	-0.0057	-0.0050	-0.0036	-0.0048	-0.0053
Standard error	(0.0051)	(0.0041)	(0.0044)	(0.0041)	(0.0041)	(0.0052)	(0.0059)	(0.0050)	(0.0043)

Panel C : Above-median minus below-median portfolios' weighted average returns

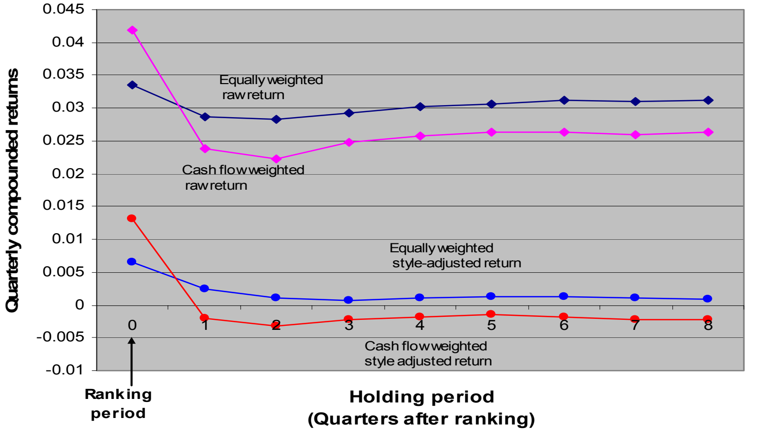
	Ranking period	Holding period (quarters)							
	0	1	2	3	4	5	6	7	8
CashFlowWeighted	0.0177	0.0031	0.0010	0.0018	0.0016	0.0004	-0.0016	-0.0009	-0.0009
	(0.0074)	(0.0053)	(0.0061)	(0.0051)	(0.0055)	(0.0065)	(0.0074)	(0.0061)	(0.0056)
Equally Weighted	0.0102	0.0027	0.0005	-0.0009	-0.0011	-0.0018	-0.0021	-0.0026	-0.0030
	(0.0023)	(0.0020)	(0.0020)	(0.0024)	(0.0026)	(0.0027)	(0.0029)	(0.0025)	(0.0027)

Figure 4

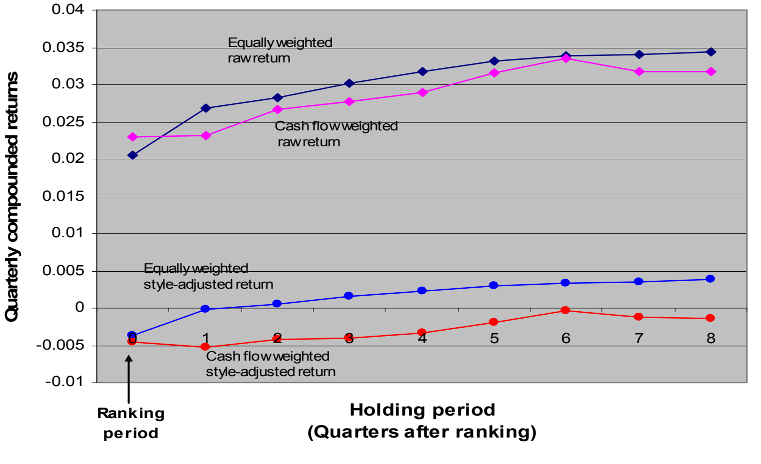
Time-series Averages of Cash Flow Weighted Returns and Equally Weighted Returns for Different Holding Periods

Hedge funds are ranked every quarter from 1994Q4 to 2004Q3 based on the net cash flows they experienced during that quarter. Cash flows are measured as growth rates. We evaluate the compounded returns of each fund for different holding periods, from one to eight quarters after ranking. The figure shows time-series averages of cross-sectional average returns for all funds with positive cash flows (the "investment portfolio") and negative cash flows (the "divestment portfolio"). Whenever a fund disappears from the dataset, we implement a "follow the money" approach by assuming that investors place the money in the style index. We obtain the cross-sectional average of compounded returns in each quarter either as an equally weighted return or as a cash flow weighted return that takes into account investors' allocations. We use two definitions of a fund's returns: a) raw returns, and b) style-adjusted returns. We include the performance in the ranking period for comparison. We adjust for autocorrelation using Newey-West standard errors.

Panel A: Investment Portfolio



Panel B: Divestment Portfolio



Manifestly, hedge fund investors' allocations fail to appropriately discriminate funds' expected returns. That is, they invest more in some funds than is justified by subsequent quarterly returns. As a result, the opportunity cost is substantial, had they equally allocated their money across all funds in the investment set[45]. Moreover, given liquidity restrictions, it seems unlikely that hedge fund investors can benefit from the short-lived high returns occurring contemporaneously to flows.

On the other hand, Panel B in Table IX shows no significant differences between cash flow weighted and equally weighted returns for the divestment portfolio. However the magnitude of these differences is indicative that the divestment allocations work pretty well by allowing investors to reduce to some extent the return they give up by divesting. For example, in the quarter subsequent to ranking, the cash flow weighted style-adjusted return underperforms both the equally weighted return and the style index by more than 50 basis points. In terms of raw returns the difference is somewhat reduced, as shown in Panel B, Figure 4. Remarkably though, the actual investors' (de)allocation strategy consistently underperforms the equally weighted strategy for holding periods up to 8 quarters.

In Panel C, Table IX, we compare the performance of the investment and the divestment portfolios. Cash flows to hedge funds appear to have a strong sorting capacity of contemporaneous performance. In the ranking period, the equally weighted return for the investment portfolio significantly outperforms the divestment portfolio, by 1.02% and 1.31% in terms of style-adjusted returns and absolute returns respectively. Furthermore, if we look at cash flow weighted returns, this difference is considerably magnified, becoming 1.77% on a style-adjusted basis, and 1.91% in terms of raw returns (Figure 4). We find here the short-run equivalent of the result of Gruber [1996] for mutual funds at a one-year horizon: "high returns occur during the period of time when cash flows occur"[46].

However, we do not find evidence of smart money, defined by the extent to which returns of the investment portfolio outperform the divestment portfolio after the ranking period (see Gruber [1996] and Zheng [1999]). There are no significant differences between both portfolios in Panel C up to holding periods of four quarters,

45 A likely explanation is that fund managers cannot maintain those high returns for long periods of time, not even for one more quarter, as profitable investment opportunities are scarce. Thus, the huge inflows of money attracted by short-lived high returns end up allocated in less attractive investment opportunities. This enhances the fall in performance of those funds.

46 This poses an obvious endogeneity problem. It could be that an improvement in performance within the quarter (e.g. inferred by reported monthly performance) induces higher concurrent flows of money, conditional to subscription and redemption restrictions. But it could also be the case that we are capturing a causal effect of contemporaneous flows upon performance. In the Appendix 2, we make an attempt to correct for endogeneity in a more formal model.

suggesting that hedge fund performance is unrelated to historical cash flows. Furthermore, for holding periods longer than four quarters, the divestment portfolio increasingly outperforms the investment portfolio.[47]

B. Investors' Allocations and the Persistence of the Winners

The results presented above cast doubts about investors' ability to exploit quarterly persistence patterns in hedge fund returns. One way to investigate this issue is by comparing the investors' allocation with an allocation based on funds' performance, in which funds are ranked and sorted on the basis of their raw returns in a given quarter. Baquero, Ter Horst and Verbeek [2005] showed that the top three deciles of this ranking are expected to again provide above average returns in the subsequent quarter, consistent with short-run persistence in raw returns. Table X compares both allocations. By ranking funds upon performance (Panel A), above-median funds receive on average 3.82 million U.S.$ while below-median funds experience outflows

Table X

A Comparison between the Repeat-Winner Strategy Allocation and the Investors' Allocation

This table compares two allocation strategies, one in which funds are ranked in terms of quarterly raw returns, another in which funds are ranked in terms of money flows experienced in a given quarter. Hedge funds are ranked every quarter from 1994Q4 to 2004Q3. We evaluate the performance of all funds above the median and all funds below the median at the end of the ranking period and over the subsequent quarter. The table shows the time-series averages of cross-sectional average returns for both portfolios. For the allocation based on money flows, we obtain the cross-sectional average return in each quarter as a cash flow weighted return that takes into account investors' allocations.

	Ranking of funds based upon raw returns (A)			Ranking of funds based upon money flows (growth rates) (B)		
Portfolio	Average dollar flow	Returns Ranking period	Returns in Subsequent quarter	Average dollar flow	Returns Ranking period	Returns in Subsequent quarter
Above-median funds	3824051	0.0946	0.0332	13898287	0.0336	0.0287
Below-median funds	-43847	-0.0411	0.0226	-10300220	0.0205	0.0268
Difference		0.1357 (0.0070)	0.0106 (0.0063)		0.0131 (0.0025)	0.0019 (0.0022)

[47] Zheng [1999] also documents a mean-reversion phenomenon for mutual funds, but it takes place only after month 30.

of about –44000 U.S.$ on average. These figures are in absolute value far below the averages obtained in Panel B for the investment and divestment portfolios (of about 13.9 and -10.3 million U.S.$, respectively), indicating that only few investors are able to exploit positive persistence. The Spearman rank correlation coefficient between the two strategies is on average 0.086, with some quarters exhibiting a negative correlation. Obviously, the two allocations are very different, while for mutual funds, Zheng [1999] documented that both allocations are somewhat related, with a rank correlation coefficient of 0.27. Zheng also reported that the investors' allocation (the "smart money" strategy) predicts winners better than the allocation based on performance (the repeat-winner strategy). We find the opposite result for hedge funds: the investment portfolio performs substantially worse than above-median funds in the repeat-winner strategy (2.87% against 3.32%). Finally, the below median funds in Panel A underperform the divestment portfolio in Panel B (2.26% against 2.68%), meaning that the repeat-winner strategy also predicts losers somewhat better.

Below we provide concrete evidence that most investors are indeed unable to exploit the persistence of the winners. To do so, we first characterize the funds in the investment and divestment sets more accurately. We consider again the ranking period and sort funds in ten deciles, where the top five deciles correspond to the investment set and the bottom five deciles are the divestment targets. Here, whether we rank upon growth rates or dollar flows becomes essential, as it provides two different perspectives on investors' allocations. Table XI summarizes our results.

Ranking upon dollar flows (Panel A) gives an average of 56 million U.S.$ of net inflows for the top decile, which is around 80% of the average dollar inflow to all above-median portfolios. Yet, it appears that most of investors' money is not directed towards the very best in the ranking period. On average, funds in the top portfolio exhibit raw returns of 4.19% per quarter (fifth column), performing better than most of above-median portfolios and significantly outperforming the style index. However, in the first quarter after ranking (sixth column), the average raw return of funds in the top decile falls to 2.51%, underperforming almost all other deciles, which means that most dollars are invested in funds that do not persist. The fall of the top decile drives the fall of the entire investment portfolio, as documented in Table IX, given the enormous amounts of dollar flows concentrated in these funds. We observe a comparable fall in style-adjusted returns (last column).

How to explain that hedge fund investors take disproportionate positions in the funds in their investment set that subsequently perform so poorly? The third column of Panel A reports the time series averages of the mean size of funds per decile. By ranking upon dollar flows, the extreme two deciles contain the largest funds,

Table XI

Results from Sorting Funds in Deciles Based on Cash Flow Information

In each quarter, from 1994Q4 until 2004Q3, we rank funds based on the net cash flows they experienced during that quarter. We assume that flows take place at the end of the period. Then we sort funds in 10 portfolios and we look at the performance of every decile at the end of the quarter and over the subsequent quarter. Decile 1 corresponds to those funds that experienced the highest cash flows. In panel A ranking of funds is based upon dollar flows. In panel B, ranking of funds is based upon normalized cash flows (i.e. growth rates). In each quarter, we compute an equally weighted return of all funds belonging to a given decile in that quarter. Then we average over 40 quarters when we evaluate the performance at the end of the ranking period. We average over 39 quarters when we evaluate the performance in the quarter subsequent to ranking. We use two definitions of a fund's returns: a) raw returns and b) style-adjusted returns. We report in parentheses the standard error of the time series average for style-adjusted returns and for the high-minus-low portfolio.

Panel A: Ranking of funds based upon dollar flows

				Raw return		Style-adjusted return	
Decile	Average Dollar Flow	Average Size (TNA)	Average StDev of returns	Ranking Period	Subsequent period	Ranking Period	Subsequent Period
High 1	55900930	465657768	0.0343	0.0419	0.0251	0.0139 (0.0027)	0.0005 (0.0019)
2	9564762	138455918	0.0392	0.0398	0.0299	0.0109 (0.0029)	0.0040 (0.0025)
3	3017546	80184704	0.0472	0.0368	0.0326	0.0091 (0.0027)	0.0054 (0.0030)
4	848498	39688887	0.0555	0.0281	0.0254	0.0003 (0.0035)	-0.0005 (0.0028)
5	159699	25429502	0.0651	0.0214	0.0271	-0.0012 (0.0045)	0.0025 (0.0044)
6	-48760	17783877	0.0660	0.0178	0.0337	-0.0064 (0.0047)	0.0072 (0.0050)
7	-369890	23234202	0.0631	0.0220	0.0274	-0.0007 (0.0043)	0.0001 (0.0045)
8	-1407583	47167102	0.0555	0.0226	0.0305	-0.0027 (0.0040)	0.0004 (0.0043)
9	-5000210	90379421	0.0466	0.0215	0.0216	-0.0020 (0.0031)	-0.0050 (0.0030)
Low 10	-44674655	339522152	0.0418	0.0186	0.0262	-0.0066 (0.0031)	-0.0018 (0.0028)
High-Low	100575586	126135616	-0.0075 (0.0014)	0.0232 (0.0046)	-0.0012 (0.0043)	0.0205 (0.0042)	0.0022 (0.0038)

Panel B: Ranking of funds based upon growth rates

				Raw return		Style-adjusted return	
Decile	Average Growth Rate	Average Size(TNA)	Average StDev of returns	Ranking Period	Subsequent period	Ranking period	Subsequent period
High 1	0.5471	105797406	0.0466	0.0503	0.0286	0.0215 (0.0035)	0.0033 (0.0034)
2	0.1481	158078935	0.0438	0.0368	0.0311	0.0084 (0.0024)	0.0059 (0.0023)
3	0.0714	181324888	0.0466	0.0299	0.0274	0.0040 (0.0033)	0.0012 (0.0025)
4	0.0297	175868652	0.0482	0.0280	0.0298	0.0019 (0.0034)	0.0034 (0.0034)
5	0.0076	125604661	0.0565	0.0229	0.0265	-0.0016 (0.0038)	0.0006 (0.0042)
6	-0.0047	94129139	0.0588	0.0140	0.0293	-0.0115 (0.0043)	-0.0007 (0.0043)
7	-0.0230	141629053	0.0566	0.0149	0.0236	-0.0062 (0.0038)	-0.0020 (0.0038)
8	-0.0549	112913438	0.0545	0.0172	0.0268	-0.0061 (0.0040)	-0.0002 (0.0037)
9	-0.1190	112703657	0.0523	0.0232	0.0267	-0.0031 (0.0034)	-0.0010 (0.0038)
Low 10	-0.3384	59550927	0.0503	0.0335	0.0297	0.0071 (0.0041)	0.0023 (0.0035)
High-Low	0.8854	46246479	-0.0036 (0.0016)	0.0169 (0.0060)	-0.0011 (0.0041)	0.0145 (0.0053)	0.0010 (0.0034)

experiencing proportionally larger dollar inflows and outflows. Funds in the top and bottom portfolios have on average 465 million and 340 million dollars in assets under management, respectively, together accounting for almost 64% of the total in the cross section. They also concentrate nearly 83% of dollars moved per quarter (both inflows and outflows). Understandably, hedge fund investors are attracted towards funds that are more easily and safely to assess, either because they are large, or because they are old and known with proven track records. Unfortunately, these funds are likely to experience serious limits to scale and to exhibit a very disappointing subsequent performance. Conversely, investors heavily divest an average of nearly 44.7 million U.S.$ from the bottom decile, corresponding to 87% of all net outflows on average in below-median portfolios. Funds in the bottom portfolio are significantly older than funds in the top decile (77 months vs. 66 months old, not reported), although both figures are above the average life of a hedge fund in our sample (around 55 months). Our evidence suggests that these big and relatively old funds have reached a maturity phase, and they are presumably closed to new investors while distributing only dividends or returning back the shares. These funds experience important negative growth rates of –21% (not reported).[48]

The above results help to improve our understanding of one of the main conclusions from the switching regression model in Section 3.4. Let us state again our findings. Large funds experience more extreme variations of money flows in dollar terms than small funds (see Table A1). Conditional to receiving inflows of money, large funds experience more important amounts of dollar flows than small funds, while conditional upon the regime of negative flows, they also experience considerably larger dollar outflows. This section has displayed both regimes at work, confirming in both cases the importance of limits to growth in the hedge fund industry. On the one hand, the largest dollar outflows take place at large, old and mature funds, which are likely to be closed to new investors, as was also reported by Goetzmann, Ingersoll and Ross [2003] for annual horizons. On the other hand, our evidence also indicates that at quarterly horizons, many large funds with good enough and consistent performance are willing to accept new money, but –while attracting the bulk of all money inflows – on average perform very poorly in the subsequent quarters.

[48] It is worthwhile to emphasize that these large funds in the bottom decile have reached a maturity phase and start declining. In other words, they are not the funds most likely to liquidate soon because of bad performance. In fact, the pattern of liquidation rates across deciles over subsequent quarters after ranking shows that the highest liquidation rates take place in the middle deciles, which correspond to small and young funds, reaching more than 20% for some of the below-median portfolios after 8 quarters, while only 9.5% of funds in the bottom decile and 2.6% in the top decile close down. This is consistent with the results reported by Boyson [2003] and Baquero, ter Horst and Verbeek [2005]: young funds are much more likely than old to be terminated for poor performance.

We turn our attention to Panel B in Table XI, where we used a different ranking criterion, based on growth rates. A comparison with our previous results shows an opposite picture concerning the size distribution across deciles (third column of Panel B). Ranking upon growth rates is likely to assemble small funds in the extreme deciles. Instead, the middle deciles assemble large funds, with assets under management of 125 million dollars or more on average[49]. Funds in the top decile experience huge average growth rates of nearly 55% and exhibit the highest rates of return in the ranking period, of about 5% (2.15% on a style-adjusted basis). However, in the quarter subsequent to ranking (sixth column), the equally weighted raw return on the top portfolio falls by 2.14% towards levels around 2.86%, underperforming several other above-median deciles. Results not reported reveal that the cash flow weighted return underperforms the equal allocation strategy by 0.82% and also the style index by about 0.46%. Thus, also among the subset of young, small and successful funds, most of the money flows are not directed to funds that persist, failing to discriminate funds' expected returns and incurring in important opportunity costs.

We can conclude that most of hedge fund investors are unable to chase the winners at short horizons. This is consistent with our findings in Section 3.4 that money inflows are not sensitive to short-term past performance. By the same token, investors are unable to exploit persistence, which is largely a feature in the short run, while Baquero, ter Horst and Verbeek [2005] showed that the persistent winners are not closed to new investors, meaning that persistence is susceptible of exploitation. Therefore, it can also be argued that persistence among the winners remains precisely because investors cannot actively direct their capital to the best performers, as proposed by Berk and Green [2004].

C. Investors' Allocations and Liquidation Rates of Hedge Funds

The performance of the bottom portfolio in Panel B, Table XI, deserves a separate analysis. Funds in the bottom portfolio shrink at an average rate of nearly –34%. Notice in the fifth column, however, that the bottom portfolio is not the worst performer in terms of raw returns in the ranking period. Moreover, it does not underperform the style index, contrary to the rest of below median portfolios. The distribution reported in the fifth column is depicted in Figure 5, which shows a *J*-shape distribution of average raw returns across deciles. In fact, the quarterly average

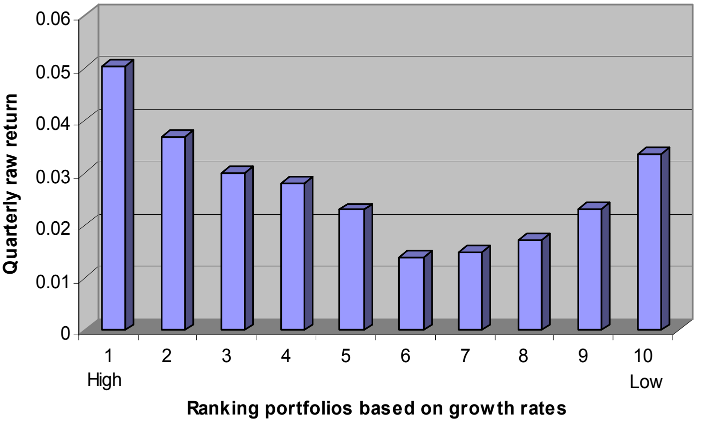
[49] Extreme growth rates are likely to be associated with small funds. Both positive and negative growth rates tend to be magnified when the total net assets at the beginning of a quarter – the denominator in equation (1) – is small. Conversely, large funds in the middle deciles experience very small positive or negative growth rates. They are either expanding slowly or contracting slowly, while performing poorly.

raw return on the portfolio that received the highest cash flows exceeds the return on the bottom portfolio by only 1.69%, while it exceeds the return on any other below-median portfolio by at least 2.71%, which is economically and statistically significant. The results are similar in terms of style adjusted returns.[50]

Figure 5

The Contemporaneous Relation between Raw Returns and Ranks Based on Growth Rates

This figure shows the distribution of returns across 10 rank portfolios formed on the basis of funds net cash flows. Funds are ranked in each quarter, from 1994Q4 until 2004Q3. Cash flows are assumed to take place at the end of the period and are measured as growth rates. We compute an equally weighted raw return for each decile at the end of the quarter. Then we average over 40 quarters. Decile 1 corresponds to those funds that experienced the highest cash flows.



The portfolio with the lowest cash flows has markedly different performance characteristics than other below-median portfolios. A closer examination of the average age and size suggests that funds in the bottom portfolio have not reached a maturity phase and are declining prematurely. They are somewhat older and bigger than funds in the top portfolio, but they have not reached the magnitude in size of the old and large funds in the middle deciles[51]. The extreme outflow rates of funds in the

[50] Along our entire investigation we have excluded the very young funds, with less than 6 quarters of historical returns, as explained in Section 2. However, if we do take them into account in our ranking exercise based upon growth rates, most of them end up allocated in the top decile. The return on the top decile increases significantly towards 5.61% (2.68% style adjusted) and the average growth rate becomes 137%. The corresponding figures in other deciles change somewhat, but in general not significantly. As a result, the difference between the top and bottom decile becomes a significant 2.11% (1.83% style adjusted).

[51] A comparison between funds in the top and bottom deciles reveals several common features but also significant differences between the two groups. It appears that the bottom 10% of funds manage around 59

bottom 10% are the result of persistent poor performance. If managers of these funds cannot make up losses to surpass the watermark threshold, they are likely to become reluctant to accept new investors, and eventually, will close down the fund.[52] This may explain the *J*-shape distribution of returns across deciles. If these funds in decline, experiencing important outflows, did survive until the end of the quarter, they are likely to have over-performed. In fact, if we follow each rank portfolio over time after the ranking period, we find that liquidation rates differ significantly across deciles, as shown by Figure 6. For example, in the subsequent quarter after ranking, around 3.9% of funds in the bottom decile liquidate compared to 0.3% in the top decile. Over an eight-quarter period more than 22% of funds initially present in the bottom decile close down, while less than 15% of funds liquidate from any above-median decile.[53] Here the crucial role of survival issues becomes evident and also the need to correct for look-ahead bias in the evaluation of hedge fund performance, as emphasized by Baquero, ter Horst and Verbeek [2005]. Investors appear to successfully discriminate between funds with high liquidation probabilities and funds that are likely to survive. Our results may also indicate that by divesting heavily from funds in the bottom decile, hedge fund investors enhance liquidation even further. Put differently, the investors' reaction has a disciplining effect for low-quality funds, an idea put forward by Ippolito [1992]. The divestment behaviour of investors poses a credible threat for managers, who, as discussed by Fung and Hsieh [1997], are concerned by reputation costs. The threat of termination is reinforced by the momentum in money outflows in response to bad performance captured by our model in Section 3.4. Thus, the quick and sustained response of investors penalizing poor performing funds seems to be the mechanism that ensures the effectiveness of

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million dollars on total net assets, significantly lower than the 105.8 million dollars on average managed by the top 10%. Both are, however, small amounts compared to funds in other portfolios that are at least twice as large on average. On the other hand, the bottom portfolio consists of significantly older funds, nearly 62 months old on average, compared to 53 months old for the top decile (not reported), while still considerably young compared to funds in the middle deciles (ages between 59 and 76 months). Funds in the top decile have not even reached the average life of a hedge fund in our sample, of about 55 months (see Table III). Thus, while the funds in the top decile seem to be very young and successful, growing at fast rates, it appears that their counterparts in the bottom decile have been operating unsuccessfully for some time without reaching a maturity phase. These funds have been increasingly underperforming the style index over the previous 5 quarters and as a consequence have faced important outflows and a substantial reduction in their asset base.

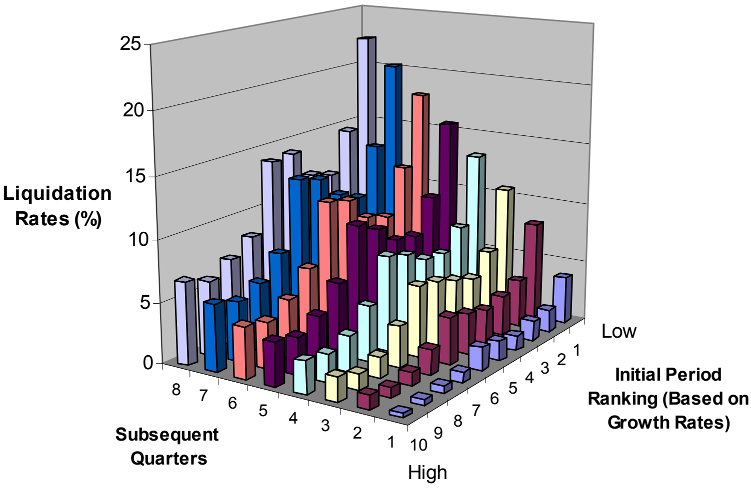
[52] This was shown by the models of hedge fund liquidation of Brown, Goetzmann and Park [2001] and Baquero, Ter Horst and Verbeek [2005]. The probability of liquidation is much higher when the aggregated return over the previous two years is negative, implying that it is unlikely for the manager to receive the incentive fee. Under this scenario of impending liquidation, managers may have the incentive to increase the risk of their portfolios, as suggested by e.g. Carpenter [2000]. However, Brown, Goetzmann and Park [2001] find little or no evidence in the hedge fund industry that poor performers increase volatility to meet their high-watermark, which they interpret in terms of reputation concerns of managers and the threat of termination. In the same line, we find that the average standard deviation of historical returns is only somewhat higher for the bottom portfolio compared to the top portfolio (a significant difference of nearly 0.36%, in column 4, Panel B).

[53] We find less dispersion in cross-sectional differences over time for self-selection rates. For example, after 8 quarters after ranking upon growth rates, 10% of funds self-select out of the bottom portfolio while 7.2% self-select out of the top portfolio.

reputation costs in mitigating the gambling behaviour of hedge fund managers when their option contract is out of the money (see Brown, Goetzmann and Park [2001]).

Figure 6
Liquidation Rates across Deciles over Subsequent Quarters after Ranking

Hedge funds are sorted every quarter from 1994Q4 to 2004Q3 into ten rank portfolios based on the net cash flows they experienced during that quarter. Then we look at the liquidation rates of every decile over the subsequent 8 quarters after formation. Liquidation rates in a given quarter are obtained as the total number of funds liquidated until that quarter with respect to the initial number of funds in the formation period. Ranking of funds is based upon normalized cash flows.



Ranking upon dollar flows and growth rates has provided us with two markedly different but complementary pictures concerning the investment and the divestment in hedge funds. Ranking upon dollar flows emphasized the interaction between investors' decisions and the performance of large funds, making plain clear the importance of diseconomies of scale in the hedge fund industry. By using growth rates as ranking criterion, the emphasis shifted towards the interaction between investors' decisions and the performance of small funds, making manifest the crucial role of survival issues. It remains clear that investors are limited in identifying and directing their capital towards the best performers in the short run. They are unable to exploit the persistence of the winners. Nor is persistence competed away. Furthermore, investors' allocations in their investment set fail to appropriately discriminate between funds' expected performance, resulting in sizable opportunity costs. However, hedge fund investors appear to be successful in their divestment strategies, de-allocating both appropriately and on time from the persistent losers.

3.6 Concluding remarks

Understanding the interrelation between money flows and performance in the hedge fund industry requires an explicit separation of the investment and divestment decisions of hedge fund investors. The results in this paper indicate that both decisions are driven by different determinants and operate over different time horizons. As a consequence, the shape of the flow-performance relation differs depending on the time horizon being analyzed.

The first part of our investigation relates money flows to past performance. We have documented a positive linear relationship in the short run between lagged quarterly performance and flows, which contrasts with a convex relationship found in previous studies in mutual funds and hedge funds using annual data. A linear relationship implies that investors allocate their money proportionally across both good and bad performance. We interpret these results in terms of liquidity restrictions that limit investors from actively shifting their capital in search of superior performance. Also, an active monitoring characterizing the post-investment behaviour of hedge fund investors makes them better able to assess bad performance on time. On the other hand, the costly and time consuming manager due diligence process may result in a lower sensitivity of hedge fund investors to good recent performance. The weaker relationship we find between asset flows and past performance among good performers compared to annual horizons is an indication of a limited short-run competition in the provision of capital in the hedge fund industry that might explain the persistence found at quarterly horizons, following Berk and Green's [2004] argument.

Our interpretation of the short-run flow-performance relation suggests that divestment and investment decisions may be driven by different evaluation horizons. Accordingly, we separately model positive and negative net cash flows using a regime switching model with endogenous switching while incorporating the combined impact of redemption and notice periods. When funds perform poorly, we find an immediate and lasting response of money outflows that gradually disappears over four quarters or so. The response of outflows to previous quarter performance accounts for 31% of the total long run effect. This response, however, is substantially reduced by 14% when liquidity restrictions are present. We find instead a weaker statistical sensitivity of money inflows to past quarter performance, which gives further support to the main argument of Berk and Green [2004]. Indeed, capital inflows are slow in chasing short-term good performance and thus would be unable to compete away the patterns of short-run persistence. On the other hand, when we aggregate flows over the year, our switching regression model captures a strong sensitivity of inflows to past annual performance while the response of outflows is very weak, suggesting a convex flow-performance relation, similar to the findings of Agarwal, Daniel and Naik [2003]. Additionally, our model unmasks important asymmetries between the decisions of investing and divesting. The impact of several control variables upon money flows remains hidden if positive and negative flows are not modeled separately.

The second part of our investigation relates money flows to subsequent performance. The asymmetric response time of investors' purchasing and selling decisions has an impact on investors' fund selection ability. In contrast to mutual fund studies on smart money, we do not find significant differences in performance between funds with positive and negative money flows. By looking into detail at the investment and divestment allocations across funds, we demonstrate that investors are limited in identifying and directing their capital towards the best performers in the short run. Their allocations are heavily concentrated in funds that subsequently perform poorly, significantly underperforming by nearly 50 basis points an equally weighted allocation. These results are consistent with our interpretation that searching costs slow down the response of investors to past good performance. As a consequence, most investors appear to be unable to exploit the persistence of the winners. It can also be argued that the market for capital provision is not competitive enough, which is precisely what ensures performance predictability at quarterly horizons. Conversely, hedge fund investors appear to be successful in their divestment strategies, responding fast and appropriately by de-allocating from the persistent losers, which exhibit high liquidation rates subsequently. This suggests that the efficacy of investors' active monitoring ensures a disciplining mechanism for low-quality funds and poses a credible threat of termination that mitigates the incentives of hedge fund managers to increase volatility to meet their high-watermark. Summing up, our findings indicate that only few investors are able to exploit the persistence of the winners, that frequent monitoring of fund managers is indeed critical, and that extended redemption restrictions or extended holding periods may have an adverse effect on investors' wealth. Short horizons indeed matter for hedge fund investors' decisions.

APPENDIX A1

Table A1

Switching Regression Model Explaining Positive and Negative Dollar Flows Subject to Liquidity Restrictions in Open-End Hedge Funds

The table reports estimates of a switching regression model explaining positive and negative dollar flows. Columns B and C report OLS coefficients estimates using cash flows as the dependent variable. The sample includes 1543 open-end hedge funds for the period 1994 Q4 till 2004 Q3. We measure cash flows as a quarterly growth rate corrected for reinvestments. The independent variables that account for relative performance include six lagged fractional ranks interacting with dummies for liquidity restrictions. The fractional rank ranges from 0 to 1 and is defined as the fund's percentile performance relative to all the funds existing in the sample in the same period, based on the fund's raw return in previous quarter. Independent variables accounting for fund specific characteristics include the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows, downside-upside potential ratio based on the entire past history of the fund and calculated with respect to the return on the U.S. Treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund and 7 dummies for investment styles defined on the basis of CSFB/Tremont indices. The model also includes 39 time dummies (estimates not reported). The two models using the truncated samples also incorporate as explanatory variable the generalized residual obtained from a probit model explaining the regime of flows (loglikelihood estimates reported in column A. The dependent variable takes value 1 if net cash flows are strictly positive). We estimate our models by pooling all fund-period observations. T-statistics based on robust standard errors as well as z-statistics for probit estimates are provided in parentheses.

Parameters	Probit model explaining positive and negative Cash flows (A)		Estimation using a truncated sample for CFlows <0 (B)		Estimation using a truncated sample for CFlows > 0 (C)	
Intercept	-0.6799	(-4.45)	359000000	(6.23)	-329000000	(-6.64)
Rank lag 1 Unrestricted	0.7232	(21.89)	219000000	(4.00)	81800000	(5.06)
Rank lag 2 Unrestricted	0.5972	(17.79)	182000000	(3.93)	64900000	(4.85)
Rank lag 3 Unrestricted	0.5160	(15.43)	153000000	(3.91)	52800000	(4.54)
Rank lag 4 Unrestricted	0.3724	(11.19)	110000000	(3.94)	36200000	(4.42)
Rank lag 5 Unrestricted	0.2243	(6.70)	69200000	(4.07)	21400000	(4.14)
Rank lag 6	0.0944	(2.88)	30100000	(3.84)	7966343	(3.51)
Rank lag 1 Restricted	0.6841	(6.20)	225000000	(3.88)	75700000	(4.97)
Rank lag 2 Restricted	0.5958	(4.99)	196000000	(4.06)	58500000	(4.53)
Rank lag 3 Restricted	0.4741	(3.90)	135000000	(3.65)	44800000	(4.25)
Rank lag 4 Restricted	0.5947	(4.87)	185000000	(3.94)	60000000	(4.56)
Rank lag 5 Restricted	0.3077	(2.51)	64800000	(2.66)	31200000	(4.24)
Ln(TNA)	0.0159	(2.52)	-5674908	(-5.30)	8328081	(11.80)
Ln(AGE)	-0.1991	(-11.93)	-61400000	(-4.05)	-18000000	(-4.20)
Flows lag 1	0.0000	(1.07)	-0.3677	(-2.03)	0.3505	(11.19)
Flows lag 2	0.0000	(2.31)	0.4439	(3.90)	0.3299	(10.04)
Flows lag 3	0.0000	(2.58)	0.2914	(3.21)	0.1194	(2.38)
Flows lag 4	0.0000	(2.51)	0.1436	(2.04)	0.1090	(2.32)
Offshore	-0.1034	(-4.87)	-37100000	(-4.50)	-5879398	(-2.66)
Incentive Fees	-0.0025	(-1.47)	-602346.9	(-2.62)	-349427.6	(-3.48)
Management Fees	-0.0279	(-2.22)	-5670261	(-3.12)	-4135592	(-4.59)
Personal Capital	-0.0604	(-3.10)	-19600000	(-4.23)	-6031916	(-4.02)
Downside-Upside Potential Ratio	-0.0556	(-4.33)	-15200000	(-3.99)	-6305356	(-4.62)
Emerging Markets	-0.1537	(-3.67)	-30600000	(-2.98)	-24200000	(-5.48)
Event Driven	-0.0079	(-0.21)	6826724	(1.99)	-6543611	(-4.28)
Fixed Income Arbitrage.	0.0038	(0.08)	5837748	(1.46)	-4223916	(-2.16)
Long/Short Equity	-0.1461	(-4.58)	-34700000	(-3.29)	-19700000	(-5.06)
Managed Futures	-0.0718	(-1.72)	-24200000	(-3.95)	-4532933	(-2.02)
Generalized Residual from Probit Model			489000000	(3.90)	175000000	(4.73)
R^2	0.0944		0.5589		0.4219	
Number of observations	21243		10367		10876	

APPENDIX A2
The Impact of Money Flows on Hedge Fund Performance

Our results in Section 3.5 indicate a strong contemporaneous relation between performance and cash flows, while performance seems unrelated to historical flows. It is not clear, however, whether the correlation we find reflects a causal effect of contemporaneous flows upon performance, or whether a change in relative performance within the quarter (e.g. inferred by reported monthly performance) induces concurrent flows of money, conditional to subscription and redemption restrictions. Below we attempt to give an answer to this endogeneity problem. Consider the following model explaining relative performance of a fund (relative to the peers) :

$$Rnk_{it} = \alpha + \beta_1.Flow_{it}^{-} + \beta_2.Flow_{it}^{+} + \sum_{j=0}^{4}\beta_{3j}.Flow_{it-j}^{-} + \sum_{j=0}^{4}\beta_{4j}.Flow_{it-j}^{+} + \sum_{j=1}^{6}\beta_{5j}.Rnk_{it-j} +$$
$$+ \beta_6.\ln(TNA_{it-1}) + \beta_7.\ln(AGE_{it-1}) + \beta_8.StDev_{it-1} + \beta_9.(StDev_{it-1})^2 + \gamma'.X_{it} + \varepsilon_{it} \quad (5)$$

where Rnk_{it} is relative performance as measured by a fund's cross sectional rank and Rnk_{it-j} is the jth lagged rank. $Flow_{it}^{-}$ and $Flow_{it}^{+}$ are negative and positive contemporaneous cash flows respectively, measured as growth rates[54]. $Flow_{it-j}$ is the jth lagged flow. We include the size and age of the fund in the previous period , $ln(TNA_{i,t-1})$ and $ln(AGE_{i,t-1})$. $StDev_{i,t-1}$ is the standard deviation of returns based on the entire past history of the fund. As in our previous models, X_{it} is a vector of fund specific characteristics like management fees, incentive fees, managerial ownership, and style. The style dummies capture the possibility that funds in a particular style may experience relative performance significantly different than for other styles. We first present OLS estimates of our model in column B of Table A2. All *t*-statistics reported are based on robust standard errors. An alternative specification that does not incorporate contemporaneous flows is presented in column A.

The impact of both positive and negative contemporaneous flows upon relative performance is significant while the coefficients have opposite signs. This is reminiscent of the pattern shown in Figure 5, where raw returns decrease as contemporaneous positive growth rates decrease (from decile 1 to decile 5), while returns increase as negative growth rates decrease (from decile 6 to decile 10). Furthermore, the impact of negative cash flows is, in absolute terms, nearly twice as large as the impact of positive cash flows. The estimates for all other variables remain pretty much the same in both specifications. Particularly, the coefficients for lagged

[54] $Flow_{it}^{-}$ and $Flow_{it}^{+}$ are defined as follows :
If $Flow_{it}>0$ then $Flow_{it}^{+}= Flow_{it}$, *otherwise* $Flow_{it}^{+}=0$
If $Flow_{it}<0$ then $Flow_{it}^{-}= Flow_{it}$, *otherwise* $Flow_{it}^{-}=0$

Table A2

A Model Explaining Relative Performance of Open-End Hedge Funds

The table reports estimates of a model explaining relative performance as measured by fractional ranks. The fractional rank ranges from 0 to 1 and is defined as the fund's percentile performance relative to all the funds existing in the sample in the same period, based on the fund's quarterly raw return. The sample includes 1543 open-end hedge funds for the period 1994 Q4 till 2004 Q3. The independent variables include six lagged fractional ranks, the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of positive flows and four lagged measures of negative flows computed as quarterly growth rates, standard deviation based on the entire past history of returns of the fund, downside-upside potential ratio based on the entire past history of the fund and calculated with respect to the return on the U.S. Treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund and 10 dummies for investment styles defined on the basis of CSFB/Tremont indices (not reported). Model specifications B and C also include contemporaneous measures of positive and negative flows. We estimate our model by pooling all fund-period observations. T-statistics based on robust standard errors are provided in parentheses.

Parameters	OLS estimates excluding contemp. cash flows (A)		OLS estimates including contemp. cash flows (B)		Estimation by instrumental variables (C)	
Intercept	0.1391	(1.04)	0.1317	(0.98)	0.1947	(1.30)
Negative Cash Flows (contemp.)			-0.0703	(-3.79)	-0.3516	(-1.79)
Positive Cash Flows (contemp.)			0.0818	(8.33)	0.1672	(1.69)
Negative Cash Flows lag 1	-0.0147	(-0.78)	-0.0053	(-0.28)	0.0340	(1.01)
Positive Cash Flows lag 1	-0.0103	(-2.42)	-0.0137	(-3.04)	-0.0169	(-2.62)
Negative Cash Flows lag 2	-0.0019	(-0.10)	0.0028	(0.15)	0.0253	(1.02)
Positive Cash Flows lag 2	-0.0029	(-0.55)	-0.0054	(-0.98)	-0.0067	(-1.01)
Negative Cash Flows lag 3	0.0132	(0.67)	0.0193	(0.98)	0.0351	(1.54)
Positive Cash Flows lag 3	-0.0041	(-1.21)	-0.0055	(-1.48)	-0.0076	(-1.65)
Negative Cash Flows lag 4	0.0239	(1.27)	0.0316	(1.67)	0.0533	(2.21)
Positive Cash Flows lag 4	-0.0057	(-2.33)	-0.0066	(-2.62)	-0.0073	(-2.57)
Rnk lag 1	0.0750	(9.60)	0.0723	(9.16)	0.0797	(6.62)
Rnk lag 2	0.0454	(5.73)	0.0437	(5.50)	0.0498	(4.69)
Rnk lag 3	0.0709	(8.95)	0.0684	(8.61)	0.0704	(7.43)
Rnk lag 4	-0.0171	(-2.15)	-0.0193	(-2.43)	-0.0187	(-2.11)
Rnk lag 5	-0.0374	(-4.71)	-0.0388	(-4.88)	-0.0392	(-4.79)
Rnk lag 6	0.0366	(4.65)	0.0360	(4.58)	0.0360	(4.53)
Ln(TNA)	0.0296	(1.94)	0.0283	(1.85)	0.0164	(0.91)
$Ln(TNA)^2$	-0.0009	(-1.95)	-0.0008	(-1.80)	-0.0004	(-0.84)
Ln(AGE)	-0.0021	(-0.57)	-0.0002	(-0.06)	0.0032	(0.73)
Offshore	-0.0085	(-1.86)	-0.0112	(-2.44)	-0.0161	(-2.75)
Incentive Fees	0.0009	(2.75)	0.0009	(2.67)	0.0008	(2.34)
Management Fees	0.0037	(1.28)	0.0038	(1.31)	0.0035	(1.19)
Personal Capital	0.0016	(0.39)	0.0024	(0.59)	0.0032	(0.74)
Leverage	0.0110	(2.26)	0.0099	(2.02)	0.0087	(1.71)
St.Dev.	0.1101	(0.96)	0.1351	(1.18)	0.1550	(1.32)
$St.Dev^2$	-0.4605	(-1.10)	-0.5014	(-1.21)	-0.5200	(-1.26)
Upside Potential Ratio	0.0053	(1.37)	0.0067	(1.75)	0.0070	(1.61)
$(\text{Upside Pot Ratio})^2$	-0.0012	(-3.75)	-0.0013	(-4.05)	-0.0013	(-3.68)
R^2	0.0244		0.0286			
Number of observations	21841		21841		21841	

Instrumented: Positive Cash Flows (contemp.), Negative Cash Flows (contemp.)

Instruments: Neg.Flows1, Pos.Flows1, Neg. Flows2, Pos.Flows2, Neg. Flows3, Pos.Flows3, Neg. Flows4, Pos.Flows4, Rnk1, Rnk2, Rnk3, Rnk4, Rnk5, Rnk6, ln(TNA), $Ln(TNA)^2$,ln(AGE), Offshore, IncFees, Mng.Fees, PCapital, Leverage, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income, Global Macro, Long/Short Equity, Managed Futures, StDev, $StDev^2$,Upside Potential Ratio, $(UpPot.Ratio)^2$, Rnk1U, Rnk2U, Rnk3U, Rnk4U, Rnk5U, Rnk1R, Rnk2R, Rnk3R, Rnk4R, Rnk5R, Time dummies (T2 till T22) flows are not statistically significant, although they are overall negative, confirming our results in Section 3.5 that relative performance is unrelated to historical cash flow rates. These results are robust to alternative specifications, where we excluded historical performance, size or other control variables. Moreover, the results remain unchanged when using lagged dollar flows instead of growth rates.

However, ranks and contemporaneous cash flows may be simultaneously determined, and OLS estimation of the current specification explaining relative performance might not provide consistent estimates for the causal impact of flows upon performance. To consistently estimate the causal effect of (endogenous) contemporaneous cash flows on performance, we rely upon instrumental variable estimators, reported in column C. The instrumented variables are both positive and negative contemporaneous cash flows and the instruments are the explanatory variables from our previous model explaining growth rates together with the additional exogenous variables included in the present model. This choice of instruments assumes that conditional upon investment style and other characteristics, trading restrictions only influence current performance through their impact on money flows. Surprisingly, after accounting for endogeneity, only the coefficient for negative contemporaneous cash flows remains marginally significant.[55] In other words, money flowing out of a fund along a quarter and motivated by an exogenous shock appears to have some immediate positive impact on relative performance. For example, if a fund shrinks at a rate of -50%, it results in an expected gain of ranking position by nearly two deciles by the end of the quarter. A likely explanation is based on survivorship, in line with our previous interpretation of the *J*-shape distribution reported in Section 3.5. If a fund in decline which experiences substantial outflows does survive until the end of the quarter, it is likely that this fund has outperformed. The OLS coefficient for positive cash flows captures mostly a reverse causality. It reflects differences across funds in some unobserved determinants of relative performance that induce in turn a concurrent response from investors. For example, our model does not account for monthly releases of performance information as an explanatory variable in order to avoid the potential return smoothing documented by Getmansky et al [2004] and explained earlier in this paper. However, if monthly performance is in some way related to future performance, and if investors respond to monthly performance along the quarter (conditional to liquidity restrictions), this would explain the positive

[55] A Hausman specification test applied to equations (3) and (5) rejects the hypothesis of exogeneity. The test proceeds as follows. We first regressed Flows upon all exogenous variables in model (5). Then we estimated model (5) including endogenous Flows and the residuals obtained from the previous regression. The *t*-test on the coefficient of the residuals gives 2.52, suggesting that the error terms of both models explaining Ranks and Flows are correlated.

contemporaneous relation reflected in the OLS estimate. Our estimates do not support the idea that a sudden amount of newly arrived money might have an immediate negative impact upon performance. Presumably, the less frequent subscription and redemption dates characterizing hedge funds in comparison to mutual funds reduce hidden costs associated to liquidity-motivated trading (see Edelen [1998]). [56]

[56] The coefficients of several control variables in our model are also significant. It is worthwhile to notice the impact of lagged performance. Our estimates indicate that relative performance is positively and significantly related to historical performance. Funds that performed well with respect to their peers are more likely to continue their superior ranking position over the next four quarters. This is consistent with previous findings of performance persistence at quarterly and annual horizons (see e.g. Baquero, ter Horst, Verbeek [2005]). Remarkably, once we account explicitly for simultaneity, the estimates for the coefficients of lagged ranks become larger by 10% compared to the OLS coefficients. With OLS estimation, part of the impact of historical performance seems to have been taken away by the strong positive relation between relative performance and positive contemporaneous flows. Finally, in an attempt to capture the impact upon performance of skewness and non normal characteristics of hedge fund return distributions, we included in our specification the upside potential ratio measured with respect to the return on the 3-month Treasury bills. For most of the values of upside potential ratio in our sample, an increase in the variation above the Treasury bills' return with respect to the variation below, will impact the ranking position of a fund significantly and positively. Only for very extreme values of this ratio, which occurs in a few cases in our sample, the impact is negative. Apparently, the upside potential ratio conveys some additional information besides standard deviation regarding the risk-return characteristics of a hedge fund, justifying to some extent the popularity of this measure among investors.

"[...] Performance numbers shown are records of past performance and as such do not guarantee future performance. The value of investments in the Company and income derived therefrom can decrease as well as increase. Before entering any transaction, you should ensure that the transaction is appropriate for you, given your objectives, experience, financial and operational resources, and other relevant circumstances.."

(Disclaimer from a typical hedge fund prospectus)

Chapter 4

Do Sophisticated Investors Believe in the Law of Small Numbers?[57]

4.1 Introduction

Empirical studies that focus on the response of investors to past performance of fund managers are clear in one point: investors chase the winners. A convex flow-performance relationship has been documented at annual horizons for both mutual funds and hedge funds, meaning that flows of money are massively directed to the best performers in the previous year (see e.g. Ippolito [1992], Sirri and Tufano [1998], Agarwal, Daniel and Naik [2003])[58]. Chasing the winners, or momentum investing, is often seen as an expression of investors' overreaction and has been attributed to the representativeness heuristic: people rely too much on recent past performance signals as representative of future performance[59]. The hypothesis that

[57] This chapter is based on Baquero and Verbeek [2006]. I benefited from extensive discussions with Ben Jacobsen and Yaakov Kareev. I am also grateful to Alberta Di Giuli and Tomasso Gabrieli for very constructive comments.

[58] The convexity also implies little or no reaction of investors to poor performance. Other studies address the convexity of the flow-performance relationship in mutual funds from different perspectives, see Chevalier and Ellison [1997], Bergstresser and Poterba [2002], Lynch and Musto [2003], or Berk and Green [2004]. For the pension fund industry, Del Guercio and Tkac [2002] report instead a linear relationship.

[59] The assessment of how likely an observed pattern is replicable in the future is often evaluated by how stereotypical or how "representative" of a more general process is such a pattern (Tversky and Kahneman [1974, 1982]). Harless and Peterson [1998] investigate several implications of the representativeness heuristic in the response of investors to past performance of mutual funds, particularly to bad performance. Also Shefrin [2000, Chapter 12] describes the inadequacy of the probability heuristic of investors, who incorrectly frame the problem of picking a talented fund manager, attributing her past performance too much to skill rather than to luck, a bias enhanced by representativeness. A few studies have investigated other psychological biases potentially affecting mutual fund investors' response to past performance, like the endowment effect, the

investors overreact has almost been taken for granted on the grounds that there is little or no evidence that fund managers' performance can be predicted from past performance. Recent theoretical developments based on rational choice (see Berk and Green [2004]) suggest, however, that chasing the winners is not necessarily inconsistent with the lack of predictability in managers' performance[60]. Whether chasing the winners among fund managers is the result of a psychological bias and reflects investors' overreaction or whether it is a rational response, remains an open question that has not been empirically addressed so far.

In a recent paper, Rabin [2002] presents a theoretical model that shows how momentum investing could in fact be the result of a cognitive bias and the manifestation of investors' overreaction. Further, he derives predictions concerning the behaviour of an investor who hires or fires a fund manager depending on her beliefs about dispersion in managerial talent, providing us with an attractive frame for an empirical test. Rabin's model is to a great extent motivated by the results of experiments in which subjects are asked to reproduce a series resembling a binary random process, e.g. tossing a coin. The common tendency is to reproduce series with some degree of negative autocorrelation, alternating between heads and tails too often compared to a truly random series. Rapoport and Budescu [1997] refer to this tendency as the "alternation bias". One explanation widely cited for this bias is the concept of "local representativeness", proposed by Kahneman and Tversky [1972]: apparently, people's perception is that short sequences should have the same proportions of heads and tails, which in fact is a distribution property of large sequences.[61] More generally, people's perception that small samples replicate the probability distribution properties of the parent population, as much as large samples, is a cognitive phenomenon known as *the law of small numbers* or *sample-size neglect* (see Tversky and Kahneman [1971]).

Rabin [2002]'s model is a theoretical description of how local representativeness conduces to the alternation bias.[62] It applies to specific situations where samples are

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disposition effect and cognitive dissonance, partly accounting for the reluctance of investors to divest from bad performers (see e.g. Shefrin and Statman [1985], Goetzmann and Peles[1997]).

[60] Berk and Green [2004] argue that in equilibrium and under decreasing returns to scale, money flows chase the winners to the point where the risk-adjusted expected excess return is zero. Therefore, there is no persistence precisely *because* money rationally flows to the managers with the best track records.

[61] For a review of the theoretical explanations of the alternation bias, see Wagenaar [1972] and Bar-Hillel and Wagenaar [1991].

[62] In Rabin [2002]'s model, an infinite sequence of signals is generated from an i.i.d. random binary process. Suppose for example that the binary signal indicates either above average (A) or below average (B) performance of a manager. Investors are Bayesians, but believe that signals are drawn from an urn of finite size N *without replacement* (although the urn is renewed periodically). Suppose the manager has some talent, with a certain probability $\theta > 0.5$ to be above average. Thus an investor believes there are θN A signals and (1-θ)N B signals in the urn that corresponds to this manager. This is the key feature in the model that captures

drawn from a binary process, as for instance a series of coin tosses, or a series of signals indicating good or bad performance over time of a manager, a firm or a basketball player. Further, it is formally derived from the model that belief in the law of small numbers leads to two well known biases in pattern recognition: the *gambler's fallacy* and the *hot-hand fallacy*. When people observe a streak of signals and they are certain that the process is purely random (i.e. a fair coin, a lucky manager), in general they expect a reversal given their belief in frequent alternations. This mistaken belief in mean reversion is known as the "gambler's fallacy". On the other hand, if people *do not know* whether the process is entirely random, they may infer (mistakenly) that the series is too long to be random, attributing a causal significance to the streak of signals (i.e. the coin is not fair, the manager is talented, the player has hot hand). In that case, people expect continuation. It follows from Rabin [2002]'s model that the larger the observed streak, the larger the expected probability of continuation will be. [63] This is the rationale behind the so called "hot-hand fallacy", first documented by Gilovich, Vallone and Tversky [1985] in the context of basketball players' shots.[64] Contrarian investment strategies (trading against the trend) are often attributed to the gambler's fallacy (see De Bondt [1991], Shefrin [2000]), while momentum strategies (e.g. trend-chasing or feed-back trading) are often attributed to the hot-hand bias[65].

In the present paper we empirically investigate investors' momentum strategies in selecting fund managers and the extent to which they relate to the law of small numbers. To this end, we analyze actual money flows to and from hedge funds and their relationship with the length of past (winning and losing) performance streaks. This allows us to test the predictions of the model of Rabin [2002] concerning

local representativeness, or the belief that a sample of size N contains the same proportions of signals as the parent population.

[63] Following the previous example in footnote 7, since the urn is not replaced, after a signal *A* is drawn there are less *A* signals remaining in the urn and the drawing of another *A* signal appears less likely than it actually is. Put differently, when N is small, signals appear necessarily correlated to the eyes of the investor. More formally, given a rate θ known with certainty, the conditional probability that a streak of e.g. three *A* signals occurs, $P(AAA|\theta)$, will be underestimated, leading to the gambler's fallacy. Conversely, when the proportions in the urn are unknown, then given a streak of three *A* signals, the inferred probability that the manager has a rate θ, $P(\theta\ |AAA)$, will be overestimated (which can be shown using Bayes' rule). The overinference of the likelihood that a manager has talent leads in the medium run to the hot-hand fallacy.

[64] After successively scoring several times, people perceive a player has "hot hand" and expect she will continue scoring successfully. Gilovich et al. demonstrated that there is no such hot hand phenomenon and that shots by basketball players are largely random. Evidence from the market for organized gambling in basketball games is provided by Camerer [1989]. People seem to believe that teams with winning (alternatively losing) streaks are somewhat more likely to continue winning (losing) than they actually are. Experimental evidence of forecasts of stock prices and exchange rates is presented by De Bondt [1993]. He reports an "extrapolation bias" among non-experts, who tend to identify trends of prices when none exists, and to expect continuation, while underestimating the chances of reversal. For an overview of the psychological evidence supporting the hot hand phenomenon, see Gilovich [1991] and Falk and Konold [1997].

[65] Extrapolative expectations or trend chasing are referred to as positive feedback trading by De Long et al [1990].

investors' overinference of managers' talent, as revealed by their observed actions, viz. their investments *in* and divestments *from* a hedge fund. Specifically, we test the hypothesis that overinference is positively related to the length of the streak. The extent to which investors' decisions are determined by persistence patterns of winning and losing streaks and whether or not investors display a hot-hand bias are specific questions that have not been addressed so far in the empirical literature. One reason is that all studies on the flow-performance relationship mentioned above use annual data, and thus an investigation of the responsiveness of money flows to the length of winning or losing streaks is necessarily limited by the time periods available, persistence horizons and the survival of funds.[66]

To overcome these limitations, we use quarterly data of hedge funds which allows us to identify relatively long performance streaks. The advantages of using a database of hedge funds for the purposes of this investigation will be discussed in Section 4.3. The typical hedge fund investor has arguably more financial expertise than the average client of mutual funds. Actually, the magnitude of the minimum investments required in this industry is meant to limit participation in hedge funds to highly sophisticated investors.[67] We could therefore expect a hedge fund investor to pay attention to appropriate benchmarks, styles, risk adjusted measures of performance and tracking error and to make sound performance analyses. Thus, by studying hedge fund investors' decisions we can separate misperceptions due to the lack of experience or the lack of understanding of financial markets from a psychological bias, if any. As suggested by De Bondt [1991], especially experts may be prone to distinguish patterns where there are none.

The contribution of this paper is twofold. We first provide a model that explains relative performance of a hedge fund from historical performance streaks while controlling for size, age, style and other fund characteristics. We find that the length of the streak is to some extent indicative of future relative performance, which confirms previous findings of multi-period performance persistence of hedge funds (see Agarwal and Naik [2000]). Second and most importantly, we investigate the

[66] For example, for hedge funds, Agarwal, Daniel and Naik [2004] relate annual flows to persistent winners/losers. They define winners and losers along two years only. They find that persistent winners over two years significantly attract inflows, while persistent losers experience significant outflows, compared to those funds that revert between two consecutive years, but they do not explain investors' response in terms of an overreaction.

[67] Investments in hedge funds are limited to "accredited investors" and "sophisticated investors" (Investment Company Act, 1940). A person is a "sophisticated investor," if the investor either alone or with the investor's purchaser representative(s) has such knowledge and experience in financial and business matters that the investor is capable of evaluating the merits and risks of an investment in the hedge fund. An "accredited investor" is either an individual with a net worth of $1 million or more or an annual income of $200000 or more, either an entity with total assets above $5 million.

response of money flows to the length of the streak, while controlling for expected performance and several variables accounting for the riskiness of a fund. Our results indicate that the length of the streak of a hedge fund manager has a statistically and economically significant impact on flows, beyond what is justified by expected future performance of the fund, suggesting that investors overinfer the likelihood of performance persistence. Our findings are in line with the predictions of Rabin [2002]'s model and with previous experimental and empirical evidence of the hot-hand bias in other domains.

The remainder of this article is organized as follows. In Section 4.2 we discuss some relevant characteristics specific to the process of investing in hedge funds. In Section 4.3 we describe our dataset and variables. Section 4.4 presents stylized evidence of momentum investing of hedge fund investors in response to multi-period performance persistence. In Section 4.5 we provide a model that disentangles a rational response of investors to past performance streaks from a response presumably induced by the law of small numbers. Section 4.6 presents some robustness checks, while Section 4.7 concludes.

4.2 The process of selecting a hedge fund manager

This section describes some of the key aspects of investing in hedge funds that are necessary to understand how potential psychological factors might affect investors' decisions. Simply stated, a hedge fund is a private investment portfolio with limited regulation that combines both long and short positions on a leveraged basis.[68] The manager is usually a general partner and charges a performance-based incentive fee in addition to management fees that cover operation and administrative expenses. Relevant features are the limited transparency, implying increased searching costs for investors, and the limited liquidity offered to clients through lock-up periods and redemption restrictions. The attractiveness of hedge funds for both private and institutional investors lies in two key features. First, given the structure of managerial incentives, hedge funds seek absolute returns instead of relative returns with respect to a benchmark, as it is the case for the more traditional mutual funds.[69] Second, the

[68] Hedge funds avoid regulation either as domestic US investment companies with a limited partnership structure or as offshore investment companies operating in tax havens.

[69] Hedge fund managers are rewarded for achieving high absolute returns. The average hedge fund manager in our database receives 18% of annual profits as incentive fee besides 1.5% of total net assets annually as management fee. The manager receives the incentive fee if two conditions are met: first, the return must be greater than a hurdle rate, usually set as the risk-free rate. Second, the value of the fund has to surpass a threshold or "high water-mark", meaning that previous losses must be recovered first. This incentive structure might induce managers to take excessive risk. However, managers are in general requested to invest a substantial amount of their personal wealth in the fund, which mitigates risk-taking behavior to some extent while it aligns the interests of investors and managers.

limited regulation they enjoy allows them to make active use of short selling and derivatives and to dynamically trade in a wide array of assets, which explains the low historical correlations between hedge funds and traditional asset classes. These features make hedge funds attractive for diversification and hedging purposes in a variety of ways, depending on the specific risk and return targets of an investor's portfolio.

Any considerations about investing in hedge funds are usually preceded by a clear definition of investors' own objectives. Investors often set a target return for their portfolio with a given exposure to markets. Given these investment objectives, investors seek the most appropriate hedge fund strategy that helps diversify their portfolio and achieve their investment goals. Once the appropriate strategy has been identified, investors strive to find the most talented manager(s) in that strategy. The following is a schematic picture of the process of selecting a hedge fund manager. In a first stage, investors identify potential talented managers by their performance track records.[70] Given the information hurdles faced by investors (i.e. limited transparency and restricted advertising imposed by regulatory authorities), the track record of a manager plays a major role as the most readily available information indicative of his potential skill. It also gives the means for a screening procedure, to identify the potential targets among a large number of managers in a database that are worth a more careful analysis later. In a second stage, a quantitative and qualitative due diligence process follows, in order to determine whether the observed track record was generated by a lucky manager or by a truly skilled manager. In a quantitative analysis, return and risk characteristics and other variables are assessed over time, like the amount of leverage, the amount of capital managed, money flows, the investment strategies employed, downside deviations, upside potential ratios and expense ratios. Besides, the alignment incentive mechanisms are taken into account, like the level of incentive fees and the amount of the manager's personal wealth invested in the fund. Finally information contained in the offering memorandum, especially regarding redemption conditions, is essential. The qualitative analysis pays attention to manager's integrity and personality, his investment ideas, the quality of the organization and personnel. This is carried out through frequent personal meetings and references from former colleagues of the manager or peers in the industry. Finally, a third stage corresponds to the post-investment phase. After hiring a manager, an ongoing due diligence is crucial. Frequent monitoring and quantitative

[70] In practice, there are several channels through which managers with good performance track records are first identified, for example by word-of-mouth or references from other participants in the industry, through business conferences, where managers sell and market themselves, or through hedge fund databases, etc.

and qualitative evaluations are necessary to detect changes in investment style or major changes in the organization.[71]

From this brief account of the steps usually undertaken by investors, it should remain clear that, regardless of whether the main purpose of investing in a hedge fund is diversification or the pursuit of absolute returns or both, the first task for an investor is to find a talented manager within the strategy that better suits the investor's objectives. Notice that a primary assumption from investing in a hedge fund is that the manager *has* talent. In fact, the entire hedge fund industry is marketed on the grounds of managerial skill and defines itself as a skilled-driven industry. This is a feature with special relevance for our study. If investor's perception of a manager's track record is indeed biased due to local representativeness (i.e. the law of small numbers), it is precisely the belief or not in talent what determines, in theory, the direction of the bias. This is formally captured by the model of Rabin [2002]. Investors who are fully sceptical about managerial talent are certain about the probability of success of any manager (i.e. 50%), but also they believe in no variation in quality among managers (i.e. all managers have the same probability of success). Sceptical investors will be prone to the gambler's fallacy and will tend to underestimate the probability of performance persistence[72]. Hedge fund investors, on the contrary, firmly believe that talented managers exist.[73] Thus, by definition, they believe in quality dispersion. In theory, when investors are uncertain about the probability of success of a given manager, they will be prone to overinfer his talent from an observed performance streak and exaggerate the probability of continuation. Further, the longer the streak, the larger the overinference will be, which is precisely the feature we focus on and we test in the present paper. Curiously, an important additional result derived from the model of Rabin is that the belief in local representativeness results in an illusory belief in wider differential ability than actually exists. Further, investors' overinference of the likelihood that a manager is talented exacerbates in turn his beliefs about how talented he is.

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[71] While the process of hiring a hedge fund manager is a lengthy and costly process, the decision to redeem in response to either bad performance or style drift is taken swiftly as a result of constant monitoring. This has been shown by Baquero and Verbeek [2005] who separately model inflows and outflows over different evaluation horizons.

[72] As explained above, the model of local representativeness from Rabin distinguishes the case in which the probability of success of a binary signal is known with certainty and the case in which it is uncertain. The former case leads inevitably to gambler's fallacy. In the latter, however, the believe in local representativeness develops in an overinference of the probability of success from the observed unexpected streakiness, which in turn results in exaggerated beliefs about the probability of continuation in the medium-run (i.e. the hot-hand fallacy). For instance, a person who approaches a coin convinced of its fairness will be prone to the gambler's fallacy. But a person who is uncertain about its fairness will infer after observing an unexpected streak that the coin is not completely fair and will expect continuation.

[73] It is almost a coined expression among participants in the industry that investors' efforts target the "best and the brightest" among hedge fund managers.

One could argue that the due diligence process is precisely in place to determine whether the observed streakiness is likely to be reproduced in the future. Therefore, by assessing the extent to which investors overinfer the level of skill from the observed persistence pattern of a manager, our study implicitly provides an assessment of the effectiveness of the due diligence process to counterbalance this potential bias.

4.3 Data

We use a survivorship-free data of open-end hedge funds from TASS Management Limited, a private advisory company and provider of information services. We focus on individual open-end funds reporting in U.S.$, and exclude funds-of-funds (i.e. portfolios of hedge funds). Our sample contains 752 funds and a total of 7457 fund-period observations between the fourth quarter of 1994 and the first quarter of 2000. The funds that liquidated amount to 163, while 86 funds self-selected out of the database for different reasons. [74]

Along this paper we argue that investors are sensitive to the precise pattern of performance signals they observe. In the hedge fund industry, information on total net assets under management (TNA) and raw returns of individual funds and style indices is released periodically, typically on a quarterly basis for monitoring purposes.[75] The financial press and industry newsletters also emphasize quarterly figures. Further, most redemption restrictions take place quarterly, which imposes an implicit frame for investors' decisions. We study, therefore, the response of investors to sequences of quarterly performance signals. Returns are net of all management and incentive fees.

We employ the two standard definitions of cash flows provided in Chapter 3, namely in terms of dollar flows and growth rates (or normalized cash flows). Table I shows some descriptive statistics for normalized cash flows, dollar flows and assets under

[74] Given the limited regulation and the lack of disclosure requirements, hedge-fund participation in any database is voluntary. Therefore, a self-selection bias might arise either because poor performers do not wish to make their performance known, either because funds that performed well and reached a critical size have fewer incentives to report to data vendors to attract additional investors. Further, several countries impose restrictions to hedge funds for public advertising. Many funds may refrain from reporting as it can be interpreted as illegal marketing (see Ter Horst and Verbeek [2005]). Also, different databases have different criteria for including or maintaining funds, which can lead to a further selection bias. However, active monitoring of managers by database vendors gives an incentive to hedge funds to provide complete and accurate data to avoid being deleted from a database.

[75] Monthly figures are available in our database. However, given that performance fees are deducted from the fund's asset value on an individual-client basis, the calculation of total net assets and rates of return delays the release of monthly figures. Therefore, accurate monthly information might not be available to investors for all funds in real time.

management. Notice that the distribution of cash flows appears to be relatively symmetric, in sharp contrast with the distributions found for mutual funds.[76] This is a feature that we exploit later in our investigation, as we are interested in both investments and divestments decisions as proxies for investors' beliefs.

Table I

Distributions of Flows and Assets under Management in the Hedge Fund Industry

This table shows the cross-sectional distribution of cash flows and total net assets under management in our sample of 752 open-end hedge funds from 1994Q4 till 2000Q1. Cash flows are computed as the change in total net assets between consecutive quarters corrected for reinvestments. A growth rate is calculated as relative cash flows with respect to the fund's TNA of previous quarter.

Percentile	Cash Flows (growth rate)	Cash Flows (dollars)	Total Net Assets (million dollars)
99%	1.0506	60572000	733.3959
95%	0.3611	17720000	319.7788
90%	0.1986	7833357	175.0006
75%	0.0566	1068212	63.12327
50%	0.0000	-93.943	19.68958
25%	-0.0606	-1032387	5.489787
10%	-0.1747	-6207153	1.651972
5%	-0.2863	-14200000	0.860888
1%	-0.6003	-61684000	0.24526

Table A1 in the appendix shows descriptive statistics for several fund-specific characteristics as well as some performance and risk metrics of the funds in our dataset. A brief description of each variable is also provided.[77] Using data on hedge funds presents several advantages for the purposes of our study. First, given the persistence patterns of hedge funds at quarterly and annual horizons, it is more likely to identify relatively long series of successive wins and losses with quarterly data than for mutual funds. In fact, we could identify streaks from one up to twelve successive gains or failures. Second, mutual fund flows are subject to noise in short horizons due to the liquidity needs of investors, for whom daily withdrawals and subscriptions are possible, while hedge funds impose restrictions to both withdrawals and subscriptions, typically monthly or quarterly[78]. This makes money flows to hedge funds less subject to noise or to large variations and more suitable to be studied in horizons shorter than one year. Third, at quarterly horizons there appears to be a response of money outflows to poor performance in the previous quarter, contrary to annual horizons

[76] For example, Del Guercio and Tkac [2002] find that the top 5% of dollar inflows in mutual funds are nearly three times larger than the outflows at the bottom 5%.

where investors display little sensitivity to previous year poor performance. Therefore, with quarterly data we can also assess a “cold-hand” phenomenon whereby investors expect continuation from observed losing streaks. [79]

4.4 The response of money flows to persistence patterns

In this section we present stylized evidence describing the response of hedge fund investors to different patterns of performance persistence. Table II provides a summary of all the series of successive wins and losses we could identify in our dataset. A fund is a winner (alternatively a loser) in a given quarter if its ranking based on the raw return at the end of the quarter is above (below) the median. A winner streak starts as soon as the ranking reverses from below-median to above-median. Then we count the number of consecutive quarters in which the fund performs above the median. For example, if a fund is a loser in 1997Q1 (meaning first quarter of 1997), but is a winner over 1997Q2, 1997Q3, 1997Q4, then we actually identify a one-quarter streak (1997Q2), a two-quarter streak (1997Q2, 1997Q3) and a three-quarter streak (1997Q2, 1997Q3, 1997Q4).

According to Panel A in Table II, for instance, we identified 687 three-quarter winning streaks between 1994Q4 and 1999Q4. In the quarter that followed the series, 0.44% of funds liquidated and 0.58% self-selected. Also, 57.5% of funds remained winners (i.e. persistent funds) while 70.89% received positive net flows of money. The average money flows that investors directed towards these funds after a successful three–quarters history amounts to nearly 6.2 million U.S. dollars per fund (considering both positive and negative net flows). We interpret net flows of money as a measure reflecting the average opinion of investors about a given fund. If net flows of money are positive (i.e. inflows outweigh outflows), it means that a majority of investors expect an above-median performance of a fund in that quarter and they invest accordingly.[80]

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[77] For further details concerning this data set and a discussion of these variables, see Baquero and Verbeek [2005].

[78] In addition, hedge funds often require a written notice to the manager prior to redemption. The minimum notice period varies from fund to fund and typically ranges from 15 to 90 days. The combination of notice periods and redemption periods can become a serious liquidity restriction to investors.

[79] Baquero and Verbeek [2005] have empirically studied the dynamics of flows and hedge fund performance at quarterly horizons. They find a significant response of flows, especially outflows, to the most recent lagged performance over four quarters or so. However, they do not explicitly look at the response of flows to winning or losing streaks.

[80] Notice that for a given streak length, the number of persistent funds slightly differs from the number of funds with one additional quarter of streak length reported in the table. For example, among the 687 funds with three consecutive winning quarters, 57.5% (i.e. 395 funds) persist. However the next row reports only 388 funds with four consecutive winning quarters. The gap is due to some funds for which money flows are not

Panel A indicates that, in general, a fund is more likely to persist after longer winning streaks (see column five). While 52.77% of funds remained winners after two successful quarters, almost 70% of funds were winners after displaying a six-quarter winning streak. The pattern becomes somewhat erratic for streaks longer than six quarters, probably due to the reduced number of observations. These figures, however, favour the idea that managerial skill exists in the hedge fund industry and that hedge fund performance is to some extent predictable. We do observe a concomitant reaction of investors, who appear to pour larger amounts of money as the length of the streak increases. The average money flow that a fund experiences after a two-quarter winning streak is around 2.1 million U.S. dollars, while a fund receives on average above 9 million U.S. dollars after six successful quarters. For a given streak length, however, investors do not invest in 100% of funds, an indication of their effort to distinguish the lucky from the truly skilled managers. Noticeably, the percentage of funds receiving positive net flows of money also increases monotonically with the length of the streak, as indicated in column six. Distinguishing between luck and skill is a notoriously difficult task and a certain percentage of error is expected. The mismatch is shown in the last column of Table II. For streaks of two quarters length, positive money flows were actually directed to subsequent loser funds in 41.26% of the cases. This percentage reduces with streak length as the probabilities for a fund to remain a winner increase. However, for 6 quarters of streak length, the likelihood of an over-forecast is still a substantial 25.58%. If we repeat this exercise separately for large and small funds, the patterns remain the same and percentages do not change substantially[81]. The question of interest is how much of this forecast error is due to over-optimism, presumably induced by the length of the streak as the law of small numbers suggests?

Panel B of Table II shows the results for losing streaks. The likelihood for a fund to remain a loser after a series of successive failures increases with the length of the streak. For instance, if a fund has been ranked below the median for six quarters on a row, there is a 60.76% probability that the fund persists as a loser in the subsequent quarter, while only 47.72% of funds are persistent losers after two quarters of poor performance. These figures are likely to be underestimates given the large percentage

available in the quarter subsequent to the streak of four winning quarters, while remaining active, and therefore are not considered any longer in our analysis.

[81] According to Baquero and Verbeek [2005], there is a non linear impact of size upon quarterly relative performance of hedge funds, which presumably reflects decreasing returns to scale in this industry. There seems to be a turning point around US$ 25 million of total net assets under management. Above this level, an increase in size results in a loss of ranking position. Therefore we used this amount of assets to separate small from large funds. This threshold is slightly above the cross sectional mean of about US$18 million.

Table II

Summary of Winner and Loser Streaks Based on Quarterly Performance of Hedge Funds

In each quarter we rank funds based on their raw returns and we define the winners and the losers taking the median as a threshold. The table indicates the total number of streaks with consecutive winning quarters (Panel A) and consecutive losing quarters (Panel B) that we could identify in our database across all funds and all periods. For the quarter that follows the observed streak, the table also indicates the percentage of funds that either liquidated or self-selected, the percentage of persistent funds, the percentage of funds that experienced net positive/negative money flows and the average amount of dollar flows per fund. We interpret net money flows as the opinion of the average investor in a fund. Thus, positive money flows indicate that investors on average expected a fund to be a winner after observing a given streak. The last column in Panel A reports the percentage of cases in which these expectations were not met (i.e. the fund actually became a loser). Conversely, the last column in Panel B reports the percentage of cases in which a fund became a winner while investors expected the fund to be a loser (as indicated by negative money flows).

Panel A : Winner Streaks

Streak Length (quarters)	Number of observations	Subsequent Liquidation %	Subsequent Self-selection %	Subseq. Persistent Winner %	Subsequent Positive Money Flows (%)	Average Amount of Dollar Flows Invested	Frequency of Wrong Forecasts Up %
1	2818	1.28	1.06	48.86	57.38	1618354.31	47.31
2	1319	0.99	0.83	52.77	63.76	2143430.16	41.26
3	687	0.44	0.58	57.50	70.89	6193009.71	41.07
4	388	0.00	0.26	59.79	73.20	8142902.68	37.32
5	224	0.00	0.00	62.05	75.89	9715289.70	38.82
6	111	0.00	2.70	69.37	77.48	9288168.96	25.58
7	70	0.00	1.43	60.00	75.71	8152601.31	35.85
8	41	0.00	2.44	60.98	75.61	14411952.51	38.71
9	21	0.00	0.00	71.43	76.19	3597137.64	25.00
10	12	0.00	0.00	33.33	91.67	9763031.47	72.73
11	2	0.00	0.00	100.00	100.00	38385652.18	0.00
12	2	0.00	0.00	0.00	100.00	18654944.34	100.00

Panel B : Loser Streaks

Streak Length (quarters)	Number of observations	Subsequent Liquidation %	Subsequent Self-selection %	Subseq. Persistent Loser %	Subsequent Negative Money Flows (%)	Average Amount of Dollar Flows Invested	Frequency of Wrong Forecasts Down (%)
1	2846	1.76	1.19	48.95	44.83	787251.95	47.49
2	1335	2.02	2.02	47.72	52.28	-1838814.00	49.71
3	604	6.13	1.99	55.96	57.95	-2361213.04	39.71
4	326	8.90	3.37	55.21	60.43	-5764902.06	35.03
5	167	10.18	2.40	62.28	65.87	-10905250.07	27.27
6	79	11.39	2.53	60.76	62.03	-2555103.83	32.65
7	43	13.95	9.30	39.53	51.16	-9425391.90	40.91
8	17	5.88	0.00	70.59	64.71	-943307.74	18.18
9	11	27.27	0.00	45.45	45.45	-22592097.87	40.00
10	5	20.00	0.00	80.00	20.00	-31560684.14	0.00
11	5	20.00	0.00	0.00	40.00	-2724851.66	100.00

of funds liquidating, especially for long streaks. If a fund survived after an extended period of bad performance, it is likely that it performed better than average so as to recover past losses and surpass the high watermark.[82] Given these patterns of negative persistence, or "cold hand", investors react accordingly by withdrawing increasing amounts of money as funds persist below the median for longer periods. After two quarters on a row of bad performance, a fund experiences average outflows of around 1.8 million dollars. If bad performance persists up to five quarters, a fund will face further withdrawals of nearly 11 million dollars on average. Again, these figures are likely to be affected downwards by the high attrition rates of persistent losers. On the other hand, several factors might reduce the responsiveness of investors to losing streaks compared to winning streaks. For example, restrictions imposed to withdrawals are more important than restrictions to subscriptions. Further, investors often face switching costs relative to closing and opening accounts. Finally, several psychological biases may inhibit investors from divesting, like the endowment effect, the disposition effect or cognitive dissonance as suggested by Goetzmann and Peles [1997].

Table III reports results of a similar exercise when winners and losers are defined in terms of style-adjusted returns. Arguably, investors compare funds with each other in a given style category. A correction for style accounts for an important source of risk in hedge fund returns. Therefore, we subtract from the return of each fund the average return of all funds in the corresponding style. We then rank all funds in terms of excess returns. We find evidence of persistence also in style-adjusted returns (see column five), although the figures are in general less pronounced than in the previous table, especially for streaks longer than four quarters, an indication that persistence in raw returns accounts to some extent for a differential in risk or investment style. This also confirms the findings of multi-period performance persistence in style-adjusted returns reported by Agarwal and Naik [2000] and Baquero, Ter Horst and Verbeek [2005]. We find, however, the same previously observed pattern of investors' behaviour. Larger amounts of money are directed towards funds with longer persistence patterns (columns 6 and 7), although long streaks have less predictive ability of future relative performance. The dispersion in money flows is less pronounced than in the previous table, consistent with the findings from Baquero and Verbeek [2005] that money flows are more responsive to ranks based on raw returns than on style-adjusted returns.[83]

[82] Remember that the typical incentive contract aims at enhancing managerial effort by paying hedge fund managers a percentage of annual profits if returns are above some hurdle rate and provided the fund value is above a high watermark.
[83] This might be an indication of an insufficient adjustment of investors to style as a source of risk.

Table III

Summary of Winner and Loser Streaks Based on Quarterly Style-Adjusted Performance of Hedge Funds

In each quarter we rank funds based on their style-adjusted returns and we define the winners and the losers taking the median as a threshold. The table indicates the total number of streaks with consecutive winning quarters (Panel A) and consecutive losing quarters (Panel B) that we could identify in our database across all funds and all periods. For the quarter that follows the observed streak, the table also indicates the percentage of funds that either liquidated or self-selected, the percentage of persistent funds, the percentage of funds that experienced net positive/negative money flows and the average amount of dollar flows per fund. We interpret net money flows as the opinion of the average investor in a fund. Thus, positive money flows indicate that investors on average expected a fund to be a winner after observing a given streak. The last column in Panel A reports the percentage of cases in which these expectations were not met (i.e. the fund actually became a loser). Conversely, the last column in Panel B reports the percentage of cases in which a fund became a winner while investors expected the fund to be a loser (as indicated by negative money flows).

Panel A : Winner Streaks

Streak Length (quarters)	Number of observations	Subsequent Liquidation %	Subsequent Self-selection %	Subseq. Persistent Winner %	Subsequent Positive Money Flows (%)	Average Amount of Dollar Flows Invested	Frequency of Wrong Forecasts Up %
1	2759	1.27	1.27	51.58	56.07	1741945.60	44.47
2	1354	1.48	1.33	54.06	61.30	2299633.69	41.33
3	740	0.54	0.14	57.97	67.16	5471730.40	42.05
4	416	0.48	0.48	59.62	69.47	6121840.31	37.02
5	235	0.43	1.28	52.34	69.79	4704338.44	45.12
6	109	0.00	0.00	53.21	74.31	5835617.80	39.51
7	55	0.00	1.82	50.91	74.55	7665378.28	43.90
8	28	0.00	0.00	60.71	78.57	7408980.44	36.36
9	16	0.00	0.00	50.00	75.00	10374172.11	50.00
10	7	0.00	0.00	57.14	85.71	11991434.33	33.33
11	4	0.00	0.00	100.00	75.00	20390206.00	0.00
12	3	0.00	0.00	66.67	66.67	7237176.90	50.00

Panel B : Loser Streaks

Streak Length (quarters)	Number of observations	Subsequent Liquidation %	Subsequent Self-selection %	Subseq. Persistent Loser %	Subsequent Negative Money Flows (%)	Average Amount of Dollar Flows Invested	Frequency of Wrong Forecasts Down (%)
1	2774	1.84	1.12	50.76	44.66	964221.89	46.25
2	1332	2.48	1.73	47.90	49.10	-521866.75	49.24
3	642	5.61	2.49	57.32	52.80	-2749486.66	38.94
4	352	6.25	1.70	50.57	54.83	-3412653.53	44.04
5	163	9.82	3.68	54.60	55.83	-10746096.30	41.76
6	74	8.11	1.35	58.11	60.81	-4746180.91	40.00
7	40	15.00	2.50	40.00	50.00	-4067262.61	50.00
8	15	0.00	6.67	60.00	60.00	-7340741.85	33.33
9	9	11.11	0.00	66.67	77.78	-29151878.51	28.57
10	5	0.00	0.00	80.00	100.00	-30473724.71	20.00
11	4	0.00	0.00	75.00	100.00	-12016756.16	25.00

Intuitively, the belief on a manager's skills is eroded with very long streaks and the increasing scepticism would lead eventually to commit gambler's fallacy. This idea is also formally captured in Rabin's model.[84] The key question is for how long an investor believes talent will last. The hot-hand bias and the gambler's fallacy are obviously two related biases and compete with each other. The stylized evidence presented in Tables II and III shows a monotonic pattern in money flows as the streak length increases, up to six quarters or so. As indicated above, for longer streaks the pattern becomes less clear. It is difficult, however, to conclude from our data whether the change in pattern is the result of emergence of the gambler's fallacy, since the number of observations considerably reduces with streak length. Moreover, money inflows might be increasingly restricted as funds grow in size.

Overall, our results provide evidence of "hot hand" among the winners and "cold hand" among the losers. This is an indication of non-uniformity in quality among managers. Our results also indicate that investors recognize this feature and follow, in general, a momentum strategy while they strive to discriminate luck from skill. However, it is precisely the belief in quality dispersion what leads investors, in theory, to overestimate the degree of positive autocorrelation in a sequence. To assess the degree of investor's overinference of managerial talent, we need a benchmark that indicates what can actually be expected of a manager. The next section provides first a model explaining future relative performance of hedge funds and we exploit this model to derive an estimate of rationally expected performance. We then propose a model explaining the response of money flows to performance streaks controlling for expected performance and additional factors as fund size, age and style, in order to detect any hot-hand bias in investors' decisions.

4.5 A model explaining money flows from the length of streaks

Our results in the previous section show that money flows are increasingly directed towards funds that successfully performed for longer periods of time. In this section we investigate to what extent this seemingly overwhelming response of investors is rationally justified. Is there any component in that response that is beyond a rational expectation of future performance and risk?

[84] Knowing with certainty the true rate of success of a given manager is a sufficient condition in Rabin [2002]'s model, to commit gambler's fallacy. Precisely for very large sequences, an investor will figure out the true rate: his beliefs about the rate will converge to certainty.

In order to disentangle these two components of the response of investors to past performance, namely a sensible reaction from one presumably induced by a psychological bias, we first determine what an investor can rationally expect of future relative performance of a fund given a number of informative variables, including historical persistence patterns. Our previous analysis did not consider several factors that can also be driving performance, such as size, age, style and other fund-specific features. Arguably, investors, especially sophisticated investors, pay attention to these characteristics, as well as variables accounting for risk. Consider the following model predicting relative performance of a fund (i.e. relative to its peers):[85]

$$Rnk_{i,t} = \alpha + \sum_{j=1}^{6} \beta_{1j}.Rnk_{i,t-j} + \sum_{j=1}^{6} \beta_{2j}.W_{j,i,t} + \sum_{j=1}^{6} \beta_{3j}.L_{j,i,t} + \beta_2.\ln(TNA_{i,t-1}) +$$
$$+ \beta_4.\ln(AGE_{i,t-1}) + \sum_{j=0}^{4} \beta_{5j}.Flow_{i,t-j} + \beta_6.\sigma_{i,t-1} + \beta_7.(\sigma_{i,t-1})^2 + \gamma'.X_{i,t-1} + \varepsilon_{i,t} \quad (1)$$

where Rnk_{it} is relative performance as measured by a fund's cross sectional rank, Rnk_{it-j} is the j[th] lagged rank and $Flow_{it-j}$ is the j[th] lagged flow measured as a growth rate. The standard deviation of returns σ_{it-1} has been computed based on the entire past history of monthly returns of a fund. The model includes the log of size (total net asset value) and age of the fund in the previous period, $ln(TNA_{i,t-1})$ and $\ln(AGE_{i,t-1})$, and a vector $X_{i,t-1}$ of fund-specific characteristics like management fees, incentive fees, managerial ownership and style. To explicitly capture the extent to which the streak length predicts future performance, we define 12 mutually exclusive dummies for each fund-period observation, six accounting for winner streaks and six dummies accounting for loser streaks, in the following way:

W_1=1 if a fund is a winner in the previous quarter *only*. W_1=0 otherwise.
W_2=1 if a fund is a winner in the previous 2 quarters *only*. W_2=0 otherwise.
:
W_5=1 if a fund is a winner in the previous 5 quarters *only*. W_5=0 otherwise.
W_6=1 if a fund is a winner in the previous 6 quarters *or more*. W_6=0 otherwise.
L_1=1 if a fund is a loser in the previous quarter *only*. L_1=0 otherwise.
:
L_5=1 if a fund is a loser in the previous 5 quarters *only*. L_5=0 otherwise.
L_6=1 if a fund is a loser in the previous 6 *or more* quarters. L_6=0 otherwise.

[85] This model is close to the one estimated by Baquero and Verbeek [2005], however their model does not explicitly include the dummies accounting for streak length. Also Agarwal, Daniel and Naik [2004] estimate a model explaining future performance of hedge funds. However, their model explains annual raw returns and does not include the structure of lagged performance measures.

We capture the effects of streaks longer than 6 quarters with only one dummy as the number of observations for long streaks is considerably reduced. The lagged ranks included in equation (1) and the persistence dummies just defined are different ways of capturing past performance, although they are closely related. Lagged ranks are informative of the dynamics of the fund's performance, while the dummies have the appealing feature of explicitly capturing a persistence pattern. The interaction or the joint impact of dummies and lagged ranks might be complex and difficult to interpret as both effects might overlap to some extent. For our purposes, however, the predictions generated by the model are crucial, not the individual contribution of each of the information variables on the right-hand side.

In column B of Table IV, we report the estimation results without including the lagged ranks in model (1). The impact of the persistence dummies upon relative performance is apparent and in line with our previous results in Table II: in general, the longer the streak, the more likely that the fund persists in the subsequent quarter, for both winner and loser streaks. Also, it is apparent that not only persistence drives future performance. The control variables also have a significant impact. When these variables are not taken into account (column A), the model clearly overestimates the impact of streak length upon performance. However, when the structure of lagged ranks is included in the model in addition to the persistence dummies (column C), the lagged ranks appear to capture most of the impact of winner and loser streaks. Some of the coefficients of the dummies remain marginally significant, while some of the coefficients of lagged ranks are highly significant. Overall, the results in Table IV indicate that the relative performance of a hedge fund in the next quarter is to some extent predictable from available information and past performance, although the R^2s indicate that the level of predictability is limited. As stated previously, lagged ranks and persistence dummies capture each different aspects of past performance. Their effects upon future performance may have subtle differences difficult to be fully disentangled. The streak length has manifestly a predictive ability of relative performance. However, investors should not take it as the only predictor, nor as the best predictor.

From the latter model, including both lagged ranks and persistence dummies, we can directly obtain a prediction of the relative performance a rational investor can expect. Let us come back to our initial question. Is there any component in the response of investors to past performance that is beyond what would be justified given the expected performance and risk of a fund? And if so, is that component of flows related to the length of the streak, as suggested by the law of small numbers?

Table IV

A Model Predicting Relative Performance of Open-End Hedge Funds from Historical Persistence Patterns

The table reports estimates of a model explaining relative quarterly performance as measured by fractional ranks. The fractional rank ranges between 0 and 1 and is defined as the fund's percentile performance relative to all the funds existing in the sample in the same period, based on the fund's raw return in a given quarter. The sample includes 752 open-end hedge funds for the period 1994 Q4 till 2000 Q1. The independent variables include twelve dummies accounting for historical winner and loser streaks, six lagged fractional ranks, the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows computed as quarterly growth rates, upside potential based on the entire past history of the fund and calculated with respect to the return on the U.S. Treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund (estimate not reported) and 10 dummies for investment styles defined on the basis of CSFB/Tremont indices (estimates not reported). We estimate our model by pooling all fund-period observations. T-statistics based on robust standard errors are provided in parentheses.

Parameters	OLS estimates including only persistence dummies (A)		OLS estimates, excluding the structure of lagged ranks (B)		OLS estimates including the structure of lagged ranks (C)	
Intercept	0.4938	(69.93)	-0.2036	(-0.84)	-0.2281	(-0.93)
W2	0.0173	(1.40)	0.0092	(0.75)	0.0315	(1.86)
W3	0.0417	(2.61)	0.0255	(1.64)	0.0118	(0.60)
W4	0.0514	(2.60)	0.0250	(1.28)	-0.0116	(-0.51)
W5	0.0879	(3.62)	0.0526	(2.16)	0.0413	(1.53)
W6	0.0845	(4.85)	0.0405	(2.21)	0.0374	(1.72)
L1	-0.0091	(-0.92)	-0.0051	(-0.52)	0.0123	(0.70)
L2	0.0071	(0.58)	0.0190	(1.58)	0.0168	(1.01)
L3	-0.0631	(-3.99)	-0.0384	(-2.41)	-0.0086	(-0.44)
L4	-0.0737	(-3.74)	-0.0453	(-2.31)	0.0060	(0.26)
L5	-0.1070	(-4.26)	-0.0747	(-2.99)	-0.0444	(-1.60)
L6	-0.0860	(-3.51)	-0.0439	(-1.77)	-0.0229	(-0.84)
Rnk lag 1					0.0296	(1.21)
Rnk lag 2					-0.0002	(-0.01)
Rnk lag 3					0.0754	(4.61)
Rnk lag 4					0.0160	(1.09)
Rnk lag 5					-0.0508	(-3.66)
Rnk lag 6					-0.0172	(-1.28)
Cash Flows lag 1			-0.0119	(-1.05)	-0.0133	(-1.18)
Cash Flows lag 2			-0.0021	(-0.20)	-0.0035	(-0.33)
Cash Flows lag 3			-0.0094	(-1.14)	-0.0089	(-1.06)
Cash Flows lag 4			-0.0057	(-0.90)	-0.0026	(-0.41)
Ln(TNA)			0.0799	(2.79)	0.0783	(2.70)
$\mathrm{Ln(TNA)}^2$			-0.0024	(-2.78)	-0.0023	(-2.69)
Ln(AGE)			-0.0118	(-1.78)	-0.0117	(-1.76)
Offshore			-0.0202	(-2.63)	-0.0193	(-2.50)
Incentive Fees			0.0004	(0.83)	0.0005	(0.91)
Management Fees			-0.0053	(-1.30)	-0.0048	(-1.19)
StDev			0.7991	(4.57)	0.7970	(4.47)
StDev^2			-1.3844	(-2.80)	-1.4036	(-2.69)
Upside Potential Ratio			0.0035	(5.87)	0.0035	(5.87)
$\mathrm{(Upside\ Pot\ Ratio)}^2$			0.00001	(-4.63)	0.0000	(-4.73)
Number of observations	7457		7425		7425	
R^2	0.0159		0.0521		0.0583	

Table V provides an answer to these questions. In column A, we report the estimates of a probit model explaining the sign of cash flows from the expected rank, as obtained from our previous model, but we explicitly include the persistence dummies in order to identify any additional effect that the pattern of persistence might have on investors' decisions. The impact of the predicted rank upon flows is positive and highly significant, as can be expected. The higher the predicted rank, the more likely a fund will experience positive money flows. Besides, we find a remarkable pattern for the coefficients of the dummies. All the estimated coefficients for winning and losing streaks are highly significant, while in absolute value they increase monotonically as the length of the streak increases. The longer the winner streak, the more likely is a fund to attract further inflows of money, regardless of what is rationally justified given expected relative performance. Conversely, the longer the losing streak, ceteris paribus, the more likely that a fund experiences further outflows. In column B we provide an extended model that considers the fact that investors' decisions are also affected by their expectations about risk. If we include several control variables like age, size, style, standard deviation of historical returns, downside risk, that are informative of the fund's riskiness besides expected rank, the explanatory power of the model enhances substantially, as indicated by the value of the pseudo R^2. Several of these added variables have indeed economically and statistically significant coefficients. Statistically, the impact of expected rank upon flows reduces slightly but remains significant. However, the pattern and magnitude of coefficients for the persistence dummies remains essentially unchanged, clearly showing that flows are directed much more towards persistently winning funds and out of persistently losing funds than is justified by expected future performance.[86]

To have an idea of the economic significance of our findings, we use the coefficients of the persistence dummies in the previous model to compute the implied probability that investors invest in a fund (as indicated by a positive sign of cash flows) given a certain streak length, for different values of the expected rank. All other variables in our model are fixed at their sample average. The results are shown in figure 1, where we focus on expected ranks in the range 0.4-0.7, because this is where most observations in our sample are located.

Consider a fund which is rationally expected to be in the 70th percentile of the distribution in the next period according to our model (i.e. rank=0.70). The likelihood that investors direct their money towards this fund differs across streak lengths,

[86] In a robustness check, we allowed for the possibility of non-linearities in the response of flows to expected relative performance, by adding the square of expected rank. The added variable had no significant impact.

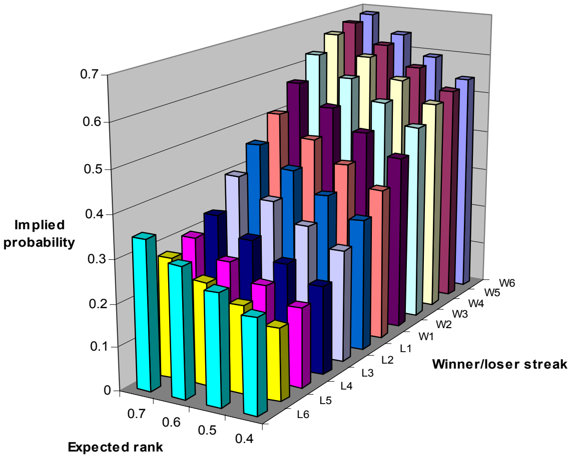
Table V

The Effect of Persistence Patterns upon Money Flows for Open-End Hedge Funds

The table reports estimates of a probit model explaining positive and negative flows. The sample includes 752 open-end hedge funds for the period 1994 Q4 till 2000 Q1. We measure cash flows as a quarterly growth rate corrected for reinvestments. The independent variable takes value 1 if cash flows are positive. Otherwise it takes value 0. The independent variables include 12 mutually exclusive dummies accounting for the length of winner and losing streaks and we control for expected rank (obtained from our model reported in Table IV, Panel C). The model reported in Panel B also controls for fund specific characteristics including the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows, upside potential based on the entire past history of the fund and calculated with respect to the return on the U.S. Treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund and seven dummies for investment styles defined on the basis of CSFB/Tremont indices (estimates not reported). The model also includes 21 time dummies (estimates not reported). We estimate each model by pooling all fund-period observations. z-statistics are provided in parentheses.

	Probit model explaining positive and negative cash flows.			
Parameters	A		B	
Intercept	-0.5493	(-4.34)	0.1341	(0.37)
Expected Rank	1.2044	(4.84)	1.2691	(2.08)
W2	0.1534	(2.87)	0.1473	(2.66)
W3	0.2954	(4.27)	0.2870	(3.97)
W4	0.4450	(4.95)	0.3864	(4.15)
W5	0.4783	(4.13)	0.4265	(3.56)
W6	0.6884	(6.97)	0.4565	(4.30)
L1	-0.0876	(-2.06)	-0.1388	(-3.17)
L2	-0.2453	(-4.70)	-0.2762	(-5.02)
L3	-0.3954	(-5.42)	-0.4652	(-5.93)
L4	-0.4889	(-5.22)	-0.5457	(-5.50)
L5	-0.6354	(-5.01)	-0.6098	(-4.42)
L6	-0.4265	(-3.59)	-0.4194	(-3.35)
Ln(TNA)			-0.0078	(-0.74)
Ln(AGE)			-0.1729	(-5.46)
Cash Flows lag 1			0.3693	(4.76)
Cash Flows lag 2			0.3120	(5.08)
Cash Flows lag 3			0.1607	(3.44)
Cash Flows lag 4			0.0887	(2.17)
Offshore			-0.1467	(-3.87)
Incentive Fees			-0.0023	(-0.94)
Management Fees			-0.0157	(-0.87)
Personal Capital			-0.0446	(-1.18)
Upside Potential Ratio			0.0052	(1.21)
StDev			-1.5398	(-2.60)
Number of observations	7195		7195	
Pseudo R^2	0.0428		0.0904	

Figure 1
Probability of investing implied
by the estimated model of flows (model B, Table V).



although the information content of a streak is already accounted for in the expected rank. This likelihood is 69% after a winning streak of six quarters, compared to 51% after a winning streak of one quarter. Similarly, if a fund is expected to be ranked in the 40th percentile, the likelihood that investors redeem is 78% after a losing streak of six quarters, compared to 69% after a losing streak of one quarter. Interestingly, there is a non negligible probability of 35% that investors invest in a fund after six losing quarters when the expected rank equals 0.7, while in 46% of cases investors will divest from a fund after six winning quarters if the fund's expected rank equals 0.4.

The results so far indicate that hedge fund investors are directing their money flows in response to winner and losing streaks much more than is justified by the expected future performance of the funds. To further investigate this issue, we consider three different investment strategies. The first one is a naïve strategy that prescribes to invest in all persistent winners and to divest from all persistent losers. The second strategy is the one followed by the average investor, as indicated by the sign of money flows. That is, this strategy invests in funds with a positive money flow (equally weighted) and divests from funds with a negative money flow. The third strategy is based on our model explaining ranks reported in Table IV, Panel C, and prescribes to invest (divest) in a fund if the model predicts that subsequent rank is above (below) the median.[87] In Table VI, Panel A, we report raw returns obtained from these three strategies, where we also decompose the returns across subsets of funds with a given (winner or losing) streak length. The investment strategy based upon the model provides an average return of 6.31% per quarter, outperforming the funds with positive money flows by 1.72%, especially the funds with losing streaks. The divestment strategy based upon the model prescribes to divest from funds that subsequently performed worse than the funds from which investors actually redeemed (1.81% against 2.98% on average)[88]. Assuming that divestments finance investments, the zero-investment strategy prescribed by the model provides an excess return of 4.5% per quarter, against 1.61% obtained by the zero-investment strategy followed by investors[89]. Panel B shows similar results in terms of style adjusted returns. We can conclude that the excessive importance that investors attribute to the length of performance streaks as indicative of future performance, is detrimental to investors' wealth. On the other hand, investors directed money inflows towards funds with winning streaks that outperformed the naïve strategy (5.27% against 4.46% on average). Conversely, investors redeemed from funds with losing streaks that underperformed, on average, the naïve divestment strategy (2.76% against 3.14%).

These figures indicate that investors strive to discriminate between skilled and lucky managers in spite of a given performance streak. However, it seems that many investors follow contrarian strategies more actively than what the model prescribes, often investing in previous losers and divesting from previous winners, which offsets to a large extent the gains from momentum investing. As a result, investors do not perform overall much better than the naïve strategy. In fact, in terms of style adjusted returns, the naïve strategy provides slightly higher returns from investments (0.59% against 0.52%) and slightly worse returns from divestments (-0.34% against -0.28%).

Our previous analysis indicates that investors' allocations are potentially suboptimal. The opportunity costs involved appear sizeable, suggesting that investors take decisions that are not adequately grounded. On the other hand, we did not take into account transaction costs or liquidity restrictions that may prevent investors from

[87] Because the model is estimated over the entire sample period, this third strategy is not an investment strategy that investors could have followed in real time. Also transaction costs and redemption restrictions are not taken into consideration. However, by using this hypothetical strategy as a benchmark, our purpose is to give some indication of the potential suboptimal allocation of resources of hedge fund investors. The impact of liquidity restrictions in estimating our model explaining flows is investigated in the next section.

[88] The model more often prescribes to invest in funds with long winning streaks and divest from funds with long losing streaks than what investors do. For example, the model indicates to invest in 318 funds with three successive winning quarters, while investors invested only in 294 funds (not reported). Conversely, the model indicates to divest from 373 funds with three consecutive losing quarters while investors divested from 274 funds.

[89] Remember that the distribution of cash flows in our database is almost symmetric. Moreover, the average money inflows per fund is 7.9 million US$ while the average money outflow per fund is 7.4 million US$.

Table VI

Comparison Between the Performance of Investors' Decisions and the Performance of the Model's Prescriptions, Conditional to Past Performance

The table reports the returns obtained from three different investment strategies, conditional to historical performance. Historical performance is measured by the length of winning or losing streaks and is indicated by 12 mutually exclusive dummies. The first strategy is a naïve strategy that prescribes to invest in all funds with a previous winning streak and to divest from all funds with a previous losing streak. The second strategy is the one followed by investors: if a fund experienced positive (alternatively negative) money flows, it indicates that the average investor invested (alternatively divested) in that fund. The third strategy follows the prescription of our model of ranks reported in Table IV: investing in funds with a predicted rank above the median while divesting from funds with a predicted rank below the median. Panel A reports equally weighted raw returns for a given streak length. Panel B reports equally weighted style-adjusted returns.

Panel A: Subsequent quarter raw returns

Historical performance: winning and losing streaks defined in terms of lagged raw returns	Returns from investments			Returns from divestments		
	Naïve strategy	Funds with positive money flows	Model prescription	Naïve strategy	Funds with negative money flows	Model prescription
W1	0.0377	0.0454	0.0597		0.0292	0.0209
W2	0.0402	0.0497	0.0564		0.0267	0.0202
W3	0.0484	0.0549	0.0636		0.0370	0.0143
W4	0.0698	0.0760	0.0856		0.0559	0.0224
W5	0.0681	0.0548	0.0674		0.1055	0.0734
W6	0.0609	0.0686	0.0675		0.0322	0.0076
L1		0.0373	0.0618	0.0357	0.0342	0.0199
L2		0.0491	0.0625	0.0442	0.0405	0.0285
L3		0.0237	0.0866	0.0142	0.0091	0.0045
L4		0.0103	0.0673	0.0093	0.0088	0.0053
L5		0.0181	-0.0470	0.0085	0.0055	0.0098
L6		0.0091	0.0432	0.0034	0.0007	0.0023
All winning streaks	0.0446	0.0527	0.0633	-	0.0329	0.0206
All losing streaks	-	0.0365	0.0628	0.0314	0.0276	0.0165
Average Returns	0.0446	0.0459	0.0631	0.0314	0.0298	0.0181

Panel B: Subsequent quarter style-adjusted returns

Historical performance: winning and losing streaks defined in terms of lagged style-adjusted returns	Returns from investments			Returns from divestments		
	Naïve strategy	Funds with positive money flows	Model prescription	Naïve strategy	Funds with negative money flows	Model prescription
W1	0.0004	0.0042	0.0120		-0.0038	-0.0086
W2	0.0086	0.0149	0.0114		-0.0003	0.0054
W3	0.0096	0.0105	0.0195		0.0080	-0.0127
W4	0.0129	0.0132	0.0180		0.0123	-0.0022
W5	0.0263	0.0132	0.0232		0.0635	0.0512
W6	0.0100	0.0160	0.0117		-0.0125	-0.0002
L1		0.0027	0.0026	0.0020	0.0013	0.0016
L2		0.0040	0.0059	0.0017	0.0000	-0.0017
L3		-0.0131	0.0095	-0.0156	-0.0169	-0.0189
L4		-0.0137	0.0127	-0.0102	-0.0087	-0.0117
L5		-0.0334	-0.0620	-0.0267	-0.0246	-0.0258
L6		-0.0342	0.0109	-0.0360	-0.0369	-0.0373
All winning streaks	0.0059	0.0097	0.0143	-	0.0005	-0.0046
All losing streaks	-	-0.0010	0.0041	-0.0034	-0.0052	-0.0070
Average Returns	0.0059	0.0052	0.0106	-0.0034	-0.0028	-0.0060

taking timely decisions or from shifting their capital as the model prescribes. The next section analyzes the impact of liquidity restrictions in the estimation of our model and discusses several additional robustness tests.

4.6 Robustness checks

In this section, we consider a large number of alternative model specifications and assumptions to analyze the sensitivity of our main results. First, we investigate a model that explains growth rates of cash flows rather than just their sign. Second, we experiment with different thresholds to define winners and losers. Third, we consider specifications where we use ranks and persistence dummies based on style-adjusted returns instead of raw returns. Fourth, we include expected performance over the coming year rather than just the next quarter in the model. And finally, we explore the potential effects of liquidity restrictions.

If our model explains cash flows measured as growth rates instead of the sign of flows (Table VII), the impact of the persistence dummies is virtually the same as in our previous specification, while several control variables have a highly significant impact too. Surprisingly, however, the effect of expected rank disappears. This suggests that investors decide the amount of their investments largely based upon the length of the streaks, and do not consider anything else that forecasts future rank. Again, investors appear to direct their money flows too strongly based upon persistence of winning and losing.

This main result is robust to a number of alternative specifications. We have experimented with different thresholds to define winners and losers other than the median (see Tables A4, A5, A6, A7 in the appendix). Also, we have estimated our models using ranks and persistence dummies based on style-adjusted returns instead of raw returns[90] (see Tables A2 and A3). In all these specifications we obtain similar results as before: the longer the streak, the more important is its impact on investors' decisions.

[90] In this case, the persistence dummies have also been defined in terms of funds' returns in excess of the style index. The model explains less variation in ranks than our model estimated in Table IV. We included the expected style-adjusted rank in our model explaining the sign of flows, together with the persistence dummies based on style-adjusted returns. We obtain similar results as before. The longer the streak, the more important is the impact on investors' decisions. The model, however, explains less variation in the likelihood to invest or divest in a hedge fund, compared to our model reported in Table V, an indication that investors adjust insufficiently for style as a source of risk.

Table VII

The Effect of Persistence Patterns upon Money Flows for Open-End Hedge Funds

The table reports OLS estimates of a model explaining money flows. The sample includes 752 open-end hedge funds for the period 1994 Q4 till 2000 Q1. We measure cash flows as a quarterly growth rate corrected for reinvestments. The independent variables include 12 mutually exclusive dummies accounting for winner and losing streaks. We control for expected rank (obtained from our model estimated in Table IV, Panel C) and for fund specific characteristics like the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows, upside potential based on the entire past history of the fund and calculated with respect to the return on the U.S. Treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund and seven dummies for investment styles defined on the basis of CSFB/Tremont indices (estimates not reported). The model also includes 21 time dummies (estimates not reported). We estimate each model by pooling all fund-period observations (t-statistics are provided in parentheses).

	OLS estimates of a model explaining growth rates			
Parameters	A		B	
Intercept	0.0256	(0.89)	0.3174	(3.52)
Expected Rank	0.0169	(0.31)	0.1250	(1.24)
W2	0.0096	(0.82)	0.0109	(0.91)
W3	0.0846	(4.00)	0.0846	(4.02)
W4	0.0796	(4.09)	0.0697	(3.50)
W5	0.1353	(3.46)	0.1239	(3.24)
W6	0.1219	(5.37)	0.0849	(3.77)
L1	-0.0232	(-2.44)	-0.0285	(-3.04)
L2	-0.0372	(-2.28)	-0.0411	(-2.48)
L3	-0.0719	(-5.21)	-0.0756	(-5.43)
L4	-0.1032	(-6.43)	-0.1068	(-6.32)
L5	-0.1100	(-4.07)	-0.1022	(-3.75)
L6	-0.0733	(-2.58)	-0.0758	(-2.59)
Ln(TNA)			-0.0156	(-4.80)
Ln(AGE)			-0.0232	(-3.67)
Cash Flows lag 1			0.0526	(2.89)
Cash Flows lag 2			0.0501	(3.44)
Cash Flows lag 3			0.0350	(2.00)
Cash Flows lag 4			0.0162	(1.50)
Offshore			0.0005	(0.07)
Incentive Fees			-0.0015	(-3.06)
Management Fees			-0.0076	(-1.59)
Personal Capital			0.0060	(0.66)
Upside Potential Ratio			0.0009	(4.23)
StDev			0.0365	(0.21)
Number of observations	7195		7195	
Pseudo R^2	0.0275		0.0629	

The models reported so far assume that investors seek to exploit performance predictability at quarterly horizons. It is possible, however, that investors are concerned about future long run performance, over the next year for example, although previous studies find only weak evidence of predictability at annual horizons for hedge funds. We estimated an alternative model explaining future rank over a year and we included the corresponding expected performance in the model of flows, see Table A8. There are no substantial changes in the coefficients of the persistence dummies. Surprisingly, however, the coefficient for expected annual rank is negative and significant, while the coefficient for expected quarterly rank remains positive and significant. This might be an indication that investors perceive a higher risk associated to higher expected ranks in the long run.

An additional concern is the potential impact that liquidity restrictions may have in our results. The significant positive response of net money flows to winner streaks may be due to the fact that outflows are restricted. As explained earlier in this paper, hedge funds impose in general monthly or quarterly redemption periods with written-notice periods typically ranging between 15 and 90 days. To isolate the effect of liquidity restrictions, we allow for interactions between the persistence dummies and dummies accounting for the combined impact of redemption and notice periods.[91]

Table VIII reports our results. Notice first that the impact of winning streaks on money flows is indeed magnified when liquidity restrictions are in place, especially for streaks of 4 and 5 quarters length, while the response of money flows to losing streaks is virtually non-existent, as could have been expected. As a consequence, the response of unrestricted money flows to winning streaks reduces slightly compared to our results in Table V, while the response to losing streaks is enhanced. Removing the effect of restrictions, however, does not change the main result of this paper. We still find a significant and increasingly positive (negative) response of unrestricted money flows to the length of winning (losing) streaks.

[91] In each quarter t, and for each fund i, we define a dummy variable $REDR_{i,t}$ that takes value 1 if redemption restrictions do not prevent outflows in quarter t in response to a previous winner/loser streak of length n quarters. To separate the response of restricted and unrestricted net money flows, we interact dummies accounting for restrictions with dummies accounting for the length of the streak as follows:

$$W\,unrestricted_{n,i,t} = W_{n,i,t} \,.\, (REDR_{i,t}) \quad \text{and} \quad W\,restricted_{n,i,t} = W_{n,i,t} \,.\, (1\text{-}REDR_{i,t})$$
$$L\,unrestricted_{n,i,t} = L_{n,i,t} \,.\, (REDR_{i,t}) \quad \text{and} \quad L\,restricted_{n,i,t} = L_{n,i,t} \,.\, (1\text{-}REDR_{i,t})$$

Where the dummies $W_{n,i,t}$ and $L_{n,i,t}$ take value 1 if the fund i experienced a winner (loser) streak of length n quarters between t-n and t-1.

Table VIII

The Effect of Persistence Patterns Upon Money Flows Subject to Liquidity Restrictions in Open-End Hedge Funds

The table reports estimates of a probit model explaining positive and negative flows. We measure cash flows as a quarterly growth rate corrected for reinvestments. The independent variable takes value 1 if cash flows are positive. Otherwise it takes value 0. The independent variables include 12 mutually exclusive dummies accounting for winner and losing streaks interacting with dummies accounting for restrictions to liquidity. The model reported in Panel B also controls for fund specific characteristics including the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows, upside potential based on the entire past history of the fund and calculated with respect to the return on the U.S. Treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund and the dummies for investment styles defined on the basis of CSFB/Tremont indices (estimates not reported). The model also includes 21 time dummies (estimates not reported). The sample includes 752 open-end hedge funds for the period 1994 Q4 till 2000 Q1. We estimate each model by pooling all fund-period observations. z-statistics are provided in parentheses.

	Probit model explaining positive and negative cash flows			
Parameters	Panel A		Panel B	
Intercept	-0.5055	(-3.95)	0.1567	(0.43)
Expected Rank	1.1159	(4.44)	1.2683	(2.06)
W2 Unrestricted	0.1706	(3.07)	0.1707	(2.97)
W3 Unrestricted	0.2936	(4.05)	0.2902	(3.83)
W4 Unrestricted	0.4112	(4.38)	0.3566	(3.65)
W5 Unrestricted	0.4478	(3.68)	0.3921	(3.13)
W6 Unrestricted	0.6902	(6.66)	0.4743	(4.31)
L1 Unrestricted	-0.1046	(-2.39)	-0.1513	(-3.37)
L2 Unrestricted	-0.2614	(-4.89)	-0.2871	(-5.07)
L3 Unrestricted	-0.4566	(-6.00)	-0.5156	(-6.31)
L4 Unrestricted	-0.4651	(-4.91)	-0.5190	(-5.18)
L5 Unrestricted	-0.6623	(-5.09)	-0.6172	(-4.38)
L6 Unrestricted	-0.4408	(-3.67)	-0.4306	(-3.41)
W2 Restricted	0.0226	(0.16)	-0.0488	(-0.35)
W3 Restricted	0.3402	(1.87)	0.2639	(1.40)
W4 Restricted	0.7986	(2.86)	0.6819	(2.51)
W5 Restricted	0.8116	(2.30)	0.7347	(2.06)
W6 Restricted	0.7386	(2.65)	0.3107	(0.98)
L1 Restricted	0.0688	(0.67)	-0.0188	(-0.18)
L2 Restricted	-0.0201	(-0.12)	-0.1451	(-0.89)
L3 Restricted	0.2376	(1.02)	0.0822	(0.35)
L5 Restricted	-0.2636	(-0.47)	-0.4936	(-0.82)
L6 Restricted	-0.0034	(0.00)	0.0987	(0.13)
Ln(TNA)			-0.0083	(-0.79)
Ln(AGE)			-0.1747	(-5.51)
Cash Flows lag 1			0.3696	(4.79)
Cash Flows lag 2			0.3128	(5.07)
Cash Flows lag 3			0.1614	(3.45)
Cash Flows lag 4			0.0879	(2.15)
Offshore			-0.1400	(-3.63)
Incentive Fees			-0.0026	(-1.04)
Management Fees			-0.0168	(-0.93)
Personal Capital			-0.0440	(-1.17)
StDev			-1.5589	(-2.61)
Upside Potential Ratio			0.0054	(1.21)
Number of observations	7187		7187	
Pseudo R^2	0.0441		0.0912	

Finally, it is conceivable that investors' decisions are mostly determined by an aggregate measure of past performance in the long run and the persistence dummies might be just a proxy for it. To separate this effect from one strictly due to the length of the persistence pattern, we included in our model the rank based on raw returns over the previous year (see Table A9). Still, the coefficients of persistence dummies remain statistically significant and in general they increase with the length of the streak. However, their combined impact reduces by 10% for winner streaks and by 30% for losing streaks. The effect of the annual rank is positive and highly significant while the coefficient of expected rank becomes negative and significant. It seems that the effect of annual rank and expected rank overlap to some extent, and that historical long run performance is also an important determinant of investors' decisions beyond rational expectations.

4.7 Concluding remarks

Contrarian and momentum investing are often considered as irrational behaviour. The heuristic known as *the law of small numbers*, and more particularly the concept of *local representativeness*, have been proposed as the underlying psychological principles (see e.g. De Bondt and Thaler [1985], Shefrin [2000], Rabin [2002]). Our paper provides empirical evidence that supports this theory in the context of investors who select hedge fund managers. Specifically, we investigate the response of investors to performance streaks of
hedge funds and we present a model that disentangles a rational component from a heuristic-driven component in momentum investing.

We find that persistence patterns of a hedge fund do have a predictive ability of future relative performance: the longer the winner streak, the larger the probability for a fund to remain a winner subsequently. Investors, in turn, appear to be aware of the information content of performance streaks, as the pattern of money flows is positively correlated to the length of the historical persistence pattern of funds. The larger the length of a winner (loser) streak, the most likely funds will experience positive (negative) money flows, indicating that the average investor indeed follows a momentum strategy.

Our model explaining future relative performance of hedge funds shows, however, that persistence patterns should neither be taken as the only predictor, nor as the best predictor of future performance. Yet, our model explaining money flows from expectations of performance and persistence patterns, shows that the length of the streak has an economically and statistically significant impact on flows beyond rationally expected performance, which confirms a "hot-hand" bias driving to a large extent momentum investing. These results are not driven by liquidity restrictions and are robust to a number of alternative specifications using different performance measures, cash-flow measures and different definitions of winners and losers. Finally, we show that investors' decisions are suboptimal compared to a hypothetical investment strategy based on our model explaining future relative performance.

It seems that the due diligence process, if ever conducted, does not effectively counteract the excessive weight that investors place in the managers' track records as a criterion for decision. One explanation may be found in the psychological theory of *cognitive dissonance* from Festinger [1957] or in the closely related concept of *confirmation trap* documented by Wason [1960] and Enhorn and Hogarth [1978]. Once investors have persuaded themselves about the talent of a manager based on a given performance streak, they are likely to later neglect evidence that disconfirms or conflicts with their initial beliefs. In fact, for this reason several investment advisors recommend to conduct first a qualitative exploration, before starting a quantitative analysis of track records, in order to obtain preliminary indications of potential weaknesses of the manager or the organization that require further attention. The idea here is that it is not the same to approach the due diligence process with some scepticism about managerial skill than approaching it with a belief that talent exists.

Altogether, our results provide conclusive evidence that the response of investors to past performance of hedge funds is largely driven by a mistaken belief in the law of small numbers. Investors are over-sensitive to the precise sequence of performance signals they observe over time. Previous studies have ignored this feature by aggregating performance measures over annual horizons. Apparently, sophisticated investors do exhibit psychological biases that may have adverse consequences for their wealth.

APPENDIX

Table A1

Cross-Sectional Characteristics of the Hedge Fund Sample

This table presents summary statistics on cross-sectional characteristics of our sample of 752 hedge funds for the period 1994Q4 till 2000Q1. Cash flows are the change in total net assets (TNA) between consecutive quarters corrected for reinvestments. Returns are net of all management and incentive fees. Age is the number of months a fund has been in operation since its inception. In each quarter, the historical standard deviation of monthly returns, semi deviation and upside potential have been computed based on the entire past history of the fund. Semi deviation and upside potential are calculated with respect to the return on the U.S. Treasury bill taken as the minimum investor's target. Offshore is a dummy variable with value one for non-U.S. domiciled funds. Incentive fee is a percentage of profits above a hurdle rate that is given as a reward to managers. Management fee is a percentage of the fund's net assets under management that is paid annually to the manager for administering a fund. Personal capital is a dummy variable that takes the value one if the manager invests from her own wealth in the fund. The dummy leverage takes the value one if the fund makes substantial use of borrowing. We include 10 mutually exclusive dummies for investment styles defined on the basis of CSFB/Tremont indices. The dummy labelled *hedge fund index* takes value 1 whenever a fund could not be categorized in a specific investment style.

Variable	Mean	Std. Dev.	Min	Max
Cash Flows (growth rate)	0.0295	0.3215	-1.4303	8.1577
Cash Flows>0 (3676 obs)	0.1751	0.3792	0.0001	8.1577
Cash Flows<0 (3551 obs)	-0.1193	0.1549	-1.4303	-0.0001
Cash Flows=0 (407 obs)				
Cash Flows (dollars)	235008.8	3.70E+07	-1.41E+09	6.87E+08
ln(TNA)	16.7296	1.8298	8.1050	23.2966
ln(AGE)	3.8293	0.5943	2.8904	5.6168
Quarterly Returns	0.0388	0.1377	-0.9763	1.8605
Historical St.Dev.	0.0529	0.0431	0.0021	0.7753
Semi Deviation	0.0310	0.0255	0	0.3387
Upside Potential	0.0248	0.0183	0.0006	0.2914
Upside Potential Ratio	1.7025	10.934	0.0757	440.1028
Offshore	0.5418	0.4983	0	1
Incentive Fee	17.7078	7.0181	0	50
Management Fees	1.4744	1.0129	0	8
Personal Capital	0.7180	0.4500	0	1
Leverage	0.7683	0.4220	0	1
Convertible Arbitrage	0.0076	0.0871	0	1
Dedicated Short Bias	0.0118	0.1080	0	1
Emerging Markets	0.0927	0.2900	0	1
Equity Market Neutral	0.0935	0.2911	0	1
Event Driven	0.1191	0.3239	0	1
Fixed Income Arbitrage.	0.0122	0.1098	0	1
Global Macro	0.0235	0.1514	0	1
Long/Short Equity	0.2476	0.4316	0	1
Managed Futures	0.2331	0.4228	0	1
Hedge Fund Index	0.1590	0.3657	0	1

Table A2

A Model Explaining Relative Quarterly Performance of Open-End Hedge Funds from Historical Persistence Patterns (Style-adjusted)

The table reports estimates of a model explaining relative performance as measured by fractional ranks. The fractional rank ranges between 0 and 1 and is defined as the fund's percentile performance relative to all the funds existing in the sample in the same period, based on the fund's style-adjusted return. The sample includes 752 open-end hedge funds for the period 1994 Q4 till 2000 Q1. The independent variables include twelve dummies accounting for historical winner and loser streaks, six lagged fractional ranks, the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows computed as quarterly growth rates, upside potential based on the entire past history of the fund and calculated with respect to the return on the U.S. Treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund (estimate not reported) and the dummies for investment styles defined on the basis of CSFB/Tremont indices (estimates not reported). We estimate our model by pooling all fund-period observations. T-statistics based on robust standard errors are provided in parentheses.

Parameters	OLS estimates including only persistence dummies (A)		OLS estimated, excluding the structure of lagged ranks (B)		OLS estimates including the structure of lagged ranks (C)	
Intercept	0.5084	(71.31)	-0.1991	(-0.83)	-0.2066	(-0.85)
W2	0.0034	(0.28)	-0.0029	(-0.23)	-0.0219	(-1.27)
W3	0.0381	(2.58)	0.0307	(2.07)	-0.0062	(-0.32)
W4	0.0463	(2.58)	0.0363	(2.01)	-0.0134	(-0.61)
W5	0.0124	(0.55)	-0.0016	(-0.07)	-0.0386	(-1.48)
W6	0.0357	(1.80)	0.0111	(0.54)	-0.0231	(-0.98)
L1	-0.0212	(-2.11)	-0.0196	(-1.96)	-0.0253	(-1.37)
L2	-0.0220	(-1.81)	-0.0157	(-1.30)	-0.0023	(-0.14)
L3	-0.0854	(-5.64)	-0.0761	(-5.05)	-0.0442	(-2.33)
L4	-0.0645	(-3.36)	-0.0476	(-2.47)	-0.0038	(-0.17)
L5	-0.0780	(-2.95)	-0.0538	(-2.10)	-0.0209	(-0.74)
L6	-0.0910	(-3.70)	-0.0435	(-1.73)	-0.0137	(-0.49)
Rnk lag 1					0.0468	(1.90)
Rnk lag 2					0.0584	(2.37)
Rnk lag 3					0.0426	(2.59)
Rnk lag 4					0.0142	(1.00)
Rnk lag 5					-0.0240	(-1.83)
Rnk lag 6					-0.0023	(-0.18)
Cash Flows lag 1			-0.0140	(-1.23)	-0.0171	(-1.52)
Cash Flows lag 2			-0.0043	(-0.44)	-0.0054	(-0.53)
Cash Flows lag 3			-0.0067	(-0.83)	-0.0071	(-0.86)
Cash Flows lag 4			-0.0077	(-1.10)	-0.0063	(-0.91)
Ln(TNA)			0.0777	(2.74)	0.0717	(2.50)
$Ln(TNA)^2$			-0.0023	(-2.69)	-0.0021	(-2.46)
Ln(AGE)			-0.0112	(-1.69)	-0.0112	(-1.69)
Offshore			-0.0197	(-2.51)	-0.0196	(-2.50)
Incentive Fees			0.0005	(0.96)	0.0005	(0.87)
Management Fees			-0.0044	(-1.13)	-0.0037	(-0.95)
StDev			0.6533	(3.67)	0.6376	(3.55)
$StDev^2$			-1.2238	(-2.50)	-1.1996	(-2.36)
Upside Potential Ratio			0.0032	(5.47)	0.0031	(5.23)
$(Upside Pot Ratio)^2$			6.4E-6	(-3.67)	6.24E-6	(-3.58)
Number of observations	7457		7425		7425	
R^2	0.0125		0.0325		0.0356	

Table A3

The Effect of Style-Adjusted Persistence Patterns upon Quarterly Money Flows for Open-End Hedge Funds

The table reports estimates of a probit model explaining positive and negative flows. The sample includes 752 open-end hedge funds for the period 1994 Q4 till 2000 Q1. We measure cash flows as a quarterly growth rate corrected for reinvestments. The independent variable takes value 1 if cash flows are positive. Otherwise it takes value 0. The independent variables include 12 mutually exclusive dummies accounting for winner and losing streaks. Winner and losers are defined with respect to the median of the distribution of style-adjusted returns. Independent variables accounting for fund specific characteristics include the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows, upside potential based on the entire past history of the fund and calculated with respect to the return on the U.S. Treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund and the dummies for investment styles defined on the basis of CSFB/Tremont indices (estimates not reported). The model also includes 21 time dummies (estimates not reported). We estimate each model by pooling all fund-period observations. z-statistics are provided in parentheses.

	Probit model explaining positive and negative cash flows. (all ranks based on style-adjusted returns)			
Parameters	A		B	
Intercept	-0.1134	(-0.66)	-0.5395	(-1.19)
Expected Style-Adjusted Rank	0.2275	(0.69)	2.6020	(2.90)
W2	0.1489	(2.80)	0.1568	(2.85)
W3	0.3186	(4.78)	0.2368	(3.25)
W4	0.3980	(4.67)	0.3077	(3.33)
W5	0.5080	(4.83)	0.4690	(4.37)
W6	0.6454	(6.51)	0.4206	(4.02)
L1	-0.0302	(-0.69)	-0.0224	(-0.47)
L2	-0.1179	(-2.23)	-0.1038	(-1.85)
L3	-0.2636	(-3.59)	-0.1297	(-1.32)
L4	-0.2732	(-3.12)	-0.1954	(-2.01)
L5	-0.4302	(-3.46)	-0.3208	(-2.40)
L6	-0.4762	(-3.91)	-0.3924	(-2.96)
Ln(TNA)			-0.0078	(-0.73)
Ln(AGE)			-0.1501	(-4.58)
Cash Flows lag 1			0.4276	(5.27)
Cash Flows lag 2			0.3260	(5.16)
Cash Flows lag 3			0.1722	(3.76)
Cash Flows lag 4			0.0959	(2.38)
Offshore			-0.1008	(-2.49)
Incentive Fees			-0.0022	(-0.89)
Management Fees			-0.0166	(-0.91)
Personal Capital			-0.0175	(-0.45)
Upside Potential Ratio			0.0060	(0.99)
StDev			-1.6514	(-2.52)
Number of observations	7195		7195	
Pseudo R^2	0.023		0.0816	

Table A4

Four Model Specifications Explaining Relative Performance of Open-End Hedge Funds from Historical Persistence Patterns Using Different Thresholds to Define Winners and Losers

The table reports estimates of four different specifications of a model explaining relative performance of hedge funds as measured by fractional ranks. The fractional rank ranges between 0 and 1 and is defined as the fund's percentile performance relative to all the funds existing in the sample in the same period, based on the fund's raw return. The independent variables include twelve dummies accounting for historical winner and loser streaks. In each model specification reported in the table, we use a different percentile in the distribution of raw returns as a threshold to separate winners and losers. We control for six lagged fractional ranks, the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows computed as quarterly growth rates, upside potential based on the entire past history of the fund and calculated with respect to the return on the U.S. Treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund (estimate not reported) and the dummies for investment styles defined on the basis of CSFB/Tremont indices (estimates not reported). The sample includes 752 open-end hedge funds for the period 1994 Q4 till 2000 Q1. We estimate our model by pooling all fund-period observations. T-statistics based on robust standard errors are provided in parentheses.

OLS estimates of a model explaining current rank
(all ranks based on raw returns)

	Threshold to separate winners and losers			
Parameters	20^{th} percentile (A)	40^{th} percentile (B)	60^{th} percentile (C)	80^{th} percentile (D)
Intercept	-0.2130 (-0.87)	-0.2603 (-1.07)	-0.2241 (-0.91)	-0.2434 (-1.00)
W2	-0.0080 (-0.44)	0.0449 (2.70)	0.0152 (0.86)	0.0130 (0.58)
W3	-0.0339 (-1.72)	0.0176 (1.00)	-0.0239 (-1.06)	-0.0418 (-1.06)
W4	-0.0072 (-0.35)	0.0025 (0.13)	-0.0222 (-0.80)	0.0104 (0.18)
W5	-0.0435 (-2.10)	0.0202 (0.91)	0.0490 (1.40)	-0.0355 (-0.38)
W6	-0.0226 (-1.57)	0.0399 (2.43)	0.0176 (0.57)	0.1513 (1.83)
L1	-0.0239 (-1.32)	0.0319 (1.83)	-0.0062 (-0.34)	0.0007 (0.04)
L2	0.0020 (0.08)	0.0335 (1.93)	0.0054 (0.33)	0.0130 (0.75)
L3	-0.0649 (-1.56)	0.0285 (1.20)	0.0046 (0.26)	0.0020 (0.11)
L4	-0.0331 (-0.43)	-0.0229 (-0.77)	-0.0028 (-0.15)	-0.0007 (-0.04)
L5	0.1232 (1.37)	0.0113 (0.26)	-0.0285 (-1.26)	-0.0074 (-0.37)
L6	-0.1074 (-0.54)	0.0172 (0.31)	-0.0168 (-0.95)	0.0043 (0.29)
Rnk lag 1	0.0291 (1.64)	0.0515 (2.21)	0.0283 (1.21)	0.0378 (2.18)
Rnk lag 2	0.0417 (2.41)	-0.0056 (-0.24)	0.0254 (1.08)	0.0254 (1.45)
Rnk lag 3	0.0852 (5.55)	0.0861 (5.33)	0.0813 (4.92)	0.0770 (4.99)
Rnk lag 4	0.0160 (1.09)	0.0133 (0.90)	0.0088 (0.60)	0.0158 (1.08)
Rnk lag 5	-0.0335 (-2.36)	-0.0434 (-3.11)	-0.0479 (-3.43)	-0.0394 (-2.79)
Rnk lag 6	-0.0225 (-1.62)	-0.0205 (-1.51)	-0.0153 (-1.14)	-0.0151 (-1.09)
Cash Flows lag 1	-0.0131 (-1.18)	-0.0133 (-1.18)	-0.0131 (-1.16)	-0.0130 (-1.15)
Cash Flows lag 2	-0.0035 (-0.33)	-0.0036 (-0.33)	-0.0034 (-0.32)	-0.0032 (-0.29)
Cash Flows lag 3	-0.0086 (-1.03)	-0.0086 (-1.03)	-0.0089 (-1.07)	-0.0086 (-1.03)
Cash Flows lag 4	-0.0029 (-0.47)	-0.0029 (-0.46)	-0.0023 (-0.37)	-0.0025 (-0.39)
Ln(TNA)	0.0760 (2.62)	0.0786 (2.71)	0.0773 (2.67)	0.0776 (2.68)
$Ln(TNA)^2$	-0.0022 (-2.61)	-0.0023 (-2.69)	-0.0023 (-2.65)	-0.0023 (-2.66)
Ln(AGE)	-0.0109 (-1.64)	-0.0115 (-1.73)	-0.0113 (-1.70)	-0.0112 (-1.69)
Offshore	-0.0191 (-2.48)	-0.0192 (-2.50)	-0.0189 (-2.46)	-0.0195 (-2.54)
Incentive Fees	0.0005 (0.88)	0.0005 (0.94)	0.0004 (0.84)	0.0005 (0.97)
Management Fees	-0.0046 (-1.14)	-0.0046 (-1.15)	-0.0046 (-1.13)	-0.0042 (-1.04)
StDev	0.7395 (3.73)	0.8185 (4.52)	0.7774 (4.23)	0.8109 (4.14)
$StDev^2$	-1.2985 (-2.32)	-1.4356 (-2.74)	-1.3800 (-2.59)	-1.4297 (-2.65)
Upside Potential Ratio	0.0037 (6.31)	0.0035 (5.99)	0.0036 (6.18)	0.0037 (6.33)
$(\text{Upside Pot Ratio})^2$	0.0000 (-5.15)	0.0000 (-4.80)	0.0000 (-5.03)	0.0000 (-5.12)
Number of observations	7425	7425	7425	7425
R^2	0.0583	0.0586	0.0578	0.0573

Table A5

Four Model Specifications Explaining The Sign of Flows in Open-End Hedge Funds From Historical Persistence Patterns Using Different Thresholds to Define Winners and Losers

The table reports estimates of four different specifications of a probit model explaining positive and negative money flows. We measure cash flows as a quarterly growth rate corrected for reinvestments. The independent variable takes value 1 if cash flows are positive. Otherwise it takes value 0. The independent variables include 12 mutually exclusive dummies accounting for winner and losing streaks. In each model specification reported in the table, we use a different percentile in the distribution of raw returns as a threshold to separate winners and losers. Independent variables accounting for fund specific characteristics include the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows, standard deviation of returns, upside potential based on the entire past history of the fund and calculated with respect to the return on the U.S. Treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund and the dummies for investment styles defined on the basis of CSFB/Tremont indices (estimates not reported). The model also includes 21 time dummies (estimates not reported). The sample includes 752 open-end hedge funds for the period 1994 Q4 till 2000 Q1. We estimate each model by pooling all fund-period observations. z-statistics are provided in parentheses.

Probit estimates of a model explaining the sign of flows
(all ranks based on raw returns)

	Threshold to separate winners and losers							
Parameters	20th percentile (A)		40th percentile (B)		60th percentile (C)		80th percentile (D)	
Intercept	-1.4829	(-4.16)	-0.5091	(-1.43)	-0.3515	(-0.89)	-0.8403	(-1.92)
Expected Rank	4.0759	(6.78)	2.4171	(3.96)	2.1423	(3.05)	3.4397	(4.18)
W2	0.1732	(2.69)	0.1227	(2.25)	0.1692	(2.80)	0.1367	(1.56)
W3	0.2990	(4.36)	0.2339	(3.59)	0.2743	(3.33)	0.3140	(2.14)
W4	0.1801	(2.21)	0.2712	(3.44)	0.2906	(2.50)	0.1607	(0.63)
W5	0.5145	(6.31)	0.4882	(5.14)	0.2856	(1.75)	0.9274	(1.95)
W6	0.5225	(10.10)	0.3191	(4.42)	0.3824	(2.14)	0.3996	(0.59)
L1	-0.0188	(-0.33)	-0.1035	(-2.33)	-0.1417	(-3.11)	-0.1002	(-1.80)
L2	-0.3097	(-3.33)	-0.3854	(-6.34)	-0.2547	(-4.79)	-0.2304	(-3.66)
L3	0.2634	(1.45)	-0.5272	(-5.46)	-0.3775	(-5.60)	-0.2387	(-3.48)
L4	0.1047	(0.34)	-0.2928	(-2.07)	-0.3635	(-4.33)	-0.2159	(-2.78)
L5	-0.8858	(-1.97)	-0.4454	(-2.53)	-0.3358	(-3.28)	-0.3186	(-3.89)
L6	1.2283	(1.78)	-0.2790	(-1.15)	-0.3536	(-4.51)	-0.3390	(-6.26)
Ln(TNA)	-0.0156	(-1.47)	-0.0097	(-0.92)	-0.0041	(-0.39)	-0.0047	(-0.45)
Ln(AGE)	-0.1472	(-4.60)	-0.1613	(-5.05)	-0.1532	(-4.76)	-0.1350	(-4.05)
Cash Flows lag 1	0.3871	(5.09)	0.3776	(5.00)	0.4051	(5.08)	0.4209	(5.30)
Cash Flows lag 2	0.2915	(4.98)	0.3065	(5.05)	0.3205	(5.18)	0.3153	(5.24)
Cash Flows lag 3	0.1838	(4.15)	0.1726	(3.73)	0.1716	(3.70)	0.1756	(3.88)
Cash Flows lag 4	0.1030	(2.45)	0.0985	(2.36)	0.0943	(2.26)	0.0951	(2.37)
Offshore	-0.0869	(-2.28)	-0.1158	(-3.05)	-0.1169	(-3.04)	-0.0829	(-2.08)
Incentive Fees	-0.0032	(-1.28)	-0.0028	(-1.11)	-0.0032	(-1.27)	-0.0038	(-1.51)
Management Fees	0.0086	(0.48)	-0.0093	(-0.52)	-0.0102	(-0.56)	-0.0079	(-0.44)
Personal Capital	-0.0528	(-1.40)	-0.0449	(-1.19)	-0.0467	(-1.24)	-0.0532	(-1.40)
StDev	-0.9438	(-1.37)	-1.5271	(-2.33)	-2.2711	(-3.23)	-3.2199	(-3.56)
Upside Potential Ratio	0.0004	(0.31)	0.0034	(1.16)	0.0052	(1.01)	0.0044	(0.78)
Number of observations	7195		7195		7195		7195	
Pseudo R^2	0.0923		0.0908		0.085		0.0809	

Table A6

Four Model Specifications Explaining Style-Adjusted Relative Performance of Open-End Hedge Funds from Historical Persistence Patterns Using Different Thresholds to Define Winners and Losers

The table reports estimates of four different specifications of a model explaining relative performance of hedge funds as measured by fractional ranks. The fractional rank ranges from 0 to 1 and is defined as the fund's percentile performance relative to all the funds existing in the sample in the same period, based on the fund's style-adjusted return. The independent variables include twelve dummies accounting for historical winner and loser streaks. In each model specification reported in the table, we use a different percentile in the distribution of style-adjusted returns as a threshold to separate winners and losers. We control for six lagged fractional ranks, the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows computed as quarterly growth rates, upside potential based on the entire past history of the fund and calculated with respect to the return on the U.S. Treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund (estimate not reported) and the dummies for investment styles defined on the basis of CSFB/Tremont indices (estimates not reported). The sample includes 752 open-end hedge funds for the period 1994 Q4 till 2000 Q1. We estimate our model by pooling all fund-period observations. T-statistics based on robust standard errors are provided in parentheses.

OLS estimates of a model explaining current style-adjusted rank (all ranks based on style-adjusted returns)

	Threshold to separate winners and losers							
	20^{th} percentile		40^{th} percentile		60^{th} percentile		80^{th} percentile	
Parameters	(A)		(B)		(C)		(D)	
Intercept	-0.2395	(-0.98)	-0.1770	(-0.73)	-0.2136	(-0.88)	-0.2226	(-0.91)
W2	0.0185	(1.03)	-0.0032	(-0.19)	-0.0289	(-1.64)	-0.0143	(-0.63)
W3	0.0376	(2.12)	0.0034	(0.20)	-0.0225	(-1.04)	-0.0729	(-1.95)
W4	0.0246	(1.36)	-0.0322	(-1.70)	-0.0254	(-0.93)	0.0099	(0.14)
W5	-0.0211	(-1.09)	-0.0267	(-1.20)	-0.1147	(-3.19)	-0.1557	(-1.53)
W6	-0.0003	(-0.02)	-0.0136	(-0.75)	-0.0218	(-0.50)	0.1072	(0.99)
L1	0.0014	(0.08)	-0.0254	(-1.41)	-0.0173	(-0.97)	0.0217	(1.24)
L2	0.0092	(0.39)	0.0009	(0.05)	-0.0062	(-0.38)	-0.0011	(-0.06)
L3	-0.0273	(-0.63)	-0.0703	(-3.21)	-0.0281	(-1.60)	0.0087	(0.50)
L4	0.0473	(0.53)	0.0178	(0.62)	-0.0095	(-0.49)	-0.0002	(-0.01)
L5	0.0831	(0.54)	0.0308	(0.69)	-0.0095	(-0.46)	0.0338	(1.87)
L6	-0.1571	(-0.58)	-0.1085	(-2.39)	-0.0111	(-0.60)	-0.0039	(-0.28)
Rnk lag 1	0.0550	(3.12)	0.0395	(1.67)	0.0614	(2.64)	0.0788	(4.70)
Rnk lag 2	0.0291	(1.68)	0.0508	(2.18)	0.0596	(2.54)	0.0309	(1.80)
Rnk lag 3	0.0559	(3.64)	0.0495	(3.04)	0.0500	(3.07)	0.0594	(3.92)
Rnk lag 4	0.0168	(1.24)	0.0206	(1.47)	0.0124	(0.87)	0.0002	(0.02)
Rnk lag 5	-0.0182	(-1.39)	-0.0290	(-2.22)	-0.0217	(-1.64)	-0.0222	(-1.63)
Rnk lag 6	-0.0093	(-0.74)	-0.0061	(-0.48)	-0.0055	(-0.43)	-0.0123	(-0.94)
Cash Flows lag 1	-0.0169	(-1.49)	-0.0175	(-1.57)	-0.0173	(-1.54)	-0.0174	(-1.55)
Cash Flows lag 2	-0.0052	(-0.52)	-0.0047	(-0.47)	-0.0055	(-0.54)	-0.0039	(-0.39)
Cash Flows lag 3	-0.0065	(-0.79)	-0.0077	(-0.94)	-0.0062	(-0.76)	-0.0071	(-0.86)
Cash Flows lag 4	-0.0066	(-0.97)	-0.0062	(-0.91)	-0.0068	(-0.98)	-0.0068	(-0.99)
Ln(TNA)	0.0729	(2.53)	0.0690	(2.41)	0.0714	(2.48)	0.0718	(2.49)
$Ln(TNA)^2$	-0.0021	(-2.50)	-0.0020	(-2.38)	-0.0021	(-2.46)	-0.0021	(-2.46)
Ln(AGE)	-0.0103	(-1.54)	-0.0116	(-1.76)	-0.0111	(-1.68)	-0.0111	(-1.67)
Offshore	-0.0197	(-2.52)	-0.0198	(-2.52)	-0.0194	(-2.47)	-0.0195	(-2.49)
Incentive Fees	0.0005	(0.89)	0.0004	(0.76)	0.0004	(0.83)	0.0004	(0.75)
Management Fees	-0.0038	(-0.98)	-0.0039	(-1.00)	-0.0038	(-0.98)	-0.0041	(-1.06)
StDev	0.6296	(3.32)	0.6454	(3.59)	0.6474	(3.54)	0.6332	(3.37)
$StDev^2$	-1.1830	(-2.21)	-1.2104	(-2.42)	-1.2086	(-2.34)	-1.1712	(-2.23)
Upside Potential Ratio	0.0031	(5.38)	0.0030	(5.14)	0.0030	(5.11)	0.0029	(5.09)
$(\text{Upside Pot Ratio})^2$	0.0000	(-3.67)	0.0000	(-3.52)	0.0000	(-3.48)	0.0000	(-3.46)
Number of obs	7425		7425		7425		7425	
R^2	0.0366		0.0377		0.0363		0.0372	

Table A7

Four Model Specifications Explaining The Sign of Flows in Open-End Hedge Funds from Historical Persistence Patterns (Style-Adjusted) Using Different Thresholds to Define Winners and Losers

The table reports estimates of four different specifications of a probit model explaining positive and negative money flows. We measure cash flows as a quarterly growth rate corrected for reinvestments. The independent variable takes value 1 if cash flows are positive. Otherwise it takes value 0. The independent variables include 12 mutually exclusive dummies accounting for winner and losing streaks. In each model specification reported in the table, we use a different percentile in the distribution of style-adjusted returns as a threshold to separate winners and losers. Independent variables accounting for fund specific characteristics include the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows, standard deviation of returns, upside potential based on the entire past history of the fund and calculated with respect to the return on the U.S. Treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund and seven dummies for investment styles defined on the basis of CSFB/Tremont indices (estimates not reported). The model also includes 21 time dummies (estimates not reported). The sample contains 752 open-end hedge funds for the period 1994 Q4 till 2000 Q1. We estimate each model by pooling all fund-period observations. z-statistics are provided in parentheses.

Probit estimates of a model explaining the sign of flows (all ranks based on style-adjusted returns)				
	Threshold to separate winners and losers			
Parameters	20^{th} percentile (A)	40^{th} percentile (B)	60^{th} percentile (C)	80^{th} percentile (D)
Intercept	-1.3634 (-3.33)	-0.5248 (-1.24)	-1.2289 (-2.58)	-1.1830 (-2.98)
Expected Style-Adjusted Rank	4.5761 (5.51)	2.5108 (3.06)	3.9437 (4.10)	4.0206 (5.27)
W2	-0.0037 (-0.06)	0.1330 (2.48)	0.2338 (3.88)	0.0942 (1.11)
W3	-0.0108 (-0.13)	0.1696 (2.51)	0.2153 (2.62)	0.3103 (2.17)
W4	-0.0765 (-0.89)	0.3323 (4.41)	0.1658 (1.49)	0.1062 (0.42)
W5	0.4180 (5.53)	0.3517 (4.03)	0.8496 (5.16)	0.9019 (2.32)
W6	0.3283 (6.16)	0.4567 (6.22)	0.1746 (0.85)	-0.2928 (-0.62)
L1	0.0132 (0.23)	0.0134 (0.28)	-0.0279 (-0.57)	-0.0575 (-1.03)
L2	-0.2295 (-2.54)	-0.1948 (-3.30)	-0.0478 (-0.82)	-0.0522 (-0.84)
L3	0.1741 (0.90)	-0.1204 (-0.98)	-0.0015 (-0.02)	-0.1284 (-1.81)
L4	-0.1405 (-0.42)	-0.2872 (-2.49)	-0.0253 (-0.28)	-0.1491 (-1.88)
L5		-0.5766 (-2.99)	-0.3144 (-3.14)	-0.3428 (-4.68)
L6	2.4049 (2.98)	-0.0692 (-0.27)	-0.1850 (-2.09)	-0.1841 (-2.99)
Ln(TNA)	-0.0135 (-1.26)	-0.0099 (-0.93)	-0.0057 (-0.54)	-0.0036 (-0.33)
Ln(AGE)	-0.1508 (-4.51)	-0.1572 (-4.78)	-0.1330 (-3.97)	-0.1341 (-4.10)
Cash Flows lag 1	0.4458 (5.55)	0.4162 (5.25)	0.4521 (5.56)	0.4558 (5.65)
Cash Flows lag 2	0.3145 (5.25)	0.3176 (5.12)	0.3350 (5.36)	0.3238 (5.30)
Cash Flows lag 3	0.1702 (3.87)	0.1760 (3.86)	0.1743 (3.86)	0.1773 (3.91)
Cash Flows lag 4	0.1046 (2.59)	0.0972 (2.38)	0.1067 (2.61)	0.1108 (2.74)
Offshore	-0.0685 (-1.68)	-0.1004 (-2.50)	-0.0742 (-1.79)	-0.0734 (-1.88)
Incentive Fees	-0.0042 (-1.69)	-0.0026 (-1.05)	-0.0030 (-1.19)	-0.0032 (-1.31)
Management Fees	-0.0079 (-0.44)	-0.0167 (-0.92)	-0.0087 (-0.48)	-0.0048 (-0.27)
Personal Capital	-0.0015 (-0.04)	-0.0125 (-0.32)	-0.0171 (-0.44)	-0.0185 (-0.48)
StDev	-0.0872 (-1.83)	-1.3808 (-2.15)	-2.1782 (-2.83)	-2.4676 (-3.24)
Upside Potential Ratio	0.0012 (0.46)	0.0058 (1.00)	0.0040 (0.71)	0.0044 (0.75)
Number of observations	7195	7195	7195	7195
Pseudo R^2	0.084	0.083	0.0817	0.0789

Table A8

A Model explaining Annual Ranks and the Effect of Persistence Patterns Upon Money Flows in Open-End Hedge Funds

Panel A reports estimates of a model explaining relative annual performance as measured by a fractional rank. The fractional rank ranges between 0 and 1 and is defined as the fund's percentile performance relative to all the funds existing in the sample in the same year, based on the fund's annual raw return. We use this model to obtain estimates of expected annual performance. We include these estimates as regressors in the probit model reported in Panel B explaining positive and negative money flows, together with estimates of expected quarterly ranks obtained from the model reported in Table IV. The dependent variable in the probit model takes value 1 if cash flows are positive. Otherwise it takes value 0. Cash flows are measured as a quarterly growth rate corrected for reinvestments. The explanatory variables include 12 mutually exclusive dummies accounting for winner and losing streaks, the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows, upside potential based on the entire past history of the fund and calculated with respect to the return on the U.S. Treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund and the dummies for investment styles defined on the basis of CSFB/Tremont indices (estimates not reported). The model reported in Table A also includes six lagged fractional ranks while the probit model includes 21 time dummies (estimates not reported). The sample contains 752 open-end hedge funds for the period 1994 Q4 till 2000 Q1. We estimate each model by pooling all fund-period observations. T-statistics and z-statistics are provided in parentheses.

Panel A			Panel B		
Parameters	OLS estimates of a model explaining current annual rank (all ranks based on raw returns)		Parameters	Probit model explaining the sign of money flows	
Intercept	-1.0186	(-3.79)	Intercept	1.1757	(3.45)
W2	0.0153	(0.89)	Expected Annual Rank	-3.1826	(-7.18)
W3	0.0284	(1.37)	Expected Quart. Rank	2.2712	(4.34)
W4	0.0182	(0.73)	W2	0.1201	(2.22)
W5	0.0889	(2.84)	W3	0.2433	(3.43)
W6	0.0440	(1.67)	W4	0.2271	(2.41)
L1	0.0445	(2.41)	W5	0.5455	(4.19)
L2	0.0337	(1.94)	W6	0.4032	(3.44)
L3	0.0015	(0.07)	L1	-0.1754	(-4.04)
L4	0.0110	(0.42)	L2	-0.3064	(-5.60)
L5	-0.0396	(-1.20)	L3	-0.4734	(-6.35)
L6	-0.0526	(-2.28)	L4	-0.4771	(-4.98)
Rnk lag 1	0.0703	(2.68)	L5	-0.5357	(-4.27)
Rnk lag 2	-0.0561	(-2.14)	L6	-0.8161	(-7.46)
Rnk lag 3	-0.0479	(-2.72)	Ln(TNA)	-0.0101	(-1.00)
Rnk lag 4	-0.0447	(-2.86)	Ln(AGE)	-0.1994	(-6.50)
Rnk lag 5	-0.0046	(-0.31)	Cash Flows lag 1	0.2811	(3.85)
Rnk lag 6	0.0155	(1.07)	Cash Flows lag 2	0.2602	(4.31)
Cash Flows lag 1	-0.0223	(-1.90)	Cash Flows lag 3	0.0995	(2.15)
Cash Flows lag 2	-0.0119	(-0.84)	Cash Flows lag 4	0.0592	(1.52)
Cash Flows lag 3	-0.0198	(-2.00)	Offshore	-0.1976	(-5.22)
Cash Flows lag 4	-0.0079	(-1.18)	Incentive Fees	0.0004	(0.17)
Ln(TNA)	0.1784	(5.60)	Management Fees	-0.0193	(-1.09)
$Ln(TNA)^2$	-0.0053	(-5.64)	Personal Capital	-0.0654	(-1.77)
Ln(AGE)	-0.0129	(-1.80)	Upside Potential Ratio	0.0115	(2.07)
Offshore	-0.0244	(-2.97)	StDev	-1.1298	(-2.51)
Incentive Fees	0.0006	(1.22)			
Management Fees	-0.0058	(-1.31)			
StDev	0.7970	(4.11)			
$StDev^2$	-1.4339	(-2.67)			
Upside Potential Ratio	0.0034	(5.38)			
$(Upside Pot Ratio)^2$	-0.00001	(-4.59)			
Number of obs.	5905		Number of obs.	7425	
R^2	0.1021		Pseudo R^2	0.089	

Table A9

The Effect of Persistence Patterns and Aggregate Annual Performance Upon Money Flows in Open-End Hedge Funds

The table reports estimates of a probit model explaining positive and negative flows. The sample includes 752 open-end hedge funds for the period 1994 Q4 till 2000 Q1. We measure cash flows as a quarterly growth rate corrected for reinvestments. The independent variable takes value 1 if cash flows are positive. Otherwise it takes value 0. The independent variables include the previous annual rank and 12 mutually exclusive dummies accounting for winner and losing streaks. Independent variables accounting for fund specific characteristics include the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows, upside potential based on the entire past history of the fund and calculated with respect to the return on the U.S. Treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund and seven dummies for investment styles defined on the basis of CSFB/Tremont indices (estimates not reported). The model also includes 21 time dummies (estimates not reported). We estimate each model by pooling all fund-period observations. z-statistics are provided in parentheses.

	Probit model explaining positive and negative cash flows.			
Parameters	A		B	
Intercept	-0.5444	(-4.27)	1.3065	(3.79)
Expected Rank	0.2130	(0.81)	-1.8034	(-3.09)
Lagged Annual Rank	0.9059	(13.37)	0.9258	(12.15)
W2	0.0904	(1.67)	0.1009	(1.80)
W3	0.1739	(2.48)	0.2123	(2.91)
W4	0.1880	(2.04)	0.1740	(1.85)
W5	0.2658	(2.26)	0.3100	(2.60)
W6	0.4867	(4.84)	0.3265	(3.10)
L1	-0.0660	(-1.53)	-0.1217	(-2.76)
L2	-0.1001	(-1.87)	-0.0838	(-1.47)
L3	-0.2281	(-3.07)	-0.3702	(-4.75)
L4	-0.2061	(-2.15)	-0.3655	(-3.66)
L5	-0.3818	(-2.96)	-0.5213	(-3.78)
L6	-0.1486	(-1.24)	-0.2538	(-2.03)
Ln(TNA)			-0.0189	(-1.78)
Ln(AGE)			-0.1975	(-6.32)
Cash Flows lag 1			0.2903	(4.07)
Cash Flows lag 2			0.2588	(4.37)
Cash Flows lag 3			0.1092	(2.41)
Cash Flows lag 4			0.0675	(1.61)
Offshore			-0.1918	(-5.09)
Incentive Fees			-0.0011	(-0.45)
Management Fees			-0.0280	(-1.54)
Personal Capital			-0.0402	(-1.07)
Upside Potential Ratio			0.0108	(2.21)
StDev			-0.8345	(-1.76)
Number of observations	7195		7195	
Pseudo R^2	0.0612		0.106	

"[...] The Event Driven category grew by 28% in 2004. The sector attracted just over USD 10 billion in new capital and returned 14.2% to investors, catalyzed by a vigorous 7.8% return in Q4. The USD 107.4 billion Global Macro category picked up inflows of only USD5.3 billion over the year, a steep drop off from the USD28.1 billion inflow seen in 2003. The category returned a lackluster 4.1% to investors..."

(A report from a style-trend analyst in the hedge fund industry)

Chapter 5

Style Investing: Evidence from Hedge Fund Investors[92]

5.1 Introduction

Classifying assets into categories or "styles" provides investors with a simple framework to organize their allocation decisions.[93] Recent theoretical models of aggregate capital flows in financial markets make the non-trivial assumption that investors' allocations at the style-level are based on relative past performance. In these models investors exhibit extrapolative expectations and form their beliefs about future performance by learning from past performance information at the style level exclusively. In this view, style investing is unrelated to fundamentals and it simply amounts to chasing the styles with better prior records. Put differently, investors' coordinated shift of capital from one category to another is the result of correlated sentiment vis-à-vis styles performance. The style-chasing hypothesis is a key feature, for instance, in the model of Barberis and Shleifer [2003] who show how style-driven demand creates comovement and temporary mispricings of securities within the favoured categories while it imposes an externality with opposite repercussions in less favoured style categories[94]. Also Shleifer and Vishny [1997] make explicit the notion

[92] I am grateful to Kees Koedijk and Ronald Mahieu for many suggestions and very constructive comments.

[93] For example, the typical top-down approach implemented mostly by institutional investors, starts with an allocation policy at the style level followed by within-style selection.

[94] Barberis and Shleifer [2003] combine extrapolative expectations with a constraint on investors' allocations to the broadest asset classes (i.e. cash, bonds and stocks) leading investors to shift their capital from poor performing styles towards good performing styles. Essentially, their model focuses on the cross effects of a coordinated demand driven by a common sentiment factor vis-à-vis style categories.

of style-chasing as a result of extrapolative expectations. However, their model captures the idea that capital from individual and institutional investors flows to different markets or style categories often via professional fund managers specialized in each style or market, like hedge funds. In this case style investing translates into chasing the best performing category of fund managers. In their model, the coordinated response of money flows to past aggregate performance of fund managers in a given style regardless of the actual opportunities available in that market conduces to the perverse effect of constraining managers' ability to counteract mispricings of securities.[95]

On this account, the purpose of the present paper is twofold. First, we empirically test the underlying assumption of the models of style investing. Concretely, we test the hypothesis that hedge fund investors chase hedge fund style-categories. Our second aim is to document the extent to which style investing is indeed the result of uninformed supply of capital. If this is the case, style driven flows should be uncorrelated with future style performance. If, on the contrary, investors are well informed, they should be able to timely direct their money into the best performing categories in the future and out of the poor performing categories. Therefore, we also test whether past style performance is informative about future performance, in a way that style-chasing could be justified, and whether there is any indication of smart money at the style level.

Several considerations suggest that especially hedge fund investors are likely to follow simple feed-back trading strategies based on past performance of investment styles. On the one hand, a large portion of capital inflows to hedge funds, currently about 50%, comes from institutional investors who tend to follow systematic portfolio allocation rules in a way they can later justify their actions to those monitoring them (as argued by Lakonishok et al [1992]). On the other hand, given the opacity and limited regulation of the industry, investors are in general poorly informed. Further, the arbitrage strategies typically used by hedge fund managers are difficult to evaluate and their understanding requires financial expertise. Under these circumstances investors may tend to fall back on the use of style classifications together with a simple decision rule based on past performance as powerful means to simplify the

[95] In their model arbitrageurs in one segment gain or lose money under management depending on their performance with respect to other segments. They refer to this mechanism as "performance-based aribitrage (PBA). Notice however, that their model does not address the cross effects of style investing (which is the focus of Barberis and Shleifer [2003]), but focuses on the particular relation between funds and past relative performance of a given segment and how sentiment-driven flows place a constraint on arbitrageurs while reducing their investment horizon, especially after adverse performance. Conversely, the model of Barberis and Shleifer [2003] makes abstraction of the intermediate role of professional fund managers specialized in a given style.

processing of complex and noisy information. Finally, at least one study has provided evidence that hedge fund investors misperceive patterns of performance persistence of individual funds, and overinvest accordingly (see Baquero and Verbeek [2006b]). The question arises whether or not investors display any cognitive bias also in their perception of aggregate performance at the style level. For instance, De Bondt [1991, 1993] describes the results of experiments in which both professional and naïve investors tend to see trends in aggregate market indices, presumably as a result of anchoring and representativeness. While naïve investors expect continuation, sophisticated investors expect a reversal in the trend.

The empirical evidence of style chasing is relatively scarce so far.[96] At the individual fund level, Cooper et al [2004] present evidence of style investing strategies among mutual fund investors. Money flows are attracted by mutual funds that change their names in order to suggest a different style focus. Their results indicate that funds with previous poor performance are the most inclined to change names. But they also find little evidence that after the name change funds indeed changed of allocation strategy. Among the few studies on aggregate money flows to investment funds, only two of them have explicitly attempted to link money flows to the performance of styles. The study by Lettau [1997] focuses on aggregate flows to different mutual fund categories and assumes adaptive learning of investors at the style level because of bounded rationality. He finds evidence that aggregate past performance determines the movements of capital into and out of mutual fund categories, especially for the riskier categories (e.g. aggressive growth and growth). Further, the sensitivity is higher for poor performing categories. Also Pomorski [1994] examines whether mutual fund flows chase styles, while using different possible style classifications of mutual funds for his test. He finds that aggregate money flows to a given category are positively related to prior returns in that category and negatively related to those in other categories, consistent with the feed-back trading model of Barberis and Shleifer [2003]. However, at the individual level, the effect disappears. Flows are negatively related to styles and chase individual manager performance.[97]

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[96] Several empirical studies have rather focused on the theoretical implications of style investing. For example, Teo and Woo [2002] test one of the predictions of Barberis and Schleifer [2003], namely that value and momentum strategies are profitable. Barberis, Shleifer and Wurgler [2002] test the prediction of comovement by looking at inclusions of stocks in the S&P500 index. They find evidence that the beta of stocks and their correlations with the index increase after the inclusion, consistent with the idea that the index itself represents a style category.

[97] Other studies of money flows at the aggregate level are Warther [1995], Brown et al [2000], Edelen and Warner [1999], which concentrate on the relation between money flows and the aggregate market, but do not study the cross effects between segments or styles. These studies also argue that money flows to investment funds, especially mutual funds are a proxy for investor sentiment. Warther [1996] for example examines the possibility that investors are, on aggregate, feed-back traders and invest by chasing aggregate stock returns. He also examines the effect of aggregate flows upon aggregate stock market returns, under the assumption of a price-pressure hypothesis. By modeling the times series of aggregate money flows, he separately analyzes the

The aforementioned studies at the aggregate level, though, suffer from two main drawbacks. First, a certain component of money flows, even at the aggregate level, reflect decisions motivated by individual fund manager evaluation. This component has not been isolated so far. Second, these studies have been conducted under the assumption that the style classifications considered in the test are the true asset classes that investors have in their minds. For this reason, Pomorski [1994] employs several criteria to define a style classification and construct an aggregate performance measure.

One contribution of our study is precisely to tackle these two issues. First, we employ hedge fund style indices which offer a neat and concrete way to identify styles as perceived by investors for an empirical test. In spite of the many criticisms they have faced, style indices are widely used by hedge fund investors for several benchmarking-related purposes. Style indices are reported monthly and are followed closely by the investment community as the only available reference tool, albeit imperfect as we will discuss below. Second, we identify and isolate the component of flows related to individual fund selection by estimating first a cross-sectional model of money flows from style adjusted performance and other fund characteristics. From this model we obtain an estimate of expected money flows driven by fund selectivity while we link the aggregate residuals to the performance of style indices.

We report two main results. First, we find evidence that investors chase the winning styles in the previous one to three quarters. Second, we do not find evidence that style-driven flows are related to subsequent style performance, nor indications of momentum in style index performance at quarterly horizons, which suggests that momentum investing is the result of a biased perception of style trends.

The remainder of the paper is organized as follows. The next section offers an overview of the main characteristics of style categories and style indices. Section 5.3 describes our data on individual funds and style indices. Section 5.4 isolates the style-allocation component from individual fund selectivity and tests the style-chasing hypothesis. Section 5.5 studies momentum in style index performance, while Section 5.6 tests the style-timing abilities of hedge fund investors. Finally Section 5.7 concludes.

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impact of expected and unexpected flows. While he finds evidence consistent with positive feedback trading, his results do not support the price pressure hypothesis.

5.2 Hedge Fund Indexation

This paper devotes attention to the style-level decisions of hedge fund investors. Specifically, we test the hypothesis that investors' allocations across style categories are determined by relative past performance. A primary requirement to test the style investment hypothesis is to have a well defined and unique set of style categories common to all investors. In the hedge fund industry, such a set of style categories can be concretely identified by a set of style indices. There are currently more than a dozen competing providers of hedge fund indices and sub indices reporting monthly figures. By reducing the vast array of trading and investment strategies pursued by fund managers to a handful of style categories, hedge fund indexation has tremendously simplified the evaluation of individual fund managers and the overall decision-making process of their investors. Accordingly, an allocation decision into hedge funds commonly proceeds in two distinct phases. Investors first determine the style category that better suits their investment objectives. In a second phase investors select funds within that specific category.

The first indices were launched in the early 1990's. Index providers are usually private investment advisors or database vendors such as CSFB/Tremont, who use their own datasets for construction of the index. Therefore each index reflects the characteristics of that particular universe, as there is little overlap of funds across datasets. More recently, a number of private firms traditionally involved in tracking and evaluating the aggregate market, such as S&P, have also started constructing their own index products.

Hedge fund indices have had a huge impact in the industry by helping disseminating the industry's overall performance among an expanding base of investors. They are widely used as the only available reference tool for comparison across managers and strategies. Hedge fund index products are seen as guidelines for investing, facilitating the comparison across asset classes, but also for style analysis, portfolio analysis and portfolio construction. The last developments include investable hedge fund indices, which allow investors to have exposure to a well diversified portfolio of hedge funds with the additional advantage of being able to buy and sell the shares in the index in a secondary market. Before investable indexes existed, investors could only diversify across hedge funds through funds of funds, at a substantial liquidity risk.

Indices of hedge funds are generally constructed as a representative average of funds with a similar investment style. Developing a taxonomy of hedge funds is, however, a notoriously difficult task since hedge funds enjoy a distinctive flexibility in the types of investment strategies they can deploy. It is difficult to refer to a given hedge fund style as a homogenous group. Hedge fund managers' nimble behaviour in moving into and out of different asset classes, their use of leverage and short selling, often with exposures to illiquid securities, makes the use of any index-based benchmarking questionable. In spite of that, several classification systems are currently in use in the industry, with large differences among them. There is no consensus yet on a unique standardized system.

Hedge fund styles encompass not only categories of securities, which might include a geographic dimension (e.g. convertible securities, fixed income securities, equity, global, etc), but also a particular trading style (long short, short bias, arbitrage, market neutral, etc). Therefore, the performance of a hedge fund style index is not only a reflection of the performance of the underlying securities, as it is the case for mutual fund styles, but above all it reflects the effectiveness of the trading style.

One important caveat in the construction of a meaningful style classification is the quality and frequency of available data. Hedge funds commonly report their performance monthly, but most do so with a considerable delay given the complexity in the computation and deduction of incentive fees. Therefore, it is likely that by the date necessary for calculation of the index, funds have been unable to report or they have reported performance estimates to be revised later. Further, hedge fund reporting is voluntary, leading to selection biases and backfilling biases[98]. Funds with unusually good performance may have incentives to report, or to report earlier in order to attract further investors. On the other hand, established funds with good track records that have reached capacity limits may decide to close to new investments and self-select out of the database. Finally, hedge funds liquidate at relatively high frequencies, conducing to survivorship biases in the construction of the index. Moreover data gathering problems might differ across strategies and periods.

The construction technology of indices of hedge funds has considerably evolved, becoming more rigorous, under increasing demand for indexing products from institutional investors. There are three broad weighting schemes used by most providers of hedge fund indices. An equally-weighted average, asset weighted average and percentile-based indices. The former is a simple average return of the constituent funds and it was the typical scheme used by the first indices as it does not require information on assets under management. It continues to be used by most indices today (MAR, S&P, VanHedge Fund Advisors, HFR, MSCI). A percentile-based

[98] Instant-history bias (or backfilling bias) has been documented by Park [1995], Ackermann et al. [1999] and Fung and Hsieh [2002], and refers to the possibility that hedge funds participate in a database conditional on having performed well over a number of periods prior to inception.

index uses a percentile –usually the median, the 10th and 90th percentile - instead of the mean of the return distribution of the constituents, while TNA are not required either. They avoid the impact of extreme values in the returns of any of its constituent funds (Zurich Capital Markets index family, PerTrac Online index family). However, they do not reflect the actual dollar returns. Three providers of indices currently offer asset weighted schemes: Credit Swiss First Boston/Tremont (CSFB/Tremont), Morgan Stanley Capital International (MSCI) and Hedge Fund Research (HFR). A weighted scheme represents more accurately the actual dollar returns across their constituent funds.

Hedge fund indices and subindices have been subject of controversy, especially concerning the consistency of hedge fund classifications, the lack of transparency of the rules and techniques of construction employed by different index providers, and how these construction techniques deal with the limited data quality. It is not surprising that a large number of academic studies have focused attention on the impact of data-related biases, on the statistical properties of style indices, their consistency, and their actual usefulness for hedge fund allocation and portfolio analysis[99]. Brooks and Kat [2001] and Amenc and Martellini [2002] have documented heterogeneity in the information content of competing indices. For a given strategy, competing indices exhibit relatively low correlations, and very large differences in returns in some periods, especially in periods of crises[100]. Other studies have instead pointed out at the potential usefulness of indices. For example, using the TASS database, Brown and Goetzmann [2002] find that style categories account for 20% in the cross sectional variation of fund returns, indicating that the classification conveys some valuable information. Finally, by studying the time series of style index returns, Amenc and Martellini [2002] suggest that style tactical allocation is profitable.

It remains an open question how investors are actually driven in their allocation decisions by style-level information. In fact the financial press, industry newsletters and providers of hedge fund indices, offer periodic reports about the past performance and expected performance of style indices, they compare indices with each other and often highlight trends in the time series. The question arises whether investors on

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[99] See for example Amenc and Martellini [2001, 2002], Amenc, El Bied and Martellini [2003], Brooks and Kat [2001], Brown and Goetzmann [2003], Fung and Hsieh [1997, 2002]. In mutual funds, two relevant studies about consistency of style classifications are those of Brown and Goetzmann [1997] and Chen, Chan, Lakonishok [2002].

[100] Amenc and Martellini [2002] give the example of Long Short index in February 2000, between Zurich Capital Market index, ZCM, (20.48%) and Evaluation Associates Capital Markets, EACM, (-1.56%). Brooks and Kat[2001] also find large differences between index families, especially for macro and Equity Market Neutral indices.

aggregate pay attention to such information and actively seek to time styles. If this is the case, it also remains to be clarified whether investors pay attention to absolute style index returns or compare style indices relative to each other. Are investors influenced by upward or downward trends of an index? Over which horizons is the information contained in an index relevant for an investor? And finally, does this information help investors to timely direct their money into the best performing categories and out of the poor performing categories? The following sections explore these interrelated questions and offer an assessment of the efficiency of capital allocation across hedge funds.

5.3 Data

Access to hedge fund data is one of the major limitations in hedge fund studies. Hedge funds are not complied to report their performance and holdings, as they are subject to limited regulation. Therefore, hedge fund datasets are based upon voluntary reporting, which gives room to several potential biases, as documented by previous researchers (see e.g. Baquero, Ter Horst and Verbeek [2005], Agarwal and Naik [2000], Brown, Goetzmann and Ibbotson [1999]). Given this major drawback, in order to make inferences about the portfolio of hedge fund investors as a whole, we require a representative sample that encompasses not only all investment styles but also a wide range of funds in terms of size, age, incentive fees, and location. Our dataset contains 1543 hedge funds spanning the period 1994Q4-2004Q3 (funds of funds and closed end funds are excluded). This is a sample of the TASS database that has been widely used in previous academic research. TASS provides a classification of mutually exclusive styles based on self-reported styles by managers and information contained in the offering memorandum. This classification matches the set of nine style indices provided by CSFB/Tremont. In this study we focus attention on quarterly returns and quarterly flows, although monthly data is available. However, a quarterly horizon is a natural investment horizon for hedge fund investors, as most redemption restrictions operate in a quarterly basis. Further, a powerful driver of investor sentiment is the coverage of media channels (e.g. press reports), and their attention focuses in general on quarterly returns. Table A1 in the appendix provides the total number of hedge funds in our sample per quarter and aggregate total net assets and cash flows. Table A2 provides summary statistics and a description of different fund-specific variables. Finally, Table A3 disaggregates the number of funds per period and per style category.

Table I

Average Quarterly Performance of Style Indices, Market Indices and Funds in our Sample, between 1994Q4 and 2004Q3

Panel A gives a summary statistics of quarterly returns of CSFB/Tremont Hedge Fund indices over 40 quarters, from 1994Q4 till 2004Q3. We also include the performance of the S&P500 index and the 90 days T-bill for comparison. Panel B gives a summary statistics of quarterly returns of hedge funds in our sample sorted per style over the same period. In this panel, the category labelled "General Hedge fund index" contains the funds in our sample for which the investment style was not clearly identified. The sample consists of 1543 open-end hedge funds taken from TASS database that have a complete series of monthly total net assets (TNA), with a minimum of 6 quarters of quarterly returns history and with computed quarterly cash flows available at least for one year. Funds of funds are not included.

Panel A: Summary Statistics of quarterly returns of CSFB/Tremont Indices and Market Indices

Index	Mean	Std. Dev.	Min	Max
Convertible Arbitrage	0.0271	0.0314	-0.0724	0.0972
Dedicated Short Bias	-0.0045	0.0984	-0.2008	0.2178
Emerging Markets	0.0189	0.1056	-0.2867	0.3066
Equity Market Neutral	0.0277	0.0161	-0.0002	0.0593
Event Driven	0.0290	0.0380	-0.1435	0.0839
Fixed Income Arbitrage	0.0182	0.0207	-0.0469	0.0483
Global Macro	0.0386	0.0583	-0.1046	0.1683
Long/Short Equity	0.0332	0.0617	-0.0781	0.2778
Managed Futures	0.0151	0.0632	-0.1046	0.1618
General Hedge fund index	0.0293	0.0417	-0.0887	0.1662
S&P500	0.0304	0.0884	-0.1728	0.2128
Tbill 90days	0.0098	0.0045	0.0023	0.0152

Panel B: Time-series averages of cross-sectional means per style in our sample

Style Category	Mean	Std. Dev.	Min	Max
Convertible Arbitrage	0.0278	0.0281	-0.0563	0.0785
Dedicated Short Bias	0.0086	0.1050	-0.1777	0.2242
Emerging Markets	0.0310	0.1132	-0.2770	0.2571
Equity Market Neutral	0.0206	0.0178	-0.0177	0.0539
Event Driven	0.0256	0.0328	-0.0997	0.0786
Fixed Income Arbitrage	0.0185	0.0254	-0.0496	0.0642
Global Macro	0.0244	0.0402	-0.0504	0.1153
Long/Short Equity	0.0337	0.0616	-0.0844	0.2150
Managed Futures	0.0231	0.0552	-0.1063	0.1449
General Hedge fund index	0.0246	0.0287	-0.0278	0.0893
All funds in our sample	0.0271	0.0350	-0.0502	0.1177

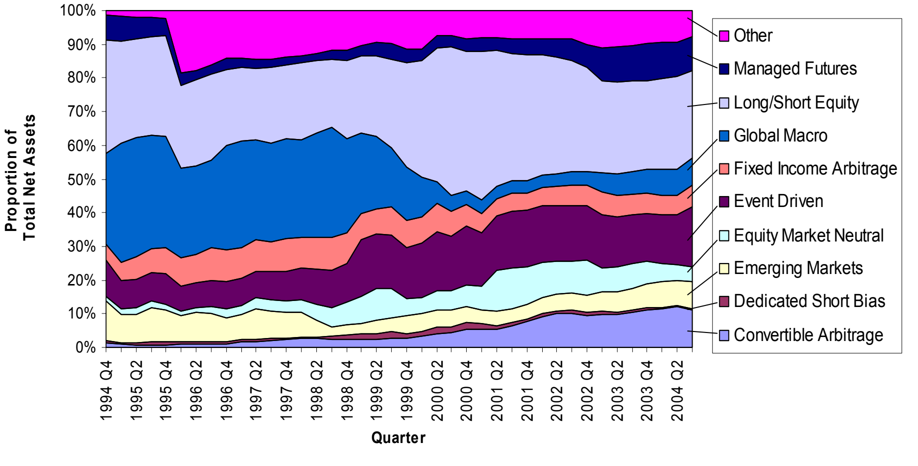
The CSFB/Tremont is an asset weighted index with 403 funds from the TASS database, rebalanced quarterly. The constituent funds are required to have a minimum TNA of $10 million, a one-year track record and an audited financial statement before being included. They are removed from the index for liquidation reasons or failure to meet reporting requirements. Some investment styles seek to time market movements and are referred to as directional strategies. Others seek to exploit arbitrage opportunities and are referred to as non directional. Table I provides a summary of quarterly performance of the general CSFB/Tremont hedge fund index and the nine sub-indices in Panel A, and the aggregate performance of hedge funds in our dataset sorted by style in panel B. Noticeably, there is wide dispersion in volatility across hedge fund categories. The most extreme returns are associated with Dedicated Short Bias and Emerging Markets styles, while Equity Market Neutral appears to be a relatively conservative category, with dispersion in returns far below the one of the market. Finally, Table I also indicates that both the general hedge fund index and the average hedge fund in our dataset have underperformed the stock market index over the sample period by 11 and 33 basis points per quarter respectively.

Figure 1 depicts the proportion of total assets under management shared by each category of funds in our database. The aggregate portfolio of hedge fund investors varies widely over time in terms of allocations across styles, sometimes dramatically. For instance, after 2002 the global macro strategy has experienced a sharp decrease in size, becoming almost unimportant. Our purpose in the following sections is to analyze more closely the behaviour of aggregate money flows to better understand the motives underlying these changes in exposure to hedge fund categories.

Figure 1

Style Allocation of Hedge Fund Investors

Hedge funds are sorted per style category every quarter from 1994Q4 to 2004Q3. The figure indicates the variations over time of holdings of hedge fund investors across styles. Our sample consists of 1543 open-end hedge funds taken from TASS database.



5.4 Style level flows vs. fund selectivity

In this paper we argue that investors' learning occurs at two distinct levels. On the one hand, allocation decisions are powerfully driven by fund indexation, as many channels of information and advice within the industry regularly highlight the performance of style indices. On the other hand, individual fund evaluation via due diligence is a major and ineluctable task, as information hurdles resulting from limited regulation and disclosure prevent investors from a transparent assessment of fund managers. Our study concentrates on style level decisions and we are confronted to the problem of isolating as neatly as possible both components. Fund selection within a given style involves both a qualitative and quantitative analysis. Besides information on returns and assets under management, the TASS database provides a number of fund specific variables that are likely to be determinants of investors' final choice, like the structure of incentives, liquidity restrictions, geographic location, etc. Our methodology consists of estimating first a cross-sectional model of flows, in which we include on the right hand side only variables strictly related to fund selection. The main specification is the following:

$$Flows_{it} = \alpha + \sum_{j=1}^{6} \beta_{1j}.RnkUnrestricted_{it-j} + \sum_{j=1}^{6} \beta_{2j}.RnkRstricted_{it-j} + \beta_2.\ln(TNA_{it-1}) + \\ + \beta_4.\ln(AGE_{it-1}) + \sum_{j=0}^{4} \beta_{5j}.Flow_{it-j} + \beta_6.\sigma_{it-1} + \gamma'.X_{i,t-1} + \lambda_t + \varepsilon_{it} \qquad (1)$$

where $Flow_{i,t}$ represents the net percentage growth in fund i in period t, and $Rnk_{i,t-j}$ is the jth lagged relative style-adjusted performance as measured by a fund's cross-sectional rank. We distinguish between *restricted* and *unrestricted* ranks by allowing for interactions between lagged ranks and dummies accounting for limits to liquidity.[101] We include the size and age of the fund in the previous period, $ln(TNA_{i,t-1})$ and $ln(AGE_{i,t-1})$. $Flow_{i,t-j}$ is the jth lagged flow. $X_{i,t}$ is a vector of fund specific characteristics like management fees, incentive fees, managerial ownership. We control for time effects by including time dummies, denoted by λ_t, to capture economy wide shocks conducing to different average flows across quarters, as suggested by Table A1. Notice that our model does not include style-related variables, as our purpose is to capture such effects within the error term.

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[101] In each quarter t, we define for each j-lagged rank and for each fund i :

$$Rank\ Unrestricted_{i,t-j} = Rank_{i,t-j} * (REDR_{i,t-j})$$
and $$Rank\ Restricted_{i,t-j} = Rank_{i,t-j} * (1-REDR_{i,t-j})$$

where $REDR_{i,t-j}$ is a dummy variable that takes value 1 if redemption restrictions do not prevent outflows in quarter t in response to j-lagged performance given by $Rank_{i,t-j}$.

Cash flows are defined as in Chapter 3, either as growth rates or dollar flows. The previous model assumes that the selectivity process is similar across styles. More particularly, it assumes that the sensitivity of investors to past style-adjusted performance is independent of style. Our estimation results in Table II confirm

Table II

The Effect of Relative Style-Adjusted Performance Subject to Liquidity Restrictions Upon Money Flows in Open-End Hedge Funds

The table reports OLS estimates of a model of flows subject to liquidity restrictions. The sample includes 1543 open-end hedge funds for the period 1994Q4 till 2003Q4. We measure cash flows as the change in total net assets between consecutive quarters corrected for reinvestments. We normalize this measure as a growth rate relative to the fund's total net assets of previous quarter. The independent variables that account for relative performance include six lagged fractional ranks interacting with dummies accounting for limits to liquidity. The fractional rank ranges from 0 to 1 and is defined as the fund's percentile performance relative to all the funds existing in the sample in the same period, based on the fund's style-adjusted return in previous quarter. Independent variables accounting for fund specific characteristics include the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows, the inverse of upside potential based on the entire past history of the fund and calculated with respect to the return on the U.S. Treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund and 39 time dummies (not reported). We estimate our model by pooling all fund-period observations. T-statistics based on robust standard errors are provided in parentheses.

Parameters	OLS estimates of a model explaining growth rates	
Intercept	0.1549	(4.98)
Style-adj. Rank lag 1 Unrestricted	0.1063	(15.47)
Style-adj. Rank lag 2 Unrestricted	0.0801	(11.70)
Style-adj. Rank lag 3 Unrestricted	0.0605	(8.68)
Style-adj. Rank lag 4 Unrestricted	0.0462	(6.82)
Style-adj. Rank lag 5 Unrestricted	0.0192	(2.74)
Style-adj. Rank lag 6	0.0060	(0.88)
Style-adj. Rank lag 1 Restricted	0.1014	(6.15)
Style-adj. Rank lag 2 Restricted	0.0718	(3.42)
Style-adj. Rank lag 3 Restricted	0.0463	(2.82)
Style-adj. Rank lag 4 Restricted	0.0491	(3.04)
Style-adj. Rank lag 5 Restricted	0.0349	(1.90)
Ln(TNA)	-0.0124	(-8.91)
Ln(AGE)	-0.0171	(-5.08)
Flows lag 1	0.0557	(4.68)
Flows lag 2	0.0501	(5.83)
Flows lag 3	0.0114	(1.67)
Flows lag 4	0.0135	(2.21)
Offshore	0.0095	(2.25)
Incentive Fees	-0.0006	(-2.06)
Management Fees	-0.0084	(-3.96)
Personal Capital Invested	-0.0031	(-0.76)
Leverage	0.0149	(3.88)
Downside-Upside Potential Ratio	-0.0192	(-7.98)
Standard Deviation of Returns	-0.2663	(-3.82)
Number of observations	21841	
R^2	0.0811	

previous evidence that money flows are directed to funds with better prior performance, and that past performance has a significant impact up to five lagged quarters or so. Liquidity restrictions, the age and the size of the fund are also important in the evaluation process of investors.[102]

Next, we obtain the residuals from the previous model, and we aggregate them per period and per style category under the assumption that both components, namely style allocation and fund selectivity are orthogonal. Put differently, we focus on the components of money flows that cannot be explained by fund-specific factors and are style-related. Table III reports estimates of a linear model explaining aggregate capital flows per style as measured by growth rates. We analyze whether differences in aggregate capital flows across styles are explained by past relative performance, by past style index returns, by the length of upward or downward trends in style performance or by any style-related fixed effects. Our sample contains 399 observations when all 10 styles indices are included and 359 observations when the general Hedge Fund index is excluded and we only consider the set of 9 subindices.[103] Table A4 in the appendix

provides summary statistics of the relevant variables included in our model of aggregate flows. Over the sample period we have identified upward trends up to four quarters length and downward trends up to five quarters length. We capture the length of the trend with nine mutually exclusive dummies. We also include on the right hand side of our model a trend variable in order to account for the increase in the number of funds over time. We consider several alternative specifications corresponding to different ways of assessing past style performance. Recall that the style-investing hypothesis is rooted on the idea that investors compare styles with each other. Accordingly, in Panel A we include the structure of lagged style ranks as a measure of relative past performance, while controlling for upward and downward trends and style dummies. The style rank variable takes values between 1 and 9 and is obtained by ranking in each quarter the nine style indices based on their raw returns (therefore the *general Hedge Fund index* is excluded from the ranking).

According to our results, investors strongly respond to relative performance over the three lagged quarters. If one style index moves from the bottom to the top of the

[102] See Baquero and Verbeek [2005] for a detailed analysis of the impact of fund-specific variables on money flows.

[103] In fact we have 40 observations per style. However, we have identified one significant outlier corresponding to the *Convertible Arbitrage* strategy in the last quarter of 2001, a negative growth rate of -83%. The models presented in Tables III and IV exclude that single observation. When this observation is included in our model specifications, the impact of the individual variables remains for the most part unchanged but the explanatory power of the model is significantly affected, with a reduction in the R^2 to levels of 2 to 3%.

Table III

The Effect of Style Performance Upon Aggregate Money Flows in Open-End Hedge Funds

The table reports OLS estimates of a model of aggregate money flows per style. Money flows are the residuals of the cross sectional model estimated in Table II explaining growth rates from style-adjusted performance and fund specific characteristics. We first obtain dollar flows per fund by multiplying the residuals by the total net assets in the previous period. Then we aggregate dollar flows per style and per period. Alternatively, we obtain an aggregate growth rate by dividing aggregate dollar flows by the aggregate total net assets in the previous quarter. The sample consists of 399 style-period observations between 1994Q4 and 2004Q3. The independent variables include three lagged style index returns, a trend variable, eight dummies accounting for the length of upward and downward trends in the style index and 7 dummies for investment styles defined on the basis of CSFB/Tremont indices. The general hedge fund index is taken as reference category. We estimate our model by pooling all style-period observations. T-statistics are provided in parentheses.

	Model explaining style-driven growth rates							
	(A)		(B)		(C)		(D)	
Parameters	Coeff	t-test	Coeff.	t-test	Coeff.	t-test	Coeff.	t-test
Intercept	-0.0765	(-5.40)	-0.0098	(-0.97)	-0.0732	(-4.17)	0.0120	(1.05)
Style Rank lag 1	0.0070	(4.82)			0.0058	(2.92)		
Style Rank lag 2	0.0035	(2.31)			0.0044	(2.15)		
Style Rank lag 3	0.0043	(2.97)			0.0029	(1.44)		
Style Return lag 1			0.2520	(4.21)	0.0846	(1.05)		
Style Return lag 2			0.0318	(0.50)	-0.0730	(-0.87)		
Style Return lag 3			0.1902	(3.15)	0.0818	(0.98)		
Winning Streak 2							0.0109	(0.83)
Winning Streak 3							0.0098	(0.54)
Winning Streak 4							0.0372	(2.25)
Losing Streak 1							-0.0104	(-0.94)
Losing Streak 2							-0.0172	(-1.33)
Losing Streak 3							-0.0481	(-3.49)
Losing Streak 4							-0.0454	(-2.75)
Losing Streak 5							-0.0501	(-3.60)
Trend	0.0006	(2.13)	0.0005	(1.87)	0.0006	(2.15)	0.0006	(2.06)
Up 2 Quarters	0.0093	(0.81)	0.0203	(1.76)	0.0133	(1.11)	0.0049	(0.43)
Up 3 Quarters	0.0045	(0.23)	0.0122	(0.67)	0.0072	(0.37)	0.0037	(0.19)
Up 4 Quarters	-0.0880	(-2.02)	-0.1019	(-2.25)	-0.0914	(-2.08)	-0.0905	(-2.04)
Down 1 Quarter	0.0018	(0.18)	0.0085	(0.81)	0.0084	(0.78)	-0.0025	(-0.27)
Down 2 Quarters	0.0033	(0.29)	0.0074	(0.63)	0.0071	(0.59)	0.0012	(0.11)
Down 3 Quarters	0.0056	(0.25)	0.0004	(0.02)	0.0078	(0.34)	-0.0034	(-0.15)
Down 4 Quarters	0.0195	(0.55)	0.0054	(0.15)	0.0234	(0.65)	0.0046	(0.13)
Down 5 Quarters	-0.0351	(-0.58)	-0.0643	(-1.02)	-0.0319	(-0.52)	-0.0531	(-0.85)
Emerging Markets	-0.0079	(-0.67)	-0.0104	(-0.90)	-0.0083	(-0.71)	-0.0110	(-0.90)
Equity Mrkt. Neutral	0.0216	(1.84)	0.0119	(1.03)	0.0203	(1.70)	0.0209	(1.74)
Event Driven	-0.0048	(-0.40)	-0.0044	(-0.38)	-0.0050	(-0.42)	-0.0087	(-0.70)
Fixed Income	0.0055	(0.47)	-0.0088	(-0.77)	0.0041	(0.34)	0.0078	(0.65)
Global Macro	0.0010	(0.08)	0.0012	(0.11)	0.0003	(0.02)	-0.0052	(-0.39)
Long Short Equity	-0.0151	(-1.28)	-0.0249	(-2.15)	-0.0168	(-1.40)	-0.0143	(-1.18)
Managed Futures	0.0143	(1.22)	0.0037	(0.32)	0.0133	(1.12)	0.0112	(0.94)
Adj R^2	0.133		0.0798		0.132		0.0985	
No obs.	359		399		359		359	

ranking in one period, the aggregate of funds in that style experience a significant increase of 5.6% in growth rates in the subsequent quarter, and a significant 11.6% increase over the next three quarters. Investors appear to be insensitive to the longer run in relative style performance.[104] They are also somehow insensitive to the length in style trends, although the coefficient for an upward trend of four quarters is negative and significant. This long upward trend occurs in two occasions only, in June 1997 and March 2001, both in the Dedicated Short Bias strategy. This gives some indication that investors in this very volatile strategy anticipate frequent reversals and act contrarian. Overall, the results of this first specification are consistent with the style-chasing hypothesis, whereby allocations are mostly directed to the styles with better prior performance and away of poor performing styles. Panel B reports estimation results when we include absolute performance instead of relative performance. In this case we also include the aggregate money flows for the group of funds without a clear investment style and we link it to the performance of the *general Hedge Fund Index*. This increases the number of observations from 359 to 399. The lagged structure of style index returns has also a significant impact upon growth rates but the pattern is less clear than with relative performance. The effect is mostly concentrated in the first lag. A 1% difference in style index returns accounts for nearly 0.25% increase in growth of the style in the next quarter. However, this model explains substantially less variation in the cross-section of aggregate growth rates compared to the previous specification, as indicated by the reduced value of the R^2. When both style ranks and style index returns are included (Panel C), ranks appear to capture all the impact on aggregate money flows.

An alternative way to account for past relative performance is to define a dummy for winning and losing styles. In a given period we define a style as a winner if it is placed in one of the top four ranks with respect to other styles. Otherwise the style is classified as a loser. Next, we count the number of consecutive quarters over which the style remains as winner (alternatively as loser). In this way, we identified winning streaks up to 13 quarters and losing streaks up to 10 quarters length. While in our first specification we have shown that the lagged style ranks manifestly have an influence on investors' decisions, here the question of interest is how investors do perceive a *precise* sequence in relative performance information. To analyze this, we create four dummies accounting for the length of winning streaks and 5 dummies for losing streaks. With one dummy we capture the effect of winning streaks of four quarters length or more. The last dummy accounts for losing streaks of more than five quarters length. The estimation results are presented in Panel D. It is apparent that investors

[104] We have experimented with alternative specifications and additional lags do not have a significant impact on money flows.

Table IV

The Effect of Style Performance Upon Aggregate Money Flows in Open-End Hedge Funds

The table reports OLS estimates of a model of aggregate money flows per style. Money flows are the residuals of the cross sectional model estimated in Table II explaining growth rates from style-adjusted performance and fund specific characteristics. We first obtain dollar flows per fund by multiplying the residuals by the total net assets in the previous period. Then we aggregate dollar flows per style and per period. Alternatively, we obtain an aggregate growth rate by dividing aggregate dollar flows by the aggregate total net assets in the previous quarter. The sample consists of 399 style-period observations between 1994Q4 and 2004Q3. The independent variables include three lagged style index returns, a trend variable, eight dummies accounting for the length of upward and downward trends in the style index and 7 dummies for investment styles defined on the basis of CSFB/Tremont indices. The general hedge fund index is taken as reference category. We estimate our model by pooling all style-period observations. T-statistics are provided in parentheses.

	Model explaining style-driven dollar flows (coefficients expressed in thousands)							
	(A)		(B)		(C)		(D)	
Parameters	Coeff.	t-test	Coeff.	t-test.	Coeff.	t-test	Coeff.	t-test
Intercept	-609000	(-6.98)	-156000	(-2.42)	-612000	(-5.65)	-41600	(-0.60)
Style Rank lag 1	32600	(3.65)			38700	(3.15)		
Style Rank lag 2	37600	(4.05)			38800	(3.10)		
Style Rank lag 3	33200	(3.75)			25900	(2.08)		
Style Return lag1			915000	(2.41)	-314000	(-0.63)		
Style Return lag2			849000	(2.09)	-94200	(-0.18)		
Style Return lag3			1410000	(3.69)	433000	(0.84)		
Winning Streak 2							82900	(1.05)
Winning Streak 3							147000	(1.34)
Winning Streak 4							323000	(3.25)
Losing Streak 1							30700	(0.46)
Losing Streak 2							-177000	(-2.28)
Losing Streak 3							-162000	(-1.96)
Losing Streak 4							-220000	(-2.22)
Losing Streak 5							-483000	(-5.78)
Trend	6682	(3.92)	7226	(4.17)	6698	(3.92)	7118	(4.08)
Up 2 Quarters	56700	(0.80)	123000	(1.69)	68000	(0.92)	-3188	(-0.05)
Up 3 Quarters	4081	(0.03)	64400	(0.56)	8931	(0.07)	-12500	(-0.10)
Up 4 Quarters	-133000	(-0.50)	-195000	(-0.68)	-113000	(-0.42)	-169000	(-0.63)
Down 1 Quarter	-19700	(-0.33)	5701	(0.09)	-12700	(-0.19)	-26800	(-0.47)
Down 2 Quarters	-1561	(-0.02)	4806	(0.06)	-18700	(-0.25)	44500	(0.66)
Down 3 Quarters	-68500	(-0.50)	-94400	(-0.68)	-71600	(-0.51)	-69200	(-0.51)
Down 4 Quarters	110000	(0.50)	-25000	(-0.11)	97900	(0.44)	18100	(0.08)
Down 5 Quarters	121000	(0.32)	-82800	(-0.21)	144000	(0.38)	97600	(0.26)
Emerging Markets	-11500	(-0.16)	-20500	(-0.28)	-9726	(-0.13)	-46800	(-0.64)
Equity Mkt.Neutral	4494	(0.06)	-54500	(-0.75)	6170	(0.08)	-9992	(-0.14)
Event Driven	33700	(0.46)	43700	(0.60)	34900	(0.47)	-7950	(-0.11)
Fixed Income	35100	(0.49)	-59900	(-0.83)	35800	(0.49)	65900	(0.91)
Global Macro	34900	(0.47)	47500	(0.64)	35900	(0.48)	-23900	(-0.30)
Long Short Equity	-120000	(-1.66)	-180000	(-2.45)	-121000	(-1.63)	-96600	(-1.33)
Managed Futures	283000	(3.92)	215000	(2.96)	284000	(3.90)	276000	(3.83)
Adj R^2	0.201		0.122		0.196		0.208	
No obs.	359		399		359		359	

follow a momentum strategy at the style level. Longer winning streaks attract significantly larger money flows, while longer losing streaks are associated with increasingly negative growth rates. For example, if a style index has underperformed most other indices for four consecutive quarters, it triggers significant negative growth rates of -4.54% compared to one-quarter streaks. If this style index remains one additional quarter as loser, growth rates reduce even further by 50 basis points.

In Table IV, we present estimates of our model when the dependent variable is aggregate residual dollar flows. The results are similar to those presented above. Dollar flows are sensitive to past style performance either in terms of style returns or style ranks, while investors clearly follow momentum strategies in response to winning and losing streaks. However, if we compare the R^2 of models in Panel A and B, we can conclude that ranks explain a substantially larger variation in cross sectional aggregate dollar flows. Moreover, styles at the top of the ranking attract $ 293 million more than styles at the bottom, according to Panel A, while according to Panel B, a differential of 1% in style returns attracts a further $ 9 million.

It is worthwhile to highlight that investors are apparently insensitive to upward and downward trends in the time series of index returns, but they are highly sensitive to sequences of relative performance measured in the cross section. Overall, our results strongly support the essential principle behind the style-investing hypothesis, namely that investors allocations depend on style performance relative to other styles. It is plausible, however, that style-chasing behaviour is explained by investors having superior information or having performed a sophisticated analysis of style performance that motivates them to actively shift their capital across styles. If it is the case that investors exhibit style-timing abilities, it should be possible to identify a correlation between money flows and subsequent style performance. The next two sections explore this possibility.

5.5 Style indices and style momentum

The results in the previous section indicate that investors on aggregate direct their money towards those styles for which the index displayed higher returns compared to other indices. Conversely, investors on aggregate pulled out their money from those styles with corresponding index returns below other indices. This suggests not only that investors pay attention to the style indices, but apparently they also expect continuation in the performance of the index. This section explores whether there is any evidence of persistence in returns across style indices.

The question of style momentum is not trivial. Studies on persistence have identified momentum in individual hedge funds both in raw returns and style-adjusted returns. But, is momentum related to specific funds or is it also a property of a specific investment category? Is persistence related to the skills of an individual manager, or to the success of a trading style under specific market circumstances? As with individual funds, differences in returns across style indices might be associated to risk differentials. Table I, Panel A, shows for example that the indices *Dedicated Short Bias* and *Emerging Markets* are the most volatile in terms of standard deviation of historical quarterly returns. Another way to look at the riskiness of a given style index relative to other indices is by ranking the nine Tremont indices in each period in terms of returns, and then computing the frequency of rank position for each index. Table V reports the frequencies for both monthly rankings (Panel A) and quarterly rankings (Panel B) over the period January 1994-December 2004. The rank 9 corresponds to the index with the highest return in a given period. For example, the index *Dedicated Short Bias* offered the highest returns across styles in 24.24% of the 132 months,

Table V

Rank Frequencies per Style Index

In each period we rank the nine Tremont indices in terms of returns. Then we compute the frequency of rank position for each index. The table reports the frequencies for both monthly rankings (Panel A) and quarterly rankings (Panel B) over the period January 1994-December 2004. The rank 9 corresponds to the index with the highest return in a given period.

Panel A: Rank frequency (%) at monthly horizons

Rank Position	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long/Short Equity	Managed Futures
Top 9	2.27	24.24	25.00	5.30	3.79	0.00	9.09	13.64	16.67
8	12.88	8.33	15.15	3.79	9.85	6.82	18.94	14.39	9.85
7	15.15	2.27	6.82	13.64	15.15	11.36	14.39	13.64	7.58
6	13.64	4.55	7.58	14.39	25.00	12.12	12.88	5.30	4.55
5	15.15	2.27	4.55	17.42	21.97	14.39	5.30	12.12	6.82
4	14.39	3.03	3.79	19.70	11.36	20.45	10.61	9.09	7.58
3	15.91	3.03	2.27	13.64	7.58	23.48	11.36	9.09	13.64
2	7.58	12.88	12.12	10.61	4.55	10.61	10.61	15.91	15.15
Bottom 1	3.03	39.39	22.73	1.52	0.76	0.76	6.82	6.82	18.18

Panel B: Rank frequency (%) at quarterly horizons

Rank Position	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long/Short Equity	Managed Futures
Top 9	6.82	34.09	31.82	0.00	2.27	0.00	6.82	6.82	11.36
8	4.55	4.55	13.64	11.36	4.55	4.55	20.45	18.18	18.18
7	11.36	0.00	2.27	4.55	31.82	9.09	25.00	11.36	4.55
6	9.09	0.00	9.09	25.00	25.00	9.09	11.36	6.82	4.55
5	20.45	2.27	0.00	15.91	15.91	15.91	6.82	13.64	9.09
4	27.27	0.00	4.55	18.18	6.82	18.18	9.09	9.09	6.82
3	11.36	4.55	2.27	13.64	6.82	34.09	9.09	13.64	4.55
2	9.09	6.82	11.36	11.36	4.55	9.09	2.27	15.91	29.55
Bottom 1	0.00	47.73	25.00	0.00	2.27	0.00	9.09	4.55	11.36

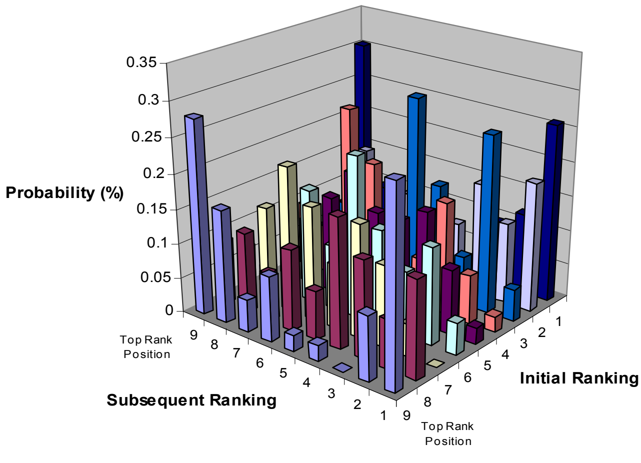
while it displayed the worst returns (rank 1) 39.39% of the time. Also the indices *Emerging Markets* and *Managed Futures* alternate very often between the extreme rank positions. All other indices are less volatile and rank most often in the middle positions. We observe similar patterns with quarterly rankings (Panel B).

In order to obtain a first indication of persistence in returns of style indices, we analyze the likelihood that the winning styles remain the winners in the subsequent period. Figure 2, shows a contingency table of quarterly index performance. In each quarter we compare the rank position of any index with its rank in the subsequent quarter. The style indices ranked in the top position (rank 9) have 28% of probabilities to remain in the top rank, but also 28% of probabilities to revert to the bottom rank.

Figure 2

Contingency Table of Quarterly Style Index Performance

The nine Tremont indices are ranked each period based on the net returns at the end of the period. We compare the initial rank position of any index with its rank in the subsequent month. The bar in cell *(i,j)* represents the conditional probability of achieving a subsequent rank position *j* given an initial rank position *i*.



Similarly, the styles in the bottom rank are very likely to alternate between the bottom rank and the top rank.[105] Although the probabilities for the extreme ranks are to a large extent driven by the three most volatile style categories mentioned above

[105] A pertinent question is to what extent these figures are the result of a survivorship bias affecting style indices performance? Arguably, the funds used to construct the indices of these highly volatile categories are more likely to liquidate in case of extremely bad outcomes. By the same token, they are likely to exhibit very high returns conditional upon survival (see Fung and Hsieh [1999]).

(namely *Dedicated Short Bias*, *Emerging Markets* and *Managed Futures*), we also observe that the ranks 6, 7 and 8 have large probabilities of nearly 20% to remain in one of the top three ranks in the subsequent quarter, while the ranks 2, 3 and 4 are more likely to remain in one of the bottom three ranks.[106]

The previous analysis indicates that some style indices tend to persist in the two extreme ranks. However, this does not necessarily imply that the winning style indices in one period offer on average higher returns than other indices in the subsequent period, given the high turnover rates of indices across ranks. Therefore, we also calculate the average returns per rank in the period following the ranking. The statistical tests presented in Table VI for the entire sample period and the two half periods do not support the idea of performance persistence at the style level. In fact, the top rank underperforms most of other above-median ranks, as also shown in Figure 3. The difference between the top and bottom portfolios is of about 0.4% per quarter, statistically insignificant.

Table VI

Persistence Estimates in Quarterly Style Index Returns

In each quarter between 1994Q1 and 2004Q4 we rank the nine Tremont indices in terms of absolute returns. The rank 9 corresponds to the index with the highest return in a given period. The table reports average returns per rank in the period following the ranking.

		Sample period (Jan 1994 – Dec2004)		First half period 1994 Q1- 1999Q1		Second half period 1999 Q2- 2004 Q3	
		Average return	t-test	Average return	t-test	Average Return	t-test
Top rank	9	0.0223	(1.55)	0.0245	(1.14)	0.0202	(1.02)
	8	0.0228	(2.75)	0.0262	(2.01)	0.0195	(1.84)
	7	0.0368	(5.94)	0.0460	(4.42)	0.0280	(4.23)
	6	0.0173	(3.05)	0.0103	(1.15)	0.0240	(3.45)
	5	0.0247	(3.16)	0.0192	(2.15)	0.0299	(2.34)
	4	0.0345	(5.51)	0.0449	(4.83)	0.0246	(3.05)
	3	0.0135	(1.88)	0.0125	(0.96)	0.0144	(2.10)
	2	0.0134	(1.33)	0.0001	(0.00)	0.0261	(1.68)
Bottom rank	1	0.0180	(1.12)	0.0205	(0.77)	0.0156	(0.82)
Top minus bottom		0.0043	(0.17)	0.0040	(0.10)	0.0046	(0.14)

[106] At monthly horizons, the style indices ranked in the top position (rank 9) have a probability of 25% to remain in the top rank. However there is a 12% probability that it reverts to the bottom rank. Similarly, the style indices in the bottom rank, have a probability of nearly 30% to remain the losers. We found some evidence of persistence at monthly horizons in style index returns. The top rank provides an average monthly return of 1.3% compared to nearly -0.4% of the bottom rank. The difference of 1.7% is statistically significant at the 1% level. However, when we repeat this analysis by splitting the sample period in two halves, we only find statistically significant evidence of persistence in the first halve, from January 1994 till April 1999.

Figure 3

Analysis of Quarterly Persistence in Style Index Performance

In each quarter between 1994Q1 and 2004Q4 we rank the nine Tremont indices in terms of absolute returns. The rank 9 corresponds to the index with the highest return in a given period. The figure shows average returns per rank in the period following the ranking.

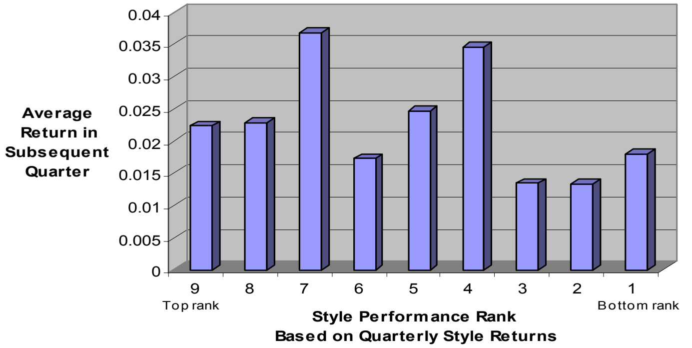


Table VII presents additional persistence tests by separating style indices between winners and losers, using different thresholds to define winners and losers. We follow the performance of each style over the four subsequent evaluation periods after ranking. For example, Panel B shows the results when we consider the style indices in the two top ranks as the winning styles. In the ranking period, the portfolio of winning styles significantly outperforms the portfolio of losing styles by 8.97%. In the subsequent quarter, however, we find no significant differences between both portfolios. For further evaluation periods, the difference becomes in some cases even negative. We observe similar patterns in the remaining panels where we use other thresholds to define the winning portfolio.

In conclusion, our tests reject the hypothesis of performance persistence of style indices at quarterly horizons. Past relative performance appears to convey no information about future performance. This is a very puzzling result, if we consider the evidence presented in Section 5.4 that investors follow momentum strategies at the style level, powerfully attracted by the best performing categories. Admittedly, the actual investors' allocation might not be entirely equivalent to the investment strategy analyzed in this section, which is strictly based on separating styles between winners and losers. Therefore, the next Section analyzes the effectiveness of investors' allocations and the possibility that they reflect informed choices.

Table VII

The Persistence of Winners and Losers in Quarterly Style Index Returns

In each quarter between 1994Q4 and 2004Q3 we rank the nine Tremont indices in terms of absolute returns. The rank 9 corresponds to the index with the highest return in a given period. Then we separate style indices between winners and losers, using different thresholds to define winners and losers. The table reports average returns over the four subsequent evaluation periods.

Momentum in Quarterly Returns

Panel A: Only the top rank is the winner

	Ranking period	Subsequent period			
	0	1	2	3	4
Winners	0.1104	0.0281	-0.0004	0.0360	0.0201
Losers	0.0116	0.0227	0.0259	0.0209	0.0242
Difference	0.0988	0.0054	-0.0263	0.0151	-0.0041
t-test	(10.36)	(0.33)	(-1.83)	(1.07)	(-0.28)

Panel B: The two top ranks are the winners

	Ranking period	Subsequent period			
	0	1	2	3	4
Winners	0.0923	0.0261	0.0106	0.0321	0.0155
Losers	0.0027	0.0225	0.0266	0.0199	0.0261
Difference	0.0897	0.0036	-0.0159	0.0122	-0.0105
t-test	(10.53)	(0.36)	(-1.44)	(1.10)	(-0.90)

Panel C: The three top ranks are the winners

	Ranking period	Subsequent period			
	0	1	2	3	4
Winners	0.0778	0.0304	0.0203	0.0307	0.0204
Losers	-0.0051	0.0197	0.0244	0.0186	0.0254
Difference	0.0829	0.0107	-0.0041	0.0121	-0.0050
t-test	(11.41)	(1.32)	(-0.43)	(1.44)	(-0.57)

Panel D: the four top ranks are the winners

	Ranking period	Subsequent period			
	0	1	2	3	4
Winners	0.0667	0.0268	0.0229	0.0301	0.0232
Losers	-0.0127	0.0205	0.0231	0.0166	0.0242
Difference	0.0794	0.0063	-0.0002	0.0135	-0.0010
t-test	(13.16)	(0.79)	(-0.03)	(1.56)	(-0.10)

Panel D: the five top ranks are the winners

	Ranking period	Subsequent period			
	0	1	2	3	4
Winners	0.0583	0.0263	0.0244	0.0294	0.0218
Losers	-0.0221	0.0195	0.0212	0.0141	0.0261
Difference	0.0804	0.0068	0.0032	0.0153	-0.0044
t-test	(14.88)	(0.96)	(0.41)	(1.78)	(-0.46)

5.6 Testing smart timing

The analysis in Section 5.4 showed that aggregate money flows are sensitive to the performance of styles in the previous one to three quarters. Ceteris paribus, investors direct their inflows to the styles with higher returns in the past. Conversely, they withdraw their money in general from those styles with lower returns in the previous quarter. These patterns suggest that investors indeed attempt to time the styles based on index performance information. This seems inconsistent, however, with the results of last section, which indicate that past relative performance of style indices is unrelated to future performance. The present section relates aggregate money flows to the subsequent performance of style indices. Specifically, we analyze whether investors succeed in their timing attempt and shift their money towards those styles with higher returns in the future. To this effect, in each quarter we rank the style indices in terms of their corresponding aggregate money flows at the end of the period. Then we form two portfolios: one contains those indices associated to styles with net positive aggregate money flows. The second portfolio of indices is associated to those styles that experienced net negative aggregate money flows. For each portfolio, we compute both an equally-weighted return and a cash flow-weighted return, in the ranking period, in the two lagged quarters, and in each of the four subsequent quarters. Finally we obtain the time series average returns of each portfolio over the 40 quarters. We compute the cash flow-weighted returns using both aggregate growth rates and aggregate dollar flows that occur in the ranking period. By using growth rates, we reduce the bias towards styles that have more numerous and larger funds. We can interpret this measure as a cash-flow-weighted return per unit of total net assets. Instead, by using dollar flows we reduce the bias towards styles for which the number of funds in our sample is not representative enough, namely the C*onvertible Arbitrage* and *Dedicated Short Bias* strategies.

Table VIII shows the results when we use the residual aggregate growth rates as the ranking variable. In the ranking period, the portfolio with positive flows significantly outperforms the portfolio with negative money flows by 2.48% in terms of cash-flow weighted returns (Panel A). In the two lagged quarters, the difference is even larger, of about 3.70% and 3.35% respectively. This is again an indication that investors select styles based on past indices performance, consistent with our previous results in Tables III and IV.

Table VIII

Investors' Returns from Style Allocation

In each quarter we rank the style indices in terms of their corresponding aggregate residual growth rates at the end of the period. Next, we form two portfolios: one contains those indices associated to styles with net positive aggregate money flows. The second portfolio of indices is associated to those styles that experienced net negative aggregate money flows. For each portfolio, we compute both an equally-weighted return and a cash flow-weighted return, in the ranking period, in the two lagged quarters, and in each of the four subsequent quarters. The table reports the time series average returns of each portfolio over the 40 quarters. Panel A reports results based on cash flow weighted returns. Panel B reports results based on equally weighted returns. Panel C reports the differences between cash flow weighted and equally weighted returns. T-statistics are provided in parentheses.

Aggregate residual growth rates							
Panel A: Cash-flow weighted returns							
	Lagged quarters		Ranking Period	Subsequent quarters			
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0363	0.0390	0.0302	0.0210	0.0163	0.0239	0.0200
Styles with net negative flows	0.0028	0.0021	0.0054	0.0221	0.0336	0.0212	0.0287
Difference	0.0335	0.0370	0.0248	-0.0011	-0.0173	0.0028	-0.0087
T-test	(3.41)	(3.40)	(2.61)	(-0.13)	(-1.71)	(0.29)	(-0.85)
Panel B: Equally weighted returns							
	Lagged quarters		Ranking Period	Subsequent quarters			
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0345	0.0367	0.0296	0.0259	0.0196	0.0243	0.0185
Styles with net negative flows	0.0062	0.0061	0.0129	0.0206	0.0276	0.0238	0.0307
Difference	0.0283	0.0307	0.0166	0.0053	-0.0079	0.0005	-0.0122
T-test	(3.70)	(3.71)	(3.06)	(0.70)	(-0.94)	(0.09)	(-1.43)
Panel C: Cash-flow weighted minus equally weighted returns							
	Lagged quarters		Ranking Period	Subsequent quarters			
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0018	0.0023	0.0006	-0.0049	-0.0034	-0.0004	0.0015
T-test	(0.43)	(0.56)	(0.17)	(-1.13)	(-0.99)	(-0.09)	(0.45)
Styles with net negative flows	-0.0034	-0.0040	-0.0076	0.0015	0.0060	-0.0026	-0.0020
T-test	(-1.04)	(-0.97)	(-1.84)	(0.46)	(1.51)	(-0.47)	(-0.67)

Table IX reports similar patterns when we use aggregate residual dollar flows as the ranking variable. Moreover, in the second lagged quarter, the cash flow weighted return significantly outperforms the equally weighted return by 1.08% for the portfolio with positive flows (Panel C). Thus, inflows are not equally distributed across styles in each portfolio. Inflows are more heavily placed in those styles with the highest index returns in the previous quarters.

Aggregate money flows appear to have a sorting capacity of contemporaneous and lagged index performance, a result that parallels the one obtained for individual funds (see Baquero and Verbeek [2005]).[107] However, money flows fail to discriminate future index performance. We do not find significant differences between the two portfolios over the four subsequent quarters. In fact, in the fourth quarter, styles with negative flows increasingly outperform those with positive flows. The results from Table VIII are depicted in Figure 4. In sum, we find evidence that investors attempt to time the styles, but apparently aggregate flows are not smart.

In Section 5.4 we showed that lagged style ranks and individual style effects explain nearly 13% of the cross-sectional variation of aggregate residual growth rates and nearly 20% of aggregate residual dollar flows (specification in Panel A, Table III). Therefore, we can obtain an estimate of the component of aggregate money flows explained by the models reported in Tables III and IV, which can be referred to as *style-driven flows*, in order to have a more accurate picture of the style-timing attempts of investors. Table A5 in the appendix reports our results when we use style-driven growth rates. In the two lagged quarters, the differences between the portfolios with positive and negative money flows are now 8.55% and 5.95% respectively in terms of cash-flow weighted returns, which are substantially larger compared to our previous results using residual growth rates (Table VIII). Table A6 reports similar results with style-driven dollar flows.

The fact that investors are unable to time the styles, suggests that investors tend to misread style index performance information. It also suggests that style indices may not be representative enough of broad investment categories, or that each style is such a heterogeneous class that it makes little sense to treat each style as a category for benchmarking purposes. Alternatively, it could also be that the coordinated shift of capital supply to some categories drives itself the performance of those categories downwards. Hedge fund strategies may not be easily scalable and superior investment opportunities to allocate a massive money inflow may become rapidly scarce. Still, the question then is why sophisticated investors fail to learn and anticipate such effects.

Our results also reveal that investors' style allocation is not exactly equivalent to the chasing-the-winning-style strategy analyzed in Section 5.5. Both strategies show little correlation. We find an average Spearman-rank correlation coefficient over time of nearly 30% (not reported). Investors tend to allocate higher amounts of money to

[107] Apparently, contemporaneous index performance has also an impact on aggregate money flows, although the effect is substantially reduced compared to the one of lagged quarters. Presumably, along a quarter, investors observe monthly index returns, which may have an effect on money flows by the end of the quarter. However, given the typical redemption restrictions imposed by most hedge funds, it is unlikely that investors profit from contemporaneous information on index returns.

styles with higher returns, but not necessarily the styles with the highest returns. On the other hand, very risky strategies are also favoured by clients. These strategies often shift from very high returns to very low returns and vice versa. Investors place large amounts of money into these strategies even when they have experienced low returns, presumably in the expectation of a reversal.

Figure 4

Investors' Returns from Style Allocation

In each quarter we rank the style indices in terms of their corresponding aggregate residual growth rates at the end of the period. Then we form two portfolios: one contains those indices associated to styles with net positive aggregate money flows. The second portfolio of indices is associated to those styles that experienced net negative aggregate money flows. For each portfolio, we compute both an equally-weighted return and a cash flow-weighted return, in the ranking period, in the two lagged quarters, and in each of the four subsequent quarters. The figure depicts the time series average returns of each portfolio over the 40 quarters.

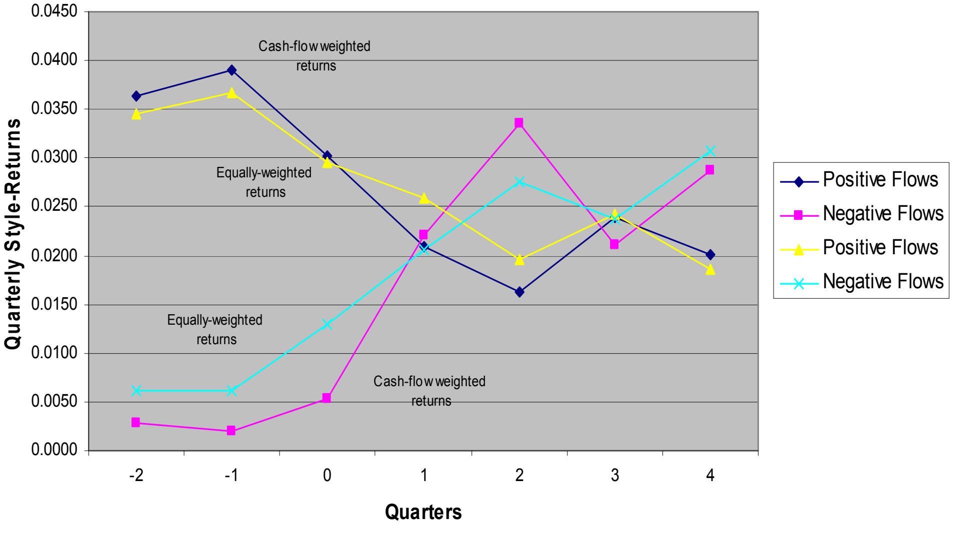


Table IX

Investors' Returns from Style Allocation

In each quarter we rank the style indices in terms of their corresponding aggregate residual dollar flows at the end of the period. Next, we form two portfolios: one contains those indices associated to styles with net positive aggregate money flows. The second portfolio of indices is associated to those styles that experienced net negative aggregate money flows. For each portfolio, we compute both an equally-weighted return and a cash flow-weighted return, in the ranking period, in the two lagged quarters, and in each of the four subsequent quarters. The table reports the time series average returns of each portfolio over the 40 quarters. Panel A reports results based on cash flow weighted returns. Panel B reports results based on equally weighted returns. Panel C reports the differences between cash flow weighted and equally weighted returns. T-statistics are provided in parentheses.

Aggregate residual dollar flows							
Panel A: Cash-flow weighted returns							
	Lagged quarters		Ranking Period		Subsequent quarters		
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0453	0.0468	0.0322	0.0268	0.0235	0.0224	0.0205
Styles with net negative flows	0.0081	0.0102	0.0192	0.0269	0.0320	0.0306	0.0385
Difference	0.0372	0.0366	0.0130	-0.0002	-0.0085	-0.0082	-0.0180
T-test	(3.76)	(4.60)	(2.01)	(-0.02)	(-1.03)	(-1.05)	(-2.22)
Panel B: Equally weighted returns							
	Lagged quarters		Ranking Period		Subsequent quarters		
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0345	0.0367	0.0296	0.0259	0.0196	0.0243	0.0185
Styles with net negative flows	0.0062	0.0061	0.0129	0.0206	0.0276	0.0238	0.0307
Difference	0.0283	0.0307	0.0166	0.0053	-0.0079	0.0005	-0.0122
T-test	(3.70)	(3.71)	(3.06)	(0.70)	(-0.94)	(0.09)	(-1.43)
Panel C: Cash-flow weighted minus equally weighted returns							
	Lagged quarters		Ranking Period		Subsequent quarters		
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0108	0.0100	0.0026	0.0009	0.0039	-0.0019	0.0020
T-test	(2.10)	(1.70)	(0.70)	(0.22)	(1.03)	(-0.36)	(0.48)
Styles with net negative flows	0.0019	0.0041	0.0062	0.0063	0.0044	0.0069	0.0078
T-test	(0.42)	(1.25)	(1.40)	(1.59)	(0.96)	(1.77)	(2.20)

5.7 Concluding Remarks

The results of this study indicate that investors learn at the style-level and invest following a momentum strategy, whereby they chase the winning styles. We find a statistically significant relation between aggregate residual money flows and the relative performance of style indices over the previous one to three quarters. Aggregate money flows exhibit a sorting ability of past style index performance. However, aggregate money flows are unrelated to future style performance. There are no significant differences in subsequent performance between those styles favoured by investors and those less favoured. Further, we do not find evidence that past style index performance contains useful information of future performance. These two facts together suggest that style investing is the result of a common sentiment factor and reflects extrapolative expectations, consistent with the hypothesis of Barberis and Shleifer [2003]. Previous studies have shown that also within-style allocations at the individual fund level are inefficient (e.g. Baquero and Verbeek [2005]). Overall, these results raise serious concerns about investors' ability to make the right allocation choices.

APPENDIX

Table A1

Aggregate Cash Flows and Total Net Assets from a Sample of Hedge Funds from TASS Database

This table gives the total number of hedge funds in the sample per quarter, aggregate cash flows, total net assets under management and average return. The sample consists of 1543 open-end hedge funds taken from TASS database, with a minimum of 6 quarters of quarterly returns history and with computed quarterly cash flows available at least for one year. Funds of funds are not included. The sample period has 40 quarters from 1994Q4 till 2004Q3. Cash flows are computed as the change in total net assets between consecutive quarters corrected for reinvestments. A growth rate is calculated as relative cash flows with respect to TNA of previous period.

	Number of funds	Aggregate Cash Flows (million dollars)	Cash flows (growth rate)	Aggregate TNA (million dollars)	Average Return
1994 Q4	231	-437.44	-0.0235	17861.15	-0.0077
1995 Q1	258	-1312.14	-0.0646	19387.67	0.0524
1995 Q2	279	-461.56	-0.0228	20469.12	0.0370
1995 Q3	315	-317.83	-0.0146	22972.14	0.0459
1995 Q4	326	-757.99	-0.0327	23215.81	0.0345
1996 Q1	348	148.85	0.0050	30969.63	0.0244
1996 Q2	360	-334.21	-0.0107	33047.34	0.0596
1996 Q3	364	377.79	0.0112	34275.64	0.0164
1996 Q4	371	945.09	0.0260	40431.19	0.0603
1997 Q1	379	2277.90	0.0561	45255.20	0.0427
1997 Q2	392	301.99	0.0066	48434.29	0.0467
1997 Q3	414	2353.93	0.0471	56745.53	0.0742
1997 Q4	438	675.00	0.0115	59948.61	-0.0136
1998 Q1	470	1821.63	0.0295	66989.86	0.0484
1998 Q2	482	1107.31	0.0167	68556.61	-0.0240
1998 Q3	496	-268.07	-0.0041	60234.29	-0.0502
1998 Q4	528	-3822.72	-0.0615	56650.24	0.0518
1999 Q1	571	-2845.61	-0.0490	55262.50	0.0324
1999 Q2	582	-850.49	-0.0152	58979.19	0.0832
1999 Q3	598	-1289.20	-0.0219	56682.70	-0.0006
1999 Q4	597	-703.00	-0.0124	63413.15	0.1177
2000 Q1	626	670.00	0.0101	69948.90	0.0607
2000 Q2	629	-2299.42	-0.0336	63643.12	-0.0139
2000 Q3	658	697.77	0.0108	67016.20	0.0185
2000 Q4	667	734.74	0.0109	68463.32	-0.0020
2001 Q1	670	3382.16	0.0456	78678.59	0.0086
2001 Q2	697	3380.75	0.0403	89049.14	0.0257
2001 Q3	699	3145.77	0.0355	89959.58	-0.0250
2001 Q4	702	-5713.63	-0.0574	97069.95	0.0482
2002 Q1	702	1533.24	0.0157	100359.61	0.0184
2002 Q2	700	2279.75	0.0222	105192.95	0.0057
2002 Q3	702	67.69	0.0006	104609.51	-0.0212
2002 Q4	697	-1099.04	-0.0104	106726.81	0.0219
2003 Q1	685	2431.55	0.0255	99383.00	0.0116
2003 Q2	687	5628.85	0.0560	112169.77	0.0775
2003 Q3	703	6970.84	0.0607	124438.64	0.0376
2003 Q4	711	6722.30	0.0539	137685.21	0.0541
2004 Q1	703	16056.57	0.1207	154496.43	0.0409
2004 Q2	712	10330.84	0.0659	163689.45	-0.0244
2004 Q3	692	2730.60	0.0170	164632.56	0.0090

Table A2

Cross-Sectional Characteristics of the Hedge Fund Sample

This table presents summary statistics on cross-sectional characteristics of our sample of 1543 hedge funds for the period 1994Q4 till 2004Q3. Cash flows are the change in total net assets between consecutive quarters corrected for reinvestments. Returns are net of all management and incentive fees. Age is the number of months a fund has been in operation since its inception. In each quarter, the historical standard deviation of monthly returns, semi deviation and upside potential have been computed based on the entire past history of the fund. Semi deviation and upside potential are calculated with respect to the return on the U.S. Treasury bill taken as the minimum investor's target. Offshore is a dummy variable with value one for non U.S. domiciled funds. Incentive fee is a percentage of profits above a hurdle rate that is given as a reward to managers. Management fee is a percentage of the fund's net assets under management that is paid annually to managers for administering a fund. Personal capital is a dummy variable indicating that the managers invests from her own wealth in the fund. We include 10 dummies for investment styles defined on the basis of the CSFB/Tremont indices.

Variable	Mean	Std. Dev.	Min	Max
Cash Flows (growth rate)	0.0287	0.2734	-0.9107	4.3656
Cash Flows>0 (10876 obs)	0.1639	0.3052	0.0001	4.3656
Cash Flows<0 (10367 obs)	-0.1115	0.1444	-0.9107	-0.0001
Cash Flows=0 (598 obs)				
Cash Flows (dollars)	2484343	6.80E+07	-7.23E+09	1.12E+09
ln(TNA)	17.1746	1.8491	8.1050	23.2959
ln(AGE)	4.0070	0.6189	2.8904	5.8171
Quarterly Returns	0.0255	0.1175	-0.9763	1.7449
Historical St.Dev.	0.0513	0.0407	0.0004	0.8318
Semi Deviation	0.0299	0.0245	0	0.3326
Upside Potential	0.0236	0.0169	0.0002	0.2797
Downside-Upside Pot. Ratio	1.2862	0.8600	0	19.2076
Offshore	0.6236	0.4845	0	1
Incentive Fee	18.4599	5.8253	0	50
Management Fees	1.4632	0.8832	0	8
Personal Capital	0.6197	0.4855	0	1
Leverage	0.7579	0.4283	0	1
Convertible Arbitrage	0.0525	0.2231	0	1
Dedicated Short Bias	0.0160	0.1256	0	1
Emerging Markets	0.1036	0.3047	0	1
Equity Market Neutral	0.0463	0.2102	0	1
Event Driven	0.1222	0.3275	0	1
Fixed Income Arbitrage.	0.0490	0.2159	0	1
Global Macro	0.0691	0.2536	0	1
Long/Short Equity	0.3468	0.4760	0	1
Managed Futures	0.1576	0.3644	0	1
Hedge Fund Index	0.0368	0.1883	0	1

Table A3

Summary of Number of Funds per Style and per Period

This table gives the total number of hedge funds in the sample per quarter and per style category. The sample consists of 1543 open-end hedge funds taken from TASS database, with a minimum of 6 quarters of quarterly returns history and with computed quarterly cash flows available at least for one year. Funds of funds are not included. The sample period has 40 quarters from 1994Q4 till 2004Q3. This results in a total of 21841 fund-period observations.

Style	Conv. Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitr.	Global Macro	Long/ Short Equity	Managed Futures	Other	**Total**
1994Q4	9	3	17	5	25	7	24	74	63	4	**231**
1995Q1	11	3	18	6	24	9	29	84	69	5	**258**
1995Q2	10	3	19	7	27	10	32	89	75	7	**279**
1995Q3	10	5	27	8	27	12	35	96	88	7	**315**
1995Q4	12	5	26	8	31	13	34	100	89	8	**326**
1996Q1	15	5	29	9	34	19	36	97	94	10	**348**
1996Q2	15	5	33	8	38	22	35	104	90	10	**360**
1996Q3	12	5	36	9	38	20	37	105	91	11	**364**
1996Q4	14	5	35	10	41	20	36	105	92	13	**371**
1997Q1	16	5	36	11	46	20	38	108	87	12	**379**
1997Q2	16	5	39	11	47	20	39	111	93	11	**392**
1997Q3	17	5	38	13	52	22	38	125	90	14	**414**
1997Q4	18	5	45	13	55	25	40	134	89	14	**438**
1998Q1	20	5	50	14	60	25	41	152	89	14	**470**
1998Q2	20	6	50	15	64	21	39	161	92	14	**482**
1998Q3	17	9	46	15	67	22	41	176	89	14	**496**
1998Q4	19	11	52	18	68	22	42	186	96	14	**528**
1999Q1	19	12	59	22	79	22	49	194	99	16	**571**
1999Q2	22	11	65	25	72	24	50	193	104	16	**582**
1999Q3	24	11	65	26	73	28	49	200	106	16	**598**
1999Q4	28	11	66	23	72	31	50	202	97	17	**597**
2000Q1	32	12	70	25	74	35	49	216	96	17	**626**
2000Q2	34	13	74	28	73	34	46	219	91	17	**629**
2000Q3	33	13	76	31	77	38	39	242	91	18	**658**
2000Q4	37	13	82	31	83	35	34	246	85	21	**667**
2001Q1	33	12	74	38	83	35	34	249	89	23	**670**
2001Q2	34	12	78	43	88	36	33	256	90	27	**697**
2001Q3	38	11	79	44	89	36	31	252	91	28	**699**
2001Q4	40	11	78	43	90	33	32	262	85	28	**702**
2002Q1	43	11	78	38	88	32	31	262	88	31	**702**
2002Q2	48	10	79	36	89	33	29	261	84	31	**700**
2002Q3	46	10	80	35	88	35	31	266	80	31	**702**
2002Q4	45	12	77	39	89	32	34	261	76	32	**697**
2003Q1	44	12	73	40	86	33	33	253	77	34	**685**
2003Q2	45	12	70	40	88	33	33	257	74	35	**687**
2003Q3	47	12	69	49	86	37	35	257	74	37	**703**
2003Q4	51	12	69	45	89	36	37	258	76	38	**711**
2004Q1	50	11	69	44	92	35	39	255	72	36	**703**
2004Q2	54	8	68	46	90	35	46	258	70	37	**712**
2004Q3	49	8	68	41	87	34	49	248	72	36	**692**
TOTAL	**1147**	**350**	**2262**	**1012**	**2669**	**1071**	**1509**	**7574**	**3443**	**804**	**21841**

Table A4

Summary Statistics of Aggregate Flows and Measures of Style Performance

This table presents summary statistics of aggregate money flows and different measures of performance at the style level. Our dataset covers 40 quarters from 1994Q4 to 2004Q3. We aggregate, per style and per period, residual growth rates and residual dollar flows obtained from the model in Table III. One significant outlier corresponding to the Convertible Arbitrage strategy in 2001Q4 is excluded. This results in 359 style-period observations when the 9 style indices are considered and 399 observations when the general Hedge Fund Index is also included. The style rank is obtained by ranking all 9 indices in each period in terms of returns. The winner/loser dummy takes value 1 if the style is ranked among the top best performing styles. A set of 9 dummies accounts for the length of winning and losing streaks. For instance, the dummy *Winning Streak 2* takes value 1 if the style index is a winner over 2 consecutive quarters. The dummy *Winning Streak 4* accounts for winning streaks of four quarters length or more. Similarly, *Losing Streak 5* accounts for losing streaks of five quarters or more. A set of 9 dummies accounts for the length of upward and downward trends in style index returns. Finally, the 10 dummies for investment styles are defined on the basis of the CSFB/Tremont indices.

Variable	Observ.	Mean	Std. Dev.	Min	Max
Aggregate Residual Growth Rates	399	0.0149	0.0648	-0.2673	0.2345
Aggregate Residual Dollar Flows	399	83400000	421000000	-2.11E+09	1.81E+09
Trend Variable	399	20.4787	11.5645	1	40
Quarterly Style Index Return	399	0.0233	0.0612	-0.2867	0.3066
Quarterly Style Rank	359	4.4962	2.8785	1	9
Winner/Loser Dummy	359	0.4429	0.4974	0	1
Winning Streak 1	399	0.2105	0.4082	0	1
Winning Streak 2	359	0.0977	0.2973	0	1
Winning Streak 3	359	0.0351	0.1842	0	1
Winning Streak 4	359	0.0551	0.2285	0	1
Losing Streak 1	359	0.2130	0.4100	0	1
Losing Streak 2	359	0.0977	0.2973	0	1
Losing Streak 3	359	0.0677	0.2515	0	1
Losing Streak 4	359	0.0451	0.2078	0	1
Losing Streak 5	359	0.0777	0.2680	0	1
Up 1 Quarters	399	0.3208	0.4674	0	1
Up 2 Quarters	399	0.1303	0.3371	0	1
Up 3 Quarters	399	0.0351	0.1842	0	1
Up 4 Quarters	399	0.0050	0.0707	0	1
Down 1 Quarter	399	0.3358	0.4729	0	1
Down 2 Quarters	399	0.1404	0.3478	0	1
Down 3 Quarters	399	0.0226	0.1487	0	1
Down 4 Quarters	399	0.0075	0.0865	0	1
Down 5 Quarters	399	0.0025	0.0501	0	1
Convertible Arbitrage	399	0.0977	0.2973	0	1
Dedicated Short Bias	399	0.1003	0.3007	0	1
Emerging Markets	399	0.1003	0.3007	0	1
Equity Market Neutral	399	0.1003	0.3007	0	1
Event Driven	399	0.1003	0.3007	0	1
Fixed Income Arbitrage	399	0.1003	0.3007	0	1
Global Macro	399	0.1003	0.3007	0	1
Long/Short Equity	399	0.1003	0.3007	0	1
Managed Futures	399	0.1003	0.3007	0	1
General Hedge fund index	399	0.1003	0.3007	0	1

Table A5

Investors' Returns From Style Allocation

In each quarter we rank the style indices in terms of style-driven growth rates at the end of the period. Then we form two portfolios: one contains those indices associated to styles with net positive aggregate money flows. The second portfolio of indices is associated to those styles that experienced net negative aggregate money flows. For each portfolio, we compute both an equally-weighted return and a cash flow-weighted return, in the ranking period, in the two lagged quarters, and in each of the four subsequent quarters. The table reports the time series average returns of each portfolio over the 40 quarters. Panel A reports results based on cash flow weighted returns. Panel B reports results based on equally weighted returns. Panel C reports the differences between cash flow weighted and equally weighted returns. T-statistics are provided in parentheses.

Style-Driven Growth Rates							
Panel A: Cash-flow weighted returns							
	Lagged quarters		Ranking Period	Subsequent quarters			
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0434	0.0535	0.0293	0.0239	0.0213	0.0191	0.0209
Styles with net negative flows	-0.0161	-0.0320	0.0072	0.0085	0.0171	0.0352	0.0274
Difference	0.0595	0.0855	0.0221	0.0154	0.0041	-0.0161	-0.0066
T-test	(4.98)	(8.16)	(2.08)	(1.29)	(0.36)	(-1.36)	(-0.50)
Panel B: Equally weighted returns							
	Lagged quarters		Ranking Period	Subsequent quarters			
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0368	0.0444	0.0276	0.0261	0.0261	0.0207	0.0228
Styles with net negative flows	-0.0080	-0.0224	0.0075	0.0146	0.0155	0.0326	0.0265
Difference	0.0448	0.0668	0.0200	0.0115	0.0106	-0.0119	-0.0038
T-test	(4.24)	(7.71)	(2.29)	(1.31)	(1.10)	(-1.21)	(-0.39)
Panel C: Cash-flow weighted minus equally weighted returns							
	Lagged quarters		Ranking Period	Subsequent quarters			
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0066	0.0091	0.0018	-0.0022	-0.0049	-0.0016	-0.0019
T-test	(2.59)	(4.04)	(0.84)	(-0.80)	(-1.92)	(-0.76)	(-0.77)
Styles with net negative flows	-0.0081	-0.0096	-0.0003	-0.0061	0.0016	0.0026	0.0009
T-test	(-2.62)	(-3.54)	(-0.08)	(-1.61)	(0.33)	(0.79)	(0.24)

Table A6

Investors' Returns From Style Allocation

In each quarter we rank the style indices in terms of style-driven dollar flows at the end of the period. Then we form two portfolios: one contains those indices associated to styles with net positive aggregate money flows. The second portfolio of indices is associated to those styles that experienced net negative aggregate money flows. For each portfolio, we compute both an equally-weighted return and a cash flow-weighted return, in the ranking period, in the two lagged quarters, and in each of the four subsequent quarters. The table reports the time series average returns of each portfolio over the 40 quarters. Panel A reports results based on cash flow weighted returns. Panel B reports results based on equally weighted returns. Panel C reports the differences between cash flow weighted and equally weighted returns. T-statistics are provided in parentheses.

Style-Driven Dollar Flows

Panel A: Cash-flow weighted returns

	Lagged quarters		Ranking Period	Subsequent quarters			
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0513	0.0439	0.0273	0.0225	0.0164	0.0131	0.0194
Styles with net negative flows	-0.0224	-0.0176	0.0051	0.0128	0.0236	0.0285	0.0302
Difference	0.0737	0.0615	0.0222	0.0096	-0.0073	-0.0153	-0.0108
T-test	(6.34)	(5.47)	(2.06)	(0.81)	(-0.67)	(-1.27)	(-0.90)

Panel B: Equally weighted returns

	Lagged quarters		Ranking Period	Subsequent quarters			
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0409	0.0395	0.0317	0.0260	0.0220	0.0207	0.0213
Styles with net negative flows	-0.0092	-0.0058	0.0053	0.0242	0.0244	0.0244	0.0320
Difference	0.0501	0.0452	0.0264	0.0017	-0.0025	-0.0037	-0.0107
T-test	(5.25)	(6.12)	(3.20)	(0.19)	(-0.28)	(-0.42)	(-1.21)

Panel C: Cash-flow weighted minus equally weighted returns

	Lagged quarters		Ranking Period	Subsequent quarters			
	- 2	- 1	0	1	2	3	4
Styles with net positive flows	0.0104	0.0044	-0.0044	-0.0035	-0.0056	-0.0075	-0.0019
T-test	(4.32)	(1.45)	(-1.34)	(-1.02)	(-2.11)	(-1.93)	(-0.72)
Styles with net negative flows	-0.0132	-0.0119	-0.0002	-0.0114	-0.0008	0.0041	-0.0018
T-test	(-2.98)	(-2.47)	(-0.04)	(-2.55)	(-0.18)	(1.05)	(-0.43)

"Institutional investors have accounted for a growing share of hedge fund investments, and they can and should protect their own interests rather than rely on the limited regulatory protections that would be provided as a result of a registration requirement."
Former FED Chairman Alan Greenspan, in a letter to the Senate, August 2004

"The primary mechanism for regulating excessive leverage and other aspects of risk-taking in a market economy is the discipline provided by creditors, counter-parties and investors,"
FED Chairman Ben Bernanke. Speech in Atlanta, May 2006

Chapter 6

Summary and Conclusions

Financial intermediaries manage other people's money. The question of what accounts for the enormous appeal of financial intermediaries among investors has called to the attention of academic research, as these intermediaries have on average failed to deliver returns above those of the market or of passive strategies. This thesis examined this question in the hedge fund industry by exploring first whether hedge fund managers exhibit persistence in their performance that may justify an active search for skilled managers; second, by characterizing the investment and divestment behaviour of hedge fund investors; and third, by testing potential behavioural explanations for the observed investment patterns.

In a relatively short period of time, hedge funds have become major players in the financial markets. Once perceived as risky alternative instruments, accessible only to institutional investors and wealthy individuals, hedge funds have rapidly evolved into a very attractive investment option, partly as a result of the perception that hedge fund managers are skilled professionals. In 2004, an estimate of 400 new hedge funds were created worldwide. The estimated total reached nearly 8000, the assets under management reached the $1 trillion. The client base has expanded beyond foundations and endowments to company pensions and public pensions. Further, hedge funds are becoming increasingly accessible to "non-sophisticated" investors. One important motivation for this thesis lies on the increasing concerns that capital is being inefficiently allocated across hedge funds. Is this overwhelming response of investors the result of a critical and careful due diligence process? Can we justify investors' response in terms of performance of the investors' portfolio? How successful have investors been in selecting the right hedge fund managers?

This thesis provides four main conclusions:

1. Look-ahead bias is quite severe, especially for the worst performing funds at one-year horizons. After correcting for look-ahead bias, we find evidence that past performance of hedge funds is to some extent informative about future performance, particularly at quarterly horizons. There is some evidence of performance persistence at annual horizons but statistically weaker.

2. Large informational asymmetries between investors and managers create differences between the investment and divestment patterns of hedge fund investors. While inflows are highly responsive to good performance in the previous year, we identify fast redemptions in response to poor performance in the previous quarter.

3. On aggregate, money flows are not directed towards funds with above average subsequent returns. On the contrary, there are no significant differences between the portfolio of funds with positive money flows and the portfolio with negative money flows.

4. Given the asymmetric information problem, investors apparently misread the information available and overreact to persistence patterns, both at the individual fund level and at the style level.

Chapter 2 deals with performance persistence. Studies about performance persistence suffer from a well known methodological bias due to survivorship. The usual methodology imposes a survival condition over the evaluation horizon. Therefore, persistence might be overestimated. We propose a correction for look-ahead bias and we show that even after corrections, performance persistence is quite pronounced at quarterly horizons. Without corrections, the performance at annual horizons of the bottom 10% of funds in terms of raw returns may be overestimated by as much as 3.8% annualized. Therefore the difference between the winning and the losing portfolio amounts to 8.1% per year after correction.

The persistence results in Chapter 2 are not driven by funds closed to new flows, implying that persistence is susceptible of exploitation. Chapter 3 analyzes whether investors are indeed able to exploit it. The links between persistence and the responsiveness of flows to past performance are subtle and not well understood yet.

For example, studies in mutual funds have shown a very strong response of investors to the group of managers with the best track records in the previous year, although the evidence of performance persistence is scarce. Berk and Green [2004] reconcile these two seemingly inconsistent empirical findings. They argue that in equilibrium and under decreasing returns to scale and competitive supply of capital, investors rationally shift their capital towards the best managers. They do so until funds reach the critical size in which the expected rents are non existent, thus competing away persistence. If this is the case, the evidence of persistence in hedge funds at quarterly horizons suggests that investors are limited in chasing the best managers. We test this hypothesis by relating money flows to past performance at quarterly horizons and we do so by separately modelling inflows and outflows as two different regimes. This separation has been neglected in previous studies, to a large extent due to data limitations. Although, we do not observe inflows or outflows from individual investors, we do observe the net flow of money of the aggregate of investors in a given fund. Therefore, we use a regime switching model with endogenous switching to understand the determinants behind the investment and the divestment decisions of the average investor. Our results show a fast withdrawing reaction of investors in response to bad performance, mostly concentrated over the subsequent quarter, and lasting two or three quarters. This result remained hidden in previous studies. In contrast, quarterly inflows show little or no response to previous quarterly performance. The response of inflows is instead captured over annual horizons, while the response of annual outflows becomes weaker, suggesting a convex relationship that confirms the results of previous studies at annual horizons.

Apparently when investors are confronted to select a manager, they evaluate past performance over relatively long horizons of one year or more. In contrast, when investors face the decision to redeem, they evaluate past performance over shorter horizons from one up to three quarters. The second part of Chapter 3 asks to what extent this differential response implies an ability of investors to make the right investment or divestment choices. Our results indicate that this is not the case. The average manager hired by investors does not outperform the average manager that was fired. Moreover, investors' inflows are not equally placed among managers. Inflows largely favour those managers with good track records over the previous four quarters or so. However this group of managers underperforms the average hired manager subsequently. Conversely, outflows are heavily concentrated on relatively poor performers. But this group continues underperforming the average fired manager subsequently. In sum, while inflows are unable to select the right hedge fund managers, outflows discriminate correctly among the bad performers.

In Chapter 4 we investigate the possibility that one component in the response of investors to past performance documented in Chapter 3, is the result of a cognitive bias. The theoretical model of Rabin [2002] suggests that momentum investing is the reflection of investors' overinference of managerial skill from past records. Our results are consistent with this theory. First, we find that persistence patterns have some predictive ability of future performance. The longer the performance streak, the larger is the probability of persistence. However, our model allows us to capture a responsiveness of money flows beyond what should be rationally justified by expected performance. Moreover, the longer the performance streak, the larger the degree of overinference, consistent with the theoretical predictions of Rabin [2002]'s model. Finally we show that investors decisions are potentially suboptimal compared to a strategy based on expected performance.

Chapter 5 investigates to what extent investors learn at the style level by testing momentum in style investing. A main hypothesis in models of aggregate demand is that investors compare styles with each other and invest in those styles with the best previous performance (e.g. Barberis and Shleifer [2003]). Testing the hypothesis of style investing requires an unequivocal definition of style categories as interpreted by investors. In that respect, the hedge fund industry constitutes a suitable setting since style categories are defined by a set of style indices closely followed by investors. Style indices play an instrumental role by offering investors a simplified and schematic taxonomy of investment strategies used by hedge fund managers. At the methodological level, we isolate the component of flows that is not explained by individual fund characteristics, and construct an aggregate per period and per style. Finally we explain these aggregates from past style ranks, style index returns and style index trends. Our model reveals that aggregate flows are strongly sensitive to style ranks up to three lags. However we do not find evidence of persistence in style relative performance at quarterly horizons, nor evidence that those styles favoured by investors subsequently outperform those styles from which they divested. Our results are consistent with the idea that style investing reflects common sentiment among investors and is unrelated to fundamentals.

Overall, the four essays in this thesis have made an attempt to portray hedge fund investors by characterizing their investment and divestment decisions. Although we better understand the nature of the interrelation between capital flows and performance, several contours in that portrait remain to be delineated. The results of Chapter 3 suggest that flows are strongly related to subsequent liquidation probabilities. Funds experiencing the largest outflows in a given quarter exhibit the highest liquidation rates over subsequent quarters. However, money flows and liquidation rates are both partly determined by past fund performance, as described by the two models presented in Chapter 2 and Chapter 3. Thus a model that disentangles the combined effect of money flows and performance on subsequent liquidation rates is crucial to understand the full economic implications of fast outflows. Here a number of intriguing issues arise pertaining to the perception of investors about the likelihood of fund liquidation. In the same line of Chapter 4, which suggests a more pronounced overreaction to persistence patterns for outflows compared to inflows, we could ask to what extent do fast outflows overreact to the likelihood of liquidation, especially for under-watermark funds? Do fast outflows further enhance liquidation probabilities? Additionally, if it is indeed the case that investors impose a credible threat of termination, this may constitute a mechanism that counterbalances the implicit gambling incentives of a convex flow-performance relation at annual horizons. Therefore a closer look at the interactions between managers' risk-taking propensity and money flows would provide additional insights into contractual issues. On another point, the most interesting aspects of style investing, as revealed by Chapter 5, remain to be analyzed. For example, what its effects are on the flow-performance relation at the individual fund level? Does chasing the winning styles create an externality on the returns of funds in other style categories? Does style investing create comovement of returns in funds within a given style? Finally, the several asymmetries between the two regimes of positive and negative net money flows reported in Chapter 3 remain open for additional scrutiny. Most particularly the asymmetric response time of inflows and outflows to past performance gives room for alternative behavioural explanations. How do sophisticated investors frame losses with respect to gains? How do investors perceive or evaluate more recent information with respect to the more distant?

We believe these are exciting paths ahead for academic research, as exciting as the future developments within the hedge fund industry will be.

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Samenvatting en Conclusies (Summary in Dutch)

De enorme groei van de beleggingsindustrie, waarin professionals het geld beheren van individuele en institutionele beleggers, trekt grote belangstelling van academici, mede doordat de gemiddelde fondsmanager niet in staat is rendementen te genereren die hoger liggen dan een vergelijkbare marktindex of een eenvoudige passieve strategie. Dit proefschrift onderzoekt dit thema voor hedgefondsen, met vier belangrijke vragen. Ten eerste, bestaan er hedgefondsen die in staat zijn om systematisch hoge rendementen te leveren, waardoor een actieve zoektocht naar gekwalificeerde managers gerechtvaardigd is? Ten tweede, op welke manier alloceren beleggers in hedgefondsen hun geld en hoe reageren deze geldstromen op historische prestaties? Ten derde, zijn beleggers in staat die hedgefondsen te selecteren die vervolgens goede rendementen laten zien? En ten slotte, wat zeggen deze waargenomen geldstromen over het gedrag van beleggers?

Hedgefondsen vormen een relatief nieuwe beleggingscategorie die erg populair is geworden sinds het eind van de jaren negentig. Pensioenfondsen als het ABP en PGGM hebben inmiddels vele honderden miljoenen belegd in hedgefondsen. Een hedgefonds lijkt veel op een traditioneel beleggingsfonds, maar is veel flexibeler in de soorten activa dat het aanhoudt en de posities die het inneemt. Hedgefondsen investeren bijvoorbeeld volop in derivaten, nemen short-posities in, of beleggen met geleend geld. Allemaal mogelijkheden die bij traditionele fondsen zeer ongebruikelijk zijn of zelfs niet toegestaan volgens de geldende regels. Een goede definitie voor hedgefondsen ontbreekt, maar het belangrijkste kenmerk is dat ze zich nauwelijks aan de richtlijnen voor traditionele beleggingsfondsen hoeven te houden. Ze zijn bijvoorbeeld niet verplicht hun prestaties en gevolgde strategie te rapporteren in de vorm van een jaarverslag. Doordat de meeste hedgefondsen streven naar een hoog absoluut rendement, onafhankelijk van de marktsituatie, bieden ze potentieel interessante diversificatiemogelijkheden ten opzichte van bestaande beleggingsportefeuilles.

In het laatste decennium zijn hedgefondsen uitgegroeid tot belangrijke spelers op financiële marken. In eerst instantie werden hedgefondsen vooral gezien als een risicovolle alternatieve beleggingscategorie, uitsluitend beschikbaar voor welvarende en institutionele beleggers. Inmiddels vormen hedgefondsen een aantrekkelijk alternatief en een interessante uitbreiding van bestaande beleggingsportefeuilles, mede door de perceptie dat de meest talentvolle fondsmanagers de overstap naar hedgefondsen gemaakt hebben. In 2004 werden naar schatting zo'n 400 nieuwe hedgefondsen opgericht, leidend tot een totaal van bijna 8000 fondsen wereldwijd, met een totaal belegd vermogen van meer dan 1 triljoen dollar. Steeds meer worden hedgefondsen ook toegankelijk voor beleggers die niet vallen onder de definitie van zogenoemde "sophisticated investors" (institutionele beleggers of individuele beleggers met een belegd vermogen van meer dan $100.000), mede door de opkomst van zgn. *funds-of-funds*, fondsen die uitsluitend beleggen in andere hedgefondsen. Ondanks de sterke groei van deze bedrijfstak is het niet evident dat er sprake is van een efficiënte allocatie van vermogen over het grote aantal hedgefondsen. Het gebrek aan transparantie van wat hedgefondsen nu werkelijk doen zou kunnen verhullen dat beleggers ten onrechte hun belegd vermogen verschuiven naar hedgefondsen. Is het inderdaad zo dat beleggers in hedgefondsen uiteindelijk hoge rendementen behalen? En hoe succesvol zijn beleggers om de juiste fondsbeheerders te kiezen?

Dit proefschrift kent vier belangrijke conclusies.

1. Hedgefondsen die in het recente verleden een bovengemiddelde prestatie hebben geleverd, zullen naar verwachting ook in de komende periode bovengemiddeld presteren. Op kwartaalbasis zou een zogenaamde winnaars-verliezers strategie tot een buitengewoon rendement hebben geleid van 12% (op jaarbasis), terwijl diezelfde strategie op jaarbasis tot een buitengewoon rendement van 8% zou hebben geleid.
2. Er is sprake van informatie-asymmetrie tussen beleggers en fondsmanagers vanwege de beperkte transparantie en rapportage, en vanwege het gebruik van soms ondoorzichtige en dynamische beleggingsstrategieën. Deze factoren veroorzaken grote verschillen tussen de manier waarop en snelheid waarmee extra beleggingen enerzijds en geldonttrekkingen anderzijds reageren op historische prestaties van hedgefondsen.
3. Gemiddeld genomen wordt additioneel vermogen niet belegd in die hedgefondsen die vervolgens bovengemiddelde rendementen behalen. Er bestaat amper verschil in de rendementen van hedgefondsen die veel geld aantrekken en hedgefondsen die veel van hun inleg verliezen.
4. In het licht van de genoemde informatie-asymmetrie worden beleggers blijkbaar misleid door de beschikbare informatie en reageren ze te sterk op historische patronen in rendementen, zowel op het niveau van individuele hedgefondsen als op het niveau van beleggingsstijlen.

In Hoofdstuk 2 is de vraag onderzocht of er sprake is van persistentie in de prestaties van hedgefondsen. In tegenstelling tot wat vaak bij traditionele beleggingsfondsen wordt gevonden, blijkt er in de periode 1994 – 2000 bij hedgefondsen wel sprake te zijn van persistentie. Een strategie waarbij in de beste 10% hedgefondsen van het afgelopen kwartaal wordt belegd, zou tot een jaarlijks rendement hebben geleid dat 12% hoger is in vergelijking met de slechtste 10% hedgefondsen van het afgelopen kwartaal. Dit impliceert dat prestaties uit het verleden een belangrijke leidraad kunnen zijn bij de selectie van hedgefondsen, en dat dit tot een beter beleggingsrendement van bijvoorbeeld pensioenfondsen kan leiden.

In Hoofdstuk 3 is onderzocht of beleggers in hedgefondsen in de praktijk in staat zijn een beter beleggingsresultaat te behalen door het kiezen van relatief goede fondsen (of het vermijden van minder goede fondsen). Het verband tussen persistentie enerzijds en de reactie van beleggers op historische fondsrendementen anderzijds is interessant. Voor traditionele beleggingsfondsen hebben studies aangetoond dat een beperkte groep fondsen met zeer goede prestaties de meerderheid van het nieuw te beleggen vermogen aantrekt, terwijl er vrijwel geen sprake is van persistentie in deze prestaties. Berk en Green [2004] verklaren deze twee schijnbaar tegenstrijdige resultaten met behulp van een evenwichtsmodel waarin er sprake is van afnemende meeropbrengsten en een concurrentie in het aanbod van nieuw kapitaal. In dit model wijzen beleggers op basis van rationele argumenten hun middelen toe aan beleggingsfondsen totdat een kritische omvang wordt bereikt en alle abnormale prestaties als het ware worden weggeconcurreerd. Indien dit beeld correct is, suggereert de gevonden persistentie voor hedgefondsen dat kapitaal onvoldoende flexibel toegewezen kan worden en dat beleggers slechts in beperkte mate (of met de nodige vertraging) in de beste fondsen inleggen. In dit hoofdstuk toetsen we deze hypothese door het verband op kwartaalniveau te onderzoeken tussen kapitaalstromen en historische beleggingsprestaties. We maken hierbij onderscheid tussen kapitaalinstromen enerzijds en uitstromen anderzijds. Door deze apart te modelleren kunnen we nagaan in hoeverre zij op dezelfde manier reageren op historische rendementen en andere fondskenmerken. De resultaten laten zien dat beleggers sterk en snel middelen onttrekken aan hedgefondsen indien zij geconfronteerd worden met lage rendementen, meestal binnen enkele kwartalen. Anderzijds zijn de kapitaalinstromen maar zeer beperkt gerelateerd aan fondsrendementen in de voorafgaande kwartalen.
Op jaarniveau wordt de reactie tussen uitstromen en rendement zwakker en ontstaat er, consistent met de bestaande literatuur, een convex verband.

De resultaten in dit hoofdstuk laten zien dat beleggers de prestaties van hedgefondsen over een relatief lange horizon van een tot twee jaar evalueren indien overwogen wordt nieuw kapitaal in te leggen, terwijl anderzijds kapitaal wordt onttrokken indien lage rendementen worden behaald over een tot drie kwartalen. Het tweede deel van Hoofdstuk 3 analyseert de vraag in hoeverre deze asymmetrische reactie beleggers in staat stelt de juiste keuzes te maken bij het sturen van hun kapitaalstromen naar de juiste fondsen. De resultaten geven aan dat hiervan geen sprake is. Het gemiddelde hedgefonds dat extra middelen ontvangt behaalt slechtere resultaten dan het gemiddelde fonds dat geld aan zich onttrokken ziet worden. Ook binnen de groep van fondsen die extra kapitaal ontvangen vindt de allocatie suboptimaal plaats. Het vermogen gaat in grote mate naar die fondsmanagers die goede rendementen behalen over de voorafgaande vier kwartalen, maar deze managers behalen vervolgens rendementen die lager zijn dan anderen. Aan de andere kant vinden onttrekkingen voornamelijk plaats bij de slecht presterende fondsen, en deze fondsen behalen vervolgens gemiddeld genomen ook een lager rendement. Samenvattend geldt dus dat kapitaalinstromen niet terecht komen bij de juiste fondsmanagers, terwijl kapitaal wel aan de juiste fondsen worden onttrokken.

In Hoofdstuk 4 onderzoeken we nog een keer de relatie tussen kapitaalstromen van en naar hedgefondsen en historische prestaties, maar nu vanuit met een psychologische inslag die bekend staat als de wet van de kleine aantallen. Indien beleggers geloven in het bestaan van kundige fondsmanagers, kunnen zij in te sterke mate verwachten dat goede prestaties uit het verleden ook in de toekomst behaald zullen worden. Dit wordt geformaliseerd in het theoretische model van Rabin [2002]. Onze resultaten zijn consistent met deze theorie. Hoe langer een hedgefonds bovengemiddeld presteert, des te meer middelen in dit fonds worden belegd. Echter, de extra toestroom van middelen wordt op geen enkele manier gerechtvaardigd door toekomstige rendementen.

Hoofdstuk 5 analyseert in hoeverre beleggers zich bij hun allocatie laten beïnvloeden door de ontwikkeling van de verschillende stijlindices die voor hedgefondsen beschikbaar zijn. Gezien het feit dat hedgefondsen weinig transparant zijn, beperkt rapporteren en een veelheid aan strategieën volgen, vormen stijlindices een belangrijke informatiebron voor geïnteresseerde beleggers. De belangrijkste hypothese in dit hoofdstuk is dat beleggers in die stijlen beleggen die in het verleden de beste rendementen laten zien (zie bijv. Barberis en Shleifer [2003]). In dit hoofdstuk isoleren we het deel van de kapitaalstromen dat niet verklaard kan worden door individuele fondskenmerken en –rendementen en aggregeren dit per periode en per stijl. Vervolgens relateren we de geaggregeerde kapitaalstromen aan historische stijlrendementen en –ontwikkelingen. Het model laat zien dat kapitaalstromen zich in sterke mate laten verklaren door de beleggingsresultaten op stijlniveau over de voorgaande drie kwartalen. Er is echter geen statistisch bewijs dat er sprake is van persistentie in stijlrendementen, noch dat beleggers die stijlen selecteren die vervolgens beter dan gemiddelde rendementen laten zien. Deze resultaten zijn consistent met het idee dat stijlbeleggen voornamelijk door sentimenten wordt gedreven en weinig gerelateerd is aan fundamentele ontwikkelingen.

De vier hoofdstukken in dit proefschrift geven samen een veelzijdig beeld van de beleggers in hedgefondsen en hun keuzes om kapitaal te (her)alloceren. Verschillende vragen blijven nog onbeantwoord. De resultaten van Hoofdstuk 3 laten zien dat kapitaalstromen een sterke invloed hebben op de mogelijke liquidatie van een fonds. Hedgefondsen met een grote kapitaaluitstroom in een gegeven periode hebben in de daarop volgende kwartalen een grote kans op liquidatie. Zowel liquidatie als kapitaalstromen worden echter in sterke mate verklaard door historische rendementen (zie Hoofdstuk 2 en 3). Een model dat specifiek aandacht schenkt aan de rol van rendementen en kapitaalstromen op liquidatie is van belang om de economische implicaties van de snelle kapitaaluitstromen te doorgronden. Een interessant punt hierbij is hoe beleggers de kans op fondsliquidatie inschatten, gegeven de beperkte informatie waarover ze beschikken. Ook Hoofdstuk 4 levert hieromtrent interessante vragen. Leiden snelle onttrekkingen tot een grote kans op liquidatie en levert dit een geloofwaardig dreigement op voor fondsmanagers, opdat een te hoge mate van risico wordt voormeden? Een convexe relatie tussen kapitaalstromen en rendementen kan immers leiden tot gokgedrag bij fondsmanagers om de kans te maximeren bij de kopgroep van fondsen terecht te komen. Een uitgebreider onderzoek naar de samenhang tussen het gokgedrag van managers en kapitaalstromen, in combinatie met de kenmerken van de contracten waaronder fondsmanagers werken, is bijzonder interessant. Ten slotte zijn er nog diverse aspecten aan de asymmetrie tussen positieve en negatieve kapitaalstromen onderbelicht gebleven, met name gerelateerd aan de psychologie van beleggers. Hoe zien beleggers winst en verlies? Hoe evalueren beleggers recente informatie versus historische informatie?

Bovengenoemde vragen beschrijven een opwindend pad voor verder onderzoek naar hedgefondsen, zonder twijfel even opwindend als de ontwikkelingen van de bedrijfstak zelf zullen zijn.

Resumen y Conclusiones (Summary in Spanish)

Fondos de Inversión Alternativa: Flujos de Capital, Rendimientos y la Psicología del Inversor.

1. Contexto General: Fondos Activos, Fondos Pasivos y el Comportamiento del Pequeño Inversor.

Un fondo de inversión es un vehículo financiero que canaliza las fortunas de una multitud de pequeños inversores hacia el mercado de activos financieros. De esta manera, el administrador o gestor del fondo genera economías de escala que le permiten crear a su vez un portafolio de activos *eficientemente* diversificado. Diversificación eficiente, y la consiguiente eliminación de riesgo sistemático, es el principal beneficio que el gestor ofrece al pequeño inversor. Distinguimos dos tipos de gestores. Un gestor *"pasivo"* se limita a crear un portafolio que replica las características de retorno y riesgo de un índice del mercado, que por definición es una reproducción relativamente fidedigna del mercado de activos en su totalidad. El índice representa pues un portafolio ideal en términos de diversificación. Un gestor *"activo"* vas más allá e intenta crear un portafolio diversificado que genere un rendimiento *superior* al del índice del mercado. Para ello, el gestor *activo* utiliza su talento y experiencia profesional con el fin de identificar activos sub-valorados o sobre-valorados con respecto a sus retornos teóricos establecidos en un modelo de equilibrio de activos financieros. Este trabajo de *selección activa* del gestor tiene un costo para el pequeño inversor: el gestor cobra en general 1% del monto total invertido en el fondo. Diversas investigaciones han demostrado, sin embargo, que en promedio, el rendimiento de fondos *activos* de inversión no supera ni el rendimiento de fondos pasivos ni el rendimiento del índice del mercado utilizado como referencial. Esto querría decir que el costo que el pequeño inversor paga al gestor por su trabajo de *selección activa,* es injustificado. Así pues, resulta inexplicable que la industria de fondos *activos* haya crecido y continúe creciendo y atrayendo a pequeños inversionistas a una tasa muy superior a la de otros vehículos financieros.

Una serie de estudios académicos se han concentrado en tratar de explicar este fenómeno. Los resultados que arrojan son aun más enigmáticos. Por un lado, estos estudios demuestran que los pequeños inversores concentran masivamente sus capitales en el 10% a 20% de fondos activos con los mejores rendimientos durante el año precedente. Sin embargo, tal estrategia de inversión es aparentemente injustificada, pues por otro lado, no existen pruebas científicas de que aquellos fondos activos que sobresalen en rendimiento en un año dado, sean capaces de *persistir* o mantener tales rendimientos durante el año siguiente. Un resultado aun más sorprendente es que los pequeños inversores, en promedio, no desinvierten de aquellos fondos con bajos rendimientos. Por lo tanto la relación entre flujos de capital y rendimiento es convexa: los flujos de capital son extremadamente sensibles en el lado de rendimientos positivos, pero insensibles en el lado de rendimientos negativos.

Las aparentes inconsistencias en el comportamiento del pequeño inversor han sido analizadas desde diferentes puntos de vista: ya sea bajo modelos de equilibrio en condiciones de competencia perfecta y racionalidad completa; ya sea poniendo en duda la racionalidad del pequeño inversor y apelando a fenómenos cognitivos; ya sea bajo modelos de información asimétrica.

El presente trabajo es un análisis empírico de las interrelaciones entre flujos de capital y rendimiento en un grupo particular de fondos activos, llamados *fondos alternativos* o *fondos de cobertura*, o mejor conocidos por su denominación en inglés: *hedge funds*. Específicamente: (1) analizamos el grado de persistencia en el rendimiento de fondos alternativos; (2) intentamos caracterizar las estrategias de inversión y desinversión del inversor en fondos alternativos; y (3) estudiamos la posibilidad de que potenciales fenómenos cognitivos estén a la base de los comportamientos de inversión observados.

2. Fondos Alternativos vs. Fondos Tradicionales. Motivación de la Tesis

Un fondo alternativo es en muchos aspectos diametralmente opuesto a un fondo activo tradicional. Un fondo alternativo tiene cuatro características esenciales: (1) está sujeto a limitado control de autoridades reguladoras; (2) el gestor no solo recibe el 1% del monto total invertido, sino también un incentivo por rendimiento, que consiste en general en un 20% del total de beneficios; (3) es un instrumento financiero de limitada liquidez, que impone plazos fijos de inversión generalmente largos a sus inversores, variando en general de un mes a más de un año, dependiendo del fondo; (4) como todo instrumento alternativo, la información disponible en cuanto a riesgo y rendimiento es limitada.

La primera característica determina gran parte de las propiedades de un fondo alternativo. Su constitución legal es tal que escapa a la definición de un fondo tradicional. En particular, el número máximo de inversionistas o asociados no puede sobrepasar los 500 (en los Estados Unidos de Norteamérica). Gracias a ello, un fondo alternativo no está obligado a presentar estados financieros anuales y por lo tanto su actividad es más bien opaca. Además, tiene una gran flexibilidad para utilizar estrategias de inversión que no le están permitidas a un fondo tradicional, como por ejemplo, ventas cortas y uso de derivados financieros. Esa misma flexibilidad le permite invertir y desinvertir en múltiples categorías de activos y hacer uso importante de apalancamiento. Por esta razón, un análisis de los componentes de riesgo de un fondo alternativo es una tarea compleja. Debido al incentivo de rendimiento que recibe el gestor, el fondo procura activamente superar el índice de mercado. Un fondo tradicional, por el contrario, está limitado en general a pocas categorías de activos y una rotación baja, y por lo tanto tiene menos herramientas para diferenciarse del índice.

El monto mínimo de inversión en un *hedge fund*, es en general de 1 millón de dólares. Esto limita el acceso en estos fondos exclusivamente a inversores institucionales e individuos con una gran fortuna personal. El término legal para tales inversores es el de "*inversor sofisticado*". Esto supone que el inversor tiene un conocimiento técnico del mercado financiero y es capaz de evaluar las propiedades de riesgo de una inversión cualquiera. Sin embargo el rápido crecimiento de la industria ha traído consigo una mayor competencia entre fondos para atraer flujos de capital, y en consecuencia, los montos mínimos de inversión tienden a reducirse, permitiendo el acceso en estos fondos a pequeños inversores, menos *"sofisticados"*. Otro canal de acceso en fondos alternativos para estos pequeños inversores está constituido por *los fondos de fondos alternativos*. Estos son portafolios de fondos, que ofrecen en principio diversificación y una cuidadosa selección de gestores de fondos.

Contrariamente a lo que podría suponerse a través de su nombre en inglés (i.e. *hedge fund)*, cuya traducción literal es *fondo de cobertura* o *fondo de protección*, un fondo alternativo es en realidad un instrumento de alto riesgo y tiene fines especulativos. Los casos de fraude y bancarrota son frecuentes, en tanto el inversor no está debidamente protegido en términos legales, dado el limitado control por parte de las autoridades de regulación. El alto riesgo se debe precisamente a los niveles de apalancamiento y al uso de derivados financieros. Sin embargo, gracias a sus estrategias de inversión de alta rotación en múltiples mercados y categorías de activos, los fondos alternativos presentan correlaciones históricas muy bajas con dichas categorías. De aquí se deriva la principal ventaja para un inversor sofisticado:

la posibilidad de alcanzar un mayor grado de diversificación a través de la inclusión de un fondo alternativo en un portafolio dado, pero en proporciones limitadas, que en general varían entre 1% y 15% del valor total del portafolio.

La industria de fondos alternativos ha crecido espectacularmente a lo largo de los últimos diez años. A fines del año 2004 alcanzó un trillón de dólares en total de activos invertidos, repartidos en un total estimado de 8000 fondos, en tanto en 1994 la industria manejaba tan solo 100 billones de dólares. En ese mismo lapso de tiempo, el rendimiento promedio de un fondo alternativo fue de 2.7% trimestral, inferior al rendimiento del mercado en 0.3%. Esto pone en serias dudas la capacidad del inversor sofisticado de tomar las decisiones de inversión y desinversión adecuadas, generando una preocupación creciente por la posibilidad de que los flujos de capital hacia la industria de fondos alternativos estén ineficientemente colocados. A esto se añade la potencial situación de vulnerabilidad de los inversores, especialmente de los menos sofisticados. Estas constituyen las principales motivaciones que nos conducen en este estudio a intentar comprender el comportamiento y la dinámica de inversión y desinversión de un inversor en fondos alternativos.

3. Marco Conceptual de la Tesis.

La relación contractual entre un inversor y un gestor de fondos supone una situación de información asimétrica al momento de firmar el contrato. Esto es, el inversor ignora la verdadera capacidad y talento del gestor y por lo tanto debe inferirlos sobre la base de señales de rendimiento pasado. Dado este marco conceptual, tres problemas de interés teórico surgen:

(1) Cuán informativo es el rendimiento pasado acerca del rendimiento futuro?
(2) Cuán sensibles son los flujos de capital a las señales de rendimiento pasado?
(3) Cuál es la relación entre flujos de capital y rendimiento futuro?

Estas son las tres relaciones esenciales en las cuales se centra nuestro estudio. El primer problema se refiere a la cuestión de persistencia en el rendimiento, y es abordado en el Capítulo 2. El segundo problema se refiere a los factores que determinan la toma de decisión del inversor en cuanto a invertir o desinvertir. Este problema es ampliamente analizado en la primera parte del Capítulo 3. El tercer problema se refiere a la capacidad del inversor de tomar la decisión adecuada en términos de rendimiento futuro, lo cual es analizado en la segunda parte del Capítulo 3. Finalmente, los Capítulos 4 y 5 integran las tres cuestiones a través de un potencial fenómeno cognitivo. A continuación detallamos la metodología de cada capítulo y los resultados principales de esta tesis. Los resultados empíricos han sido obtenidos utilizando la base de datos de fondos alternativos de *TASS Management Limited* en el periodo 1994-2004 y el conjunto de índices de rendimiento por categorías *CSFB/Tremont*.

4. Metodología y Resultados

En el Capítulo 2 analizamos la cuestión de persistencia en el rendimiento de fondos alternativos. Los estudios de persistencia están sujetos a un sesgo metodológico de supervivencia. Esto se debe a que la metodología usual consiste primero en obtener los deciles de la distribución de retornos de fondos en un periodo dado, para luego evaluar el rendimiento de cada decil en el periodo siguiente. Por lo tanto, tal metodología impone necesariamente una condición de supervivencia en el periodo de evaluación: dado que solo observamos los fondos que sobreviven de un periodo al siguiente, es muy probable que ello conduzca a una sobre-estimación de rendimientos de cada decil en el periodo de evaluación, y por consiguiente también una sobre-estimación de persistencia. La magnitud del sesgo depende obviamente de la tasa de mortalidad de dichos fondos. En este capítulo proponemos un mecanismo de corrección de este sesgo. El factor de corrección de retornos es la razón entre la probabilidad condicional y la probabilidad incondicional de mortalidad. La probabilidad condicional, a su vez, requiere estimar un modelo de mortalidad correctamente especificado. Es importante recalcar que al utilizar bases de datos de fondos alternativos, existe un potencial problema de auto-selección de fondos. Puesto que los fondos alternativos no están obligados legalmente a presentar estados financieros, su participación en una base de datos es enteramente voluntaria. Asimismo, un fondo puede decidir voluntariamente dejar de participar en la base de datos, sin que ello signifique que el fondo ha dejado de existir. Por lo tanto es primordial distinguir el caso de mortalidad del caso de auto-selección. Nuestro modelo de mortalidad incluye como variables independientes, entre otras, la edad del fondo (en meses), el tamaño del fondo (total de activos) y el rendimiento relativo en los pasados 6 trimestres (medido en términos de percentiles de la distribución). A partir de este modelo, obtenemos una estimación de la probabilidad condicional de mortalidad, y de allí, el factor de corrección del sesgo. Obtenemos dos resultados importantes. Primero, el sesgo es particularmente notorio en horizontes anuales, y en el último decil de la distribución, precisamente debido a su alta tasa de mortalidad. Si el sesgo no es debidamente corregido, el rendimiento de este decil puede ser sobreestimado en un 3.8% anual. Segundo, una vez implementada la corrección del sesgo, un claro patrón de persistencia existe en horizontes trimestrales, e incluso en horizontes anuales, aunque menos significativo estadísticamente. La diferencia en rendimiento entre el primer decil y el último decil de la distribución llega a 8.1%

anuales. En otras palabras, el rendimiento pasado de los fondos en el primer decil tiene una capacidad predictiva de su rendimiento futuro.

En el Capítulo 3, analizamos la sensibilidad del inversor al rendimiento pasado de fondos alternativos y su capacidad de explotar los patrones de persistencia identificados en el Capítulo 2. De acuerdo a la teoría de Berk y Green [2004], el hecho de que el patrón de persistencia es más acentuado en horizontes trimestrales con respecto a horizontes anuales, implicaría que los flujos de capital son menos competitivos y sensibles en horizontes trimestrales. En el Capítulo 3 ponemos a prueba esta hipótesis. Para ello estimamos un modelo que nos permite diferenciar la decisión de inversión (dada por flujos netos de capital positivos) y la decisión de desinversión (flujos netos de capital negativos) del inversor promedio en un fondo. Nuestro modelo demuestra una fuerte sensibilidad de flujos negativos a rendimientos bajos en el trimestre precedente, en tanto los flujos positivos son sensibles a los rendimientos altos únicamente en el largo plazo. Otras asimetrías en la respuesta de flujos positivos y negativos existen también a nivel de las variables de control. Cabe anotar que los estudios anteriores al nuestro no consideran la posibilidad de esta asimetría y por lo tanto integran flujos positivos y negativos en un mismo modelo. Los flujos positivos son mucho mas lentos en su respuesta, debido a la opacidad de los fondos alternativos y la asimetría de información, lo cual incrementa los costos y el tiempo de obtención de información, así como el tiempo necesario para su análisis. Por el contrario, los flujos negativos son relativamente rápidos debido al monitoreo frecuente al que está sujeto el gestor por parte de sus inversores. La segunda parte del Capítulo 3, demuestra, adicionalmente, que el inversor no tiene la capacidad de respuesta necesaria para explotar los patrones de persistencia en horizontes trimestrales. Como consecuencia los flujos positivos de capital terminan siendo colocados en fondos que no logran mantener altos rendimientos. Por el contrario, el inversor tiene una capacidad de respuesta suficientemente rápida en su decisión de desinversión que le permite explotar la persistencia de fondos con bajo rendimiento.

En el Capítulo 4 analizamos la posibilidad de que un componente en la respuesta del inversor al rendimiento pasado de fondos alternativos tenga su origen en un fenómeno cognitivo conocido como *la ley de los pequeños números*, inicialmente estudiado por los psicólogos Tversky y Kahneman [1971]. Este es un heurístico que tiende a ignorar la importancia del tamaño de una muestra al hacer inferencias acerca de una población. Como resultado, las inferencias realizadas a partir de una pequeña muestra suelen ser excesivas. Este es potencialmente el caso de un inversor que realiza inferencias acerca del rendimiento futuro de un fondo de inversión a partir de una secuencia corta de señales de rendimiento pasado. Si la secuencia muestra un patrón de persistencia, en teoría cuanto más extenso es el patrón, más excesivas son las inferencias realizadas, y más exagerada es la respuesta del inversor. Ponemos a prueba esta hipótesis a través de dos modelos. El primero es un modelo del rendimiento relativo de un fondo (en términos de percentiles de la distribución) a partir de secuencias de persistencia y otras variables de control. Los resultados de este primer modelo confirman la existencia de patrones de persistencia en el caso de fondos alternativos. Más aun, cuanto más extenso es el patrón de persistencia, mayor es la probabilidad de que el fondo *continúe* persistiendo. Por ejemplo, si un fondo ha mantenido rendimientos superiores a la media de la distribución durante cuatro trimestres, la probabilidad de que su rendimiento sea superior a la media en el quinto trimestre es alrededor del 60%. Pero si la secuencia es de 6 trimestres, la probabilidad de que el fondo tenga un rendimiento superior a la media durante un séptimo trimestre es del 70%. A partir de este primer modelo, obtenemos una estimación del rendimiento futuro de un fondo, e incorporamos esta variable en un modelo de flujos de capital. Entre las variables de control incluimos las secuencias de persistencia nuevamente. En principio, si el inversor es racional, su respuesta debería concentrarse por completo en el valor esperado de rendimiento, mientras las secuencias de persistencia no deberían tener ninguna influencia adicional. Sin embargo, los resultados demuestran lo contrario: las secuencias de persistencia tienen un efecto residual en la respuesta del inversor, y cuanto más extensa es la secuencia, más exagerada es la respuesta. Cabe anotar que los estudios anteriores al nuestro consideran el rendimiento pasado tan solo en horizontes anuales e ignoran el efecto de una secuencia bien definida de señales de rendimiento trimestrales en la respuesta del inversor.

Finalmente, el Capítulo 5 analiza la posibilidad de que un componente en la decisión de inversión o desinversión del inversor se concentre al nivel de *categorías (o estilos)* de fondos alternativos. En que medida el rendimiento promedio de una categoría de fondos tiene un efecto en la respuesta del agregado de inversores? La hipótesis de *inversión por estilos* -o *categorías*-, formulada por Barberis y Shleifer [2003], supone que los inversores toman en cuenta el rendimiento *relativo* entre categorías en su proceso de inversión. Por lo tanto este capítulo estudia la sensibilidad de flujos de capital *agregados* por categoría de fondos. El rendimiento de cada categoría de fondos esta a su vez dado por un índice. La complejidad y variedad de las estrategias de inversión utilizadas por fondos alternativos, ha llevado a la necesidad de crear una taxonomía de estilos de inversión que permita simplificar la evaluación y toma de decisión de los inversores. No hay una taxonomía única y universalmente aceptada. En general, para cada sistema de clasificación, existe un conjunto de índices de rendimiento por cada categoría. Los resultados de nuestro estudio indican una alta sensibilidad del agregado de inversores al rendimiento relativo de índices de categorías durante los tres trimestres anteriores. Sin embargo, este movimiento coordinado de flujos de capital del agregado de inversores no está justificado en manera alguna por el rendimiento en los trimestres posteriores a la inversión. De hecho, no existen diferencias significativas en rendimiento entre aquellas categorías con flujos positivos y aquellas con flujos negativos. Esto sugiere que los flujos de capital responden a percepciones erradas de rendimiento esperados y reflejan simplemente sentimientos generalizados de optimismo o pesimismo del conjunto de inversores en relación al rendimiento de una u otra categoría.

En resumen, esta tesis arroja cuatro conclusiones importantes:

- El rendimiento pasado de un fondo alternativo tiene un valor predictivo de rendimiento futuro. El sesgo de supervivencia es especialmente marcado en el último decil.
- Las decisiones de inversión y desinversión son asimétricas a varios niveles. En particular, los flujos negativos de capital responden rápidamente a rendimientos bajos en el trimestre anterior. Los flujos positivos responden más lentamente, y son sensibles a rendimientos altos en el largo plazo (horizontes anuales).
- El inversor no tiene la capacidad de respuesta para explotar los patrones de persistencia positiva. Sin embargo tiene la capacidad de explotar la persistencia de los fondos con rendimientos bajos.
- Los inversores aparentemente tienen una percepción errada de los patrones de persistencia, potencialmente debido a fenómenos cognitivos, tanto a nivel de fondos individuales como a nivel agregado por categorías de fondos.

Quedan por analizarse varios temas, apropiados para futura investigación. Cuáles son las implicaciones de los flujos negativos rápidos? Cuál es la percepción de los inversores acerca de las probabilidades de mortalidad? Es acaso su respuesta exagerada, de forma tal que incrementen a su vez las probabilidades de mortalidad? Por otro lado, las asimetrías entre flujos positivos y negativos quedan completamente abiertas a futuro análisis. Finalmente, los aspectos más interesantes de la hipótesis de inversión por estilos, quedan aun por ser abordados. Por ejemplo, existe acaso co-movimiento de retornos de fondos dentro de una misma categoría? Acaso las masivas inversiones en una categoría crean externalidades en otras categorías?

Son estas todas fascinantes preguntas, en la misma medida de la evolución futura de la industria de fondos alternativos.

Biography

Guillermo Baquero (Quito, 1967) is assistant professor of Finance and Investments at the *Rotterdam School of Management* of *Erasmus University Rotterdam* since 2005. He holds a degree in mechanical engineering (Quito, 1992) and has a professional experience of several years in the field of hydraulic and pneumatic automation. Later he obtained an MBA from the *Université Catholique de Louvain* and an MSc in Economics from the *Katholieke Universiteit Leuven*, in Belgium. Between 1999 and 2001 he worked as a research associate at the *Centre for Economic Studies* (CES) of the *Katholieke Universiteit Leuven*. In September 2001 he joined the *Financial Management Department* of the *Rotterdam School of Management* and the ERIM PhD program.

Guillermo's research has focused on the persistence of hedge funds and mutual funds, the behaviour of hedge fund investors, behavioural finance and experimental economics. The article at the basis of Chapter 3 of this book was awarded the prize for the best paper on hedge funds at the *European Finance Association meetings* in Zurich in 2006. The article at the basis of Chapter 2 was published in the *Journal of Financial and Quantitative Analysis* in 2005 and was awarded the prize for the second best paper on hedge funds at the *European Finance Association meetings* in Glasgow in 2003.

Guillermo's teaching experience includes a number of courses in Corporate Finance, Investments and Behavioural Finance, both at the bachelor and master level, and courses in Industrial Engineering at the executive level. He has worked as a consultant for several firms and organizations in Belgium and Ecuador in matters related to Finance and Development. He is also a guest lecturer at the *Latin-American Faculty of Social Sciences* (FLACSO) in Quito, Ecuador.

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On Hedge Fund Performance, Capital Flows and Investor Psychology

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