A Portrait of Hedge Fund Investors: Flows, Performance and Smart Money[1]

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Abstract

We explore the flow-performance interrelation by explicitly separating the investment and divestment decisions of hedge fund investors. The results show that different determinants and evaluation horizons underlie both decisions. While money inflows are sensitive to past long-run performance, outflows exhibit an immediate and sustained response to past performance in the short run. As a consequence, the shape of the flow-performance relation differs depending on the time horizon being analyzed. We find a weaker flow-performance relation for winning funds at quarterly horizons compared to annual horizons, which may explain why quarterly persistence in hedge fund performance is not competed away. Indeed, we also find evidence that most investors are unable to exploit the persistence of the winners. Conversely, investors are fast and successful in de-allocating from the persistent losers, ensuring a disciplining mechanism for low-quality funds. Further, our findings do not support the existence of smart money.

Keywords: hedge funds, flow-performance relation, performance persistence, liquidity restrictions, fund monitoring, searching costs, smart money.

JEL-codes : G11, G23, G14

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 signaling 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.

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]) [4], 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.

[4] 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).

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 behavior of hedge fund investors is instead characterized by a regular monitoring, especially for style drift, on a monthly or a quarterly basis[5]. Searching costs and active monitoring are also likely to have an impact on the response of money flows to past performance.[6]

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

[5] 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.

[6] 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.

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 explanation for the different shape of the flow-performance relation between time horizons, by making plain clear 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 in 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 modeled 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 presents the base specification of our model of flows and demonstrates the existence of a linear short-run flow-performance relation, while Section 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 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 6 concludes.

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 March 2000. 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)[7]. We concentrate on the period between the fourth quarter of 1994 and the first quarter of 2000 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.[8] We focus on hedge funds reporting returns in $. This is essentially the same dataset as employed by Baquero, ter Horst and Verbeek [2005], which includes a total of 1797 funds. However, we exclude 111 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 302 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 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.

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[7] 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.

[8] 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.

We use quarterly data, which allows us to explore the short-term dynamics of investment and redemption behavior. 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[9]. 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.[10]

Since we consider quarterly horizons, we take into account the most recently available value of total net assets (TNA) in each quarter.[11] 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.[12] 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 752 funds and a total of 7457 fund-period observations. The graveyard consists of 249 funds, from which 163 actually liquidated, while the remaining 86 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 177 funds at the end of the fourth quarter of 1994, accounting for about $ 13 billion in net assets, and 508 funds at the end of the first quarter of 2000, accounting for $ 50 billion. This represents nearly 15% of the total for the entire industry estimated by TASS of about $ 350 billion of assets under management as for March 2000.

[9] 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.

[10] 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.

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

[12] 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.

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 752 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. The sample period has 22 quarters 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 TNA of previous period.

	Number of funds	Aggregate Cash Flows (million dollars)	Cash flows (growth rate)	Aggregate TNA (million dollars)	Average Return
1994 Q4	177	-362.72	-0.0269	12935.96	-0.0021
1995 Q1	196	-753.28	-0.0570	12863.09	0.0572
1995 Q2	214	-442.66	-0.0324	13720.42	0.0355
1995 Q3	227	264.19	0.0185	15013.13	0.0396
1995 Q4	238	-146.53	-0.0096	15182.34	0.034
1996 Q1	256	191.88	0.0119	17167.14	0.0229
1996 Q2	266	56.48	0.0032	18426.25	0.0555
1996 Q3	273	284.42	0.0149	19569.91	0.0157
1996 Q4	286	708.69	0.0350	22566.14	0.0582
1997 Q1	291	2039.81	0.0889	25853.97	0.038
1997 Q2	303	1006.38	0.0380	28452.97	0.0438
1997 Q3	325	1473.40	0.0499	33870.24	0.0702
1997 Q4	347	1004.83	0.0282	37434.67	-0.0202
1998 Q1	379	739.64	0.0191	41338.83	0.0477
1998 Q2	390	1733.43	0.0410	45077.76	-0.024
1998 Q3	406	166.86	0.0037	42165.30	-0.0487
1998 Q4	427	-2134.98	-0.0491	40034.94	0.0594
1999 Q1	457	-1899.65	-0.0444	41447.99	0.0377
1999 Q2	478	-622.32	-0.0149	43825.66	0.0872
1999 Q3	508	-562.53	-0.0123	44341.45	-0.0019
1999 Q4	505	-509.99	-0.0114	49450.22	0.1269
2000 Q1	508	-482.42	-0.0101	49912.06	0.0586

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 $t+1$. [13]

$$CashFlow_{t+1} = \frac{TNA_{t+1} - TNA_t}{TNA_t} - r_{t+1} \qquad (1)$$

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

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

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

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 5, both definitions contribute with different information regarding the investments in hedge funds.

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 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 the 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

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.[14] 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 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.[15] A popular measure that captures the preference for positive skewness is the upside potential ratio, which combines upside potential as the numerator and downward variation as the denominator.[16] 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.[17] 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

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[14] 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.

[15] 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]).

[16] We use the following definition of upside potential ratio:

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

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)

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

inducing greater risk.[18] 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. 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 72% 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 46 months (lnAge = 3.829). 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 55% 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 their redemption periods are shorter than for 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.

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

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 752 hedge funds for the period 1994Q4 till 2000Q1. 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 US 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.

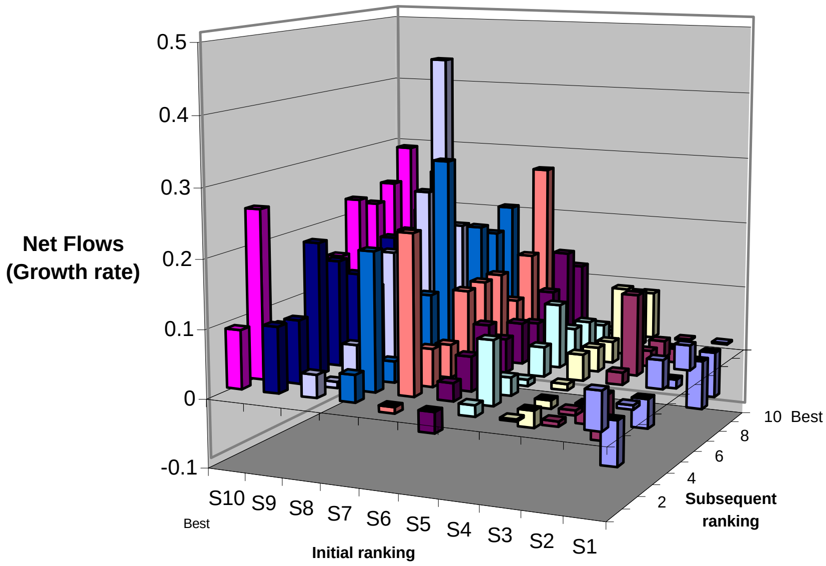
Variable	Mean	Std. Dev.	Min	Max
Cash Flows (growth rate)	0.0295	0.3215	-1.4303	8.1577
Cash Flows>0 (3676 obs)	0.1751	0.3792	0.0001	8.1577
Cash Flows<0 (3551 obs)	-0.1193	0.1549	-1.4303	-0.0001
Cash Flows=0 (407 obs)				
Cash Flows (dollars)	235008.8	3.70E+07	-1.41E+09	6.87E+08
ln(TNA)	16.7296	1.8298	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

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 – 2000Q1. 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 2000Q1 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 25% 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:

$$Flow_{i,t} = a + \sum_{j=1}^{6} b_{1,j}.(rnk_{i,t-j}) + b_2.\ln(NAV_{i,t-1}) + b_3.\ln(AGE_{i,t-1}) + \sum_{j=1}^{4} b_{4,j}.(Flow_{i,t-j}) + g'.X_{i,t} + l_t + e_{i,t} \quad (3)$$

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 l_t, to capture economy wide shocks conducing to different average flows across quarters, as suggested by Table I.

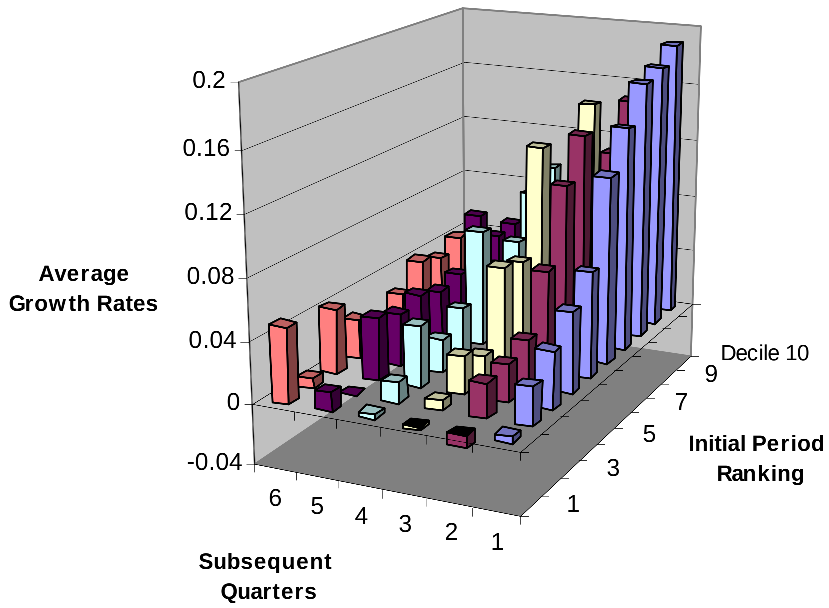
Previous research on the flow-performance relationship uses annual data and studies the impact of previous year performance upon current year flows. Here we use quarterly data and we should determine the (maximum) time horizon over which historical performance has an impact on quarterly flows of money. 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 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 and the top deciles experience huge inflows. In Panel A, these same cash outflows averaged in terms of growth rates are close to zero although hardly negative for poor performers compared to the large growth rates enjoyed by the best performers. The fact that large dollar outflows appear very small as growth rates is an indication 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 behavior.

Figure 2

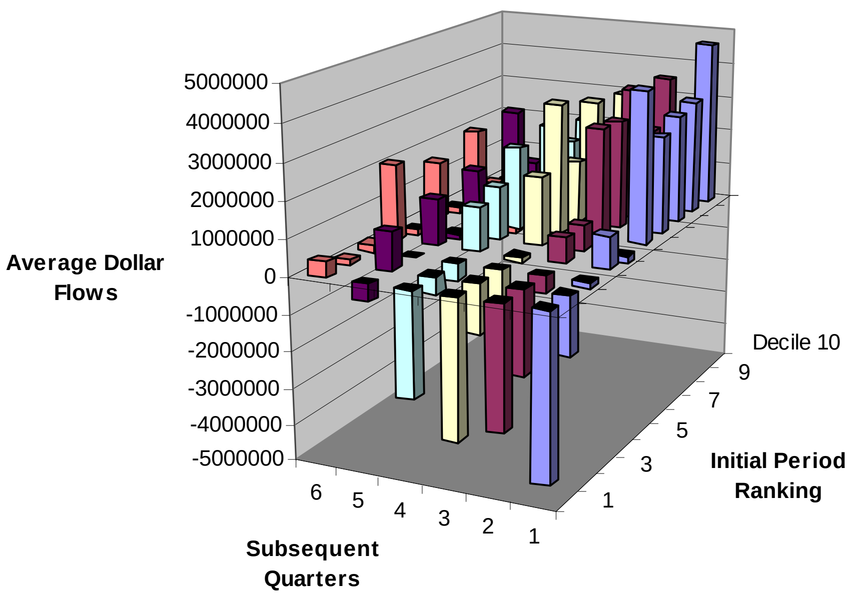
Average Flows across Deciles
Over Subsequent Quarters after Ranking

In each quarter from 1994Q4 to 2000Q1 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



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]).[19] 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 25^{th} to the 75^{th} percentile in the previous quarter, this is associated with an economically and statistically significant 6.5% quarterly growth (column A). This accounts for nearly 32% of the total long-run impact. The effect gradually disappears but is an important determinant of growth rates even up to 5 lagged quarters. In the long-run, an improvement in relative performance from the 25^{th} to the 75^{th} percentile corresponds to a growth rate of 25% 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 variables.[20] 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.[21] In an alternative specification we use raw returns instead of ranks as a measure of performance. Both

[19] 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.
[20] Results of our tests for non-linearities are available upon request.
[21] 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.

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 752 open-end hedge funds for the period 1994 Q4 till 2000 Q1. 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, upside potential based on the entire past history of the fund and calculated with respect to the return on the US 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 21 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	0.2059	(3.07)	1.50E+07	(1.07)
Rank lag 1	0.1300	(8.91)	9062120	(4.70)
Rank lag 2	0.0856	(6.35)	7134531	(4.34)
Rank lag 3	0.1064	(7.09)	5995536	(3.04)
Rank lag 4	0.0601	(4.11)	2760659	(1.62)
Rank lag 5	0.0319	(2.53)	-1017801	(-0.63)
Rank lag 6	-0.0028	(-0.22)	-1510093	(-0.97)
ln(TNA)	-0.0187	(-5.27)	-840701.9	(-1.34)
ln(AGE)	-0.0195	(-3.17)	-2512114	(-2.75)
Flows lag 1	0.0435	(2.49)	3705023	(4.47)
Flows lag 2	0.0418	(2.98)	2548164	(3.54)
Flows lag 3	0.0299	(1.75)	1585205	(2.77)
Flows lag 4	0.0154	(1.46)	603907	(1.67)
Offshore	0.0052	(0.66)	-1000580	(-1.48)
Incentive Fees	-0.0015	(-3.21)	-199067.1	(-2.61)
Management Fees	-0.0074	(-1.58)	401933.2	(1.36)
Personal Capital	0.0064	(0.71)	-815875.9	(-1.51)
Leverage	0.0071	(0.93)	-184713	(-0.27)
Upside Potential Ratio	0.0009	(4.80)	31060.62	(2.01)
Emerging Markets	-0.0391	(-2.83)	-2008305	(-1.50)
Equity Market Neutral	0.0024	(0.17)	-515577.2	(-0.43)
Event Driven	-0.0051	(-0.41)	-1023625	(-0.81)
Fixed Income Arbitrage.	-0.0331	(-1.42)	-3351667	(-2.75)
Global Macro	-0.0283	(-1.46)	-1.95E+07	(-1.35)
Long/Short Equity	-0.0391	(-3.48)	-2606461	(-2.28)
Managed Futures	-0.0281	(-1.85)	-2312161	(-2.00)
R^2	0.0702		0.0325	
Number of observations	7425		7425	

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 0.27% 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.[22]

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 0.15% per quarter. It is evident that in spite of the presumably higher managerial 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" and "long short equity" 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 4, where we show that the impact of size cannot be appropriately captured if the investment and divestment decisions are not modeled 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

[22] An F-test on the inclusion of the six lagged raw returns in our model gives the value of 3.24 (the 1% critical value being 2.80 for an F-distribution with 6 and 7372 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 ranks, 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.

existence of short-run factors conditioning money flows. We defer the discussion of this issue to Section 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 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 upside potential to downside deviation 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 10% and the total long-run impact of historical performance reduces by 7%, 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.[23] 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. Yet, we did perform a robustness check. Assuming total divestment of assets when a fund ceases reporting, only slightly enhances the sensitivity of flows. The total long-run impact of the 6 lagged ranks increases by 8% and the impact of the first lagged rank increases by 4%. Again, linearity is not rejected.

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

[23] 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.

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].[24] 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.[25] The result might be a slow reaction of hedge fund investors to hire managers 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.

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, US 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

[24] 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.

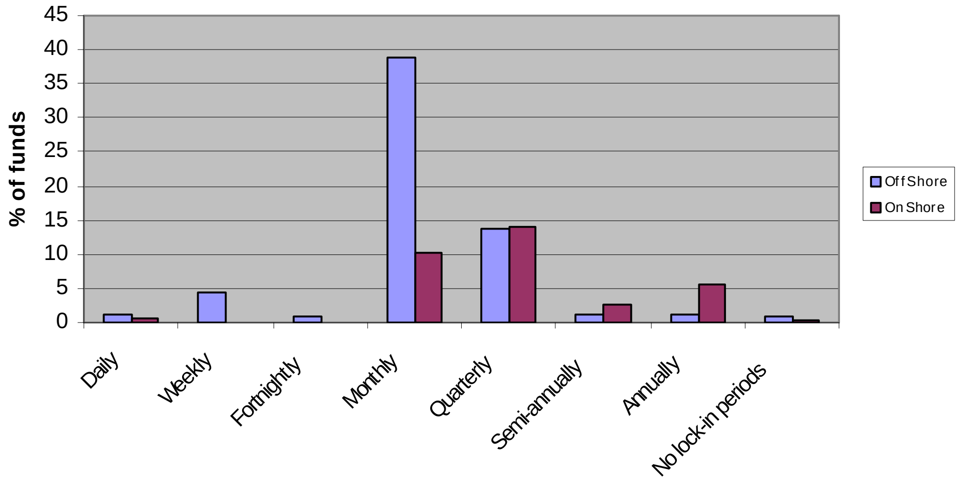
[25] See Bekier [1996] for evidence and for a detailed description of the buying process and the post-investment behaviour of hedge fund investors. Bekier quotes a hedge fund institutional investor who acknowledges that their standard process of investment may take up to 18 months, from the identification 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.

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%.

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.



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, 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.

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

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	181 to 365 days
1	0.43	0.06	0.18	0.24				
7	0.91	0.79	2.62	0.24	0.18			
15		0.12	0.30	0.30		0.06		
30	0.79	1.22	6.51	18.20	20.57	5.23		0.06
90		0.06	0.56	2.43	15.09	11.38	0.30	
183				0.06	1.52	2.37	0.06	
365					1.77	4.99	0.37	

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.[26] 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 combined impact of the five coefficients is a 10% higher for unrestricted ranks while the effects of the control variables remain basically unchanged. Nearly 80% 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.[27] Also the sensitivity of inflows and outflows might be 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

[26] 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 $Rank_{i,t-j}$.

[27] 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 752 open-end hedge funds for the period 1994 Q4 till 2000 Q1. 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, upside potential based on the entire past history of the fund and calculated with respect to the return on the US 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 21 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 Modeling growth rates (A)		OLS estimates Modeling dollar flows (B)	
Intercept	0.2018	(3.01)	1.37E+07	(0.296)
Rank lag 1 Unrestricted	0.1327	(8.63)	8095965	(5.50)
Rank lag 2 Unrestricted	0.0844	(5.85)	6172155	(4.10)
Rank lag 3 Unrestricted	0.1084	(6.76)	6362955	(3.92)
Rank lag 4 Unrestricted	0.0625	(4.00)	2835370	(1.68)
Rank lag 5 Unrestricted	0.0290	(2.16)	954970.5	(0.90)
Rank lag 6	-0.0027	(-0.20)	-1654365	(-1.02)
Rank lag 1 Restricted	0.1067	(4.42)	1.88E+07	(1.26)
Rank lag 2 Restricted	0.0952	(3.26)	1.64E+07	(2.48)
Rank lag 3 Restricted	0.0876	(4.11)	1180014	(0.09)
Rank lag 4 Restricted	0.0322	(1.20)	5859846	(1.35)
Rank lag 5 Restricted	0.0641	(2.47)	-2.21E+07	(-1.49)
ln(TNA)	-0.0185	(-5.23)	-816530.6	(-1.34)
ln(AGE)	-0.0195	(-3.16)	-2377354	(-2.78)
Flows lag 1	0.0436	(2.50)	3719029	(4.46)
Flows lag 2	0.0417	(2.97)	2510160	(3.56)
Flows lag 3	0.0298	(1.74)	1528694	(2.70)
Flows lag 4	0.0153	(1.45)	575474.4	(1.65)
Offshore	0.0025	(0.32)	-1154538	(-1.36)
Incentive Fees	-0.0015	(-3.05)	-198283.1	(-2.69)
Management Fees	-0.0073	(-1.54)	450943.6	(1.42)
Personal Capital	0.0066	(0.72)	-797154.8	(-1.46)
Leverage	0.0074	(0.96)	-31366.5	(-0.05)
Upside Potential Ratio	0.0009	(4.83)	30392.97	(1.92)
Emerging Markets	-0.0386	(-2.79)	-1801595	(-1.35)
Equity Market Neutral	0.0013	(0.09)	-451200.4	(-0.37)
Event Driven	-0.0037	(-0.30)	-551890.3	(-0.38)
Fixed Income Arbitrage.	-0.0338	(-1.45)	-3356732	(-2.73)
Global Macro	-0.0275	(-1.42)	-1.94E+07	(-1.36)
Long/Short Equity	-0.0388	(-3.45)	-2389811	(-2.00)
Managed Futures	-0.0298	(-1.95)	-2554907	(-1.97)
R2	0.0702		0.0365	
Number of observations	7425		7425	

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.[28] 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

$Flows_{n,it}$ when $S_{it}=1$,

or $Flows_{d,it}$ when $S_{it}=0$, but never both.

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

$$S_{i,t}^{*} = a + \sum_{j=1}^{6} b_{1,j}.(rnk_{i,t-j}) + b_2.\ln(TNA_{i,t-1}) + b_3.\ln(AGE_{i,t-1}) + \sum_{j=1}^{4} b_{4,j}.(Flow_{i,t-j}) + g'.X_{i,t} + l_i + m_{i,t} \qquad (4)$$

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 $Flows_{d,i}$, modeled as in equation (3) but incorporating the generalized 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

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

[28] 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.

The latter expectation reflects the generalized residual of equation (4) (see e.g. Verbeek [2004], Chapter 7).[29] 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 three quarters. Finally, several investment style dummies also have a significant impact. Event driven funds have, ceteris paribus, the highest probability to induce an investment decision from investors, while funds operating in emerging markets are the most likely to induce divestment decisions.

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, most of the coefficients for the model of positive cash flows become statistically insignificant in comparison with our previous results using the pooled model. The impact of past relative performance upon the rates of cash flows is almost 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 35% 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 67% more outflows than restricted funds.

The control variables also capture several significant asymmetries between the two regimes. Size and age of the fund play a significant role for positive rates of flows only. For example, larger and older funds experience, ceteris paribus, lower positive growth rates compared to small and younger funds, while outflows of money appear to be independent

[29] 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 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 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, upside potential based on the entire past history of the fund and calculated with respect to the return on the US 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 21 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)	Estimation using a truncated sample for CFlows <0 (B)	Estimation using a truncated sample for CFlows > 0 (C)
Intercept	-0.3662 (-1.64)	-0.1530 (-2.69)	0.6268 (2.80)
Rank lag 1 Unrestricted	0.7536 (13.23)	0.1355 (3.83)	0.1481 (1.57)
Rank lag 2 Unrestricted	0.5598 (9.72)	0.0976 (3.62)	0.0713 (1.01)
Rank lag 3 Unrestricted	0.5180 (8.99)	0.0692 (2.82)	0.1596 (2.68)
Rank lag 4 Unrestricted	0.3028 (5.26)	0.0466 (2.85)	0.0812 (1.73)
Rank lag 5 Unrestricted	0.2051 (3.57)	0.0337 (2.58)	0.0218 (0.64)
Rank lag 6	0.0362 (0.65)	0.0085 (0.89)	-0.0201 (-0.86)
Rank lag 1 Restricted	0.5934 (3.75)	0.0811 (2.30)	0.1444 (1.90)
Rank lag 2 Restricted	0.4953 (3.15)	0.0998 (2.96)	0.1159 (1.74)
Rank lag 3 Restricted	0.8069 (4.92)	0.1430 (3.27)	0.0945 (1.02)
Rank lag 4 Restricted	0.4891 (2.84)	0.0565 (1.79)	0.0309 (0.45)
Rank lag 5 Restricted	0.1184 (0.70)	0.0406 (1.54)	0.0652 (1.61)
Ln(TNA)	-0.0166 (-1.59)	0.0002 (0.09)	-0.0387 (-5.63)
Ln(AGE)	-0.1763 (-5.78)	0.0070 (0.77)	-0.0516 (-2.17)
Flows lag 1	0.3083 (4.27)	0.0480 (2.22)	0.0419 (1.29)
Flows lag 2	0.2600 (4.40)	0.0523 (2.94)	0.0341 (1.15)
Flows lag 3	0.1201 (2.74)	0.0167 (1.37)	0.0366 (1.39)
Flows lag 4	0.0753 (1.82)	0.0196 (3.02)	0.0132 (0.74)
Offshore	-0.1338 (-3.67)	-0.0497 (-5.65)	0.0455 (2.33)
Incentive Fees	-0.0040 (-1.63)	-0.0019 (-5.04)	-0.0018 (-1.70)
Management Fees	-0.0154 (-0.85)	-0.0041 (-1.35)	-0.0047 (-0.59)
Personal Capital	-0.0492 (-1.31)	0.0038 (0.54)	-0.0015 (-0.09)
Upside Potential Ratio	0.0078 (1.62)	0.0024 (3.98)	0.0008 (2.93)
Emerging Markets	-0.1521 (-2.27)	-0.0142 (-1.17)	-0.0617 (-2.13)
Event Driven	0.1626 (2.74)	0.0152 (1.32)	-0.0146 (-0.50)
Fixed Income Arbitrage.	-0.2611 (-1.86)	0.0132 (0.71)	-0.0948 (-1.78)
Long/Short Equity	-0.0356 (-0.71)	-0.0154 (-1.91)	-0.0610 (-3.16)
Managed Futures	-0.1129 (-1.99)	-0.0242 (-2.24)	-0.0391 (-1.17)
Generalized Residual from Probit Model		0.1981 (2.61)	0.1605 (0.85)
Chi^2 (51)	847.59		
Pseudo R^2	0.1037	0.0806	0.066
Number of observations	7195	3542	3653

of fund size and age. 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[30]. 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 "managed futures", which becomes significant but only for negative cash flows, while the impact of funds with styles "emerging markets" and "long short equity" remains significant only for positive growth rates. Finally, the upside potential ratio appears to affect both regimes positively and significantly, although the impact upon positive cash flows is substantially lower.

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 Table IV, 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 modeling money inflows and outflows. Summing up, while our model explaining growth rates shows a size effect entirely captured by the regime of positive flows (i.e. small funds grow faster than large funds), we also show that large funds may face important withdrawals in dollar terms, which gives further

[30] 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 in annual horizons for mutual funds and hedge funds (see, e.g., Del Guercio and Tkac [2002] and Agarwal, Daniel and Naik [2003]).

evidence in favor of diseconomies of scale playing a role. Section 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.

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 752 open-end hedge funds for the period 1994 Q4 till 2000Q1. 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, upside potential based on the entire past history of the fund and calculated with respect to the return on the US 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 21 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=7195 obs., from which 3542 are negative cash flows)			
Previous one-year rank	1.0831 (18.75)	0.1843 (2.97)	0.0994 (0.76)
Ln(TNA)	-0.0111 (-1.07)	-0.0010 (0.53)	-0.0375 (-5.54)
Panel 2 : Annual Flows (N=6408 obs., from which 3147 are negative cash flows)			
Previous one-year rank	1.1093 (18.57)	0.2028 (2.24)	1.2461 (3.04)
Ln(TNA)	-0.0525 (-4.77)	-0.0144 (-2.65)	-0.2026 (-6.62)
Panel 3 : Annual Flows (N=6408 obs., from which 3147 are negative cash flows)			
One-quarter rank lag 1	0.8738 (14.96)	-0.0150 (-0.28)	0.8356 (3.03)
One-quarter rank lag 2	0.6871 (11.78)	-0.0312 (-0.72)	0.7447 (3.22)
One-quarter rank lag 3	0.4362 (7.47)	0.0149 (0.50)	0.6553 (3.86)
Ln(TNA)	-0.0458 (-4.06)	-0.0046 (-1.14)	-0.1966 (-7.33)

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 is significant and 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.

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.

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. Since the median of money flows, either in terms of growth rates or dollar flows, is very close to zero (see Table II), the above median funds represent pretty well the set of investment opportunities available to investors. Similarly, the below median funds constitute a good approximation of their set of divestment targets. We refer to the above and below-median portfolios as the *investment portfolio* and the *divestment portfolio*, respectively. 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.[31] Table IX summarizes our results when we consider raw 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 22 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 return significantly outperforms the equally weighted return for the investment portfolio by 1.07% (Panel A, in Table IX and Figure 4). Surprisingly, the situation reverses in the subsequent quarters. While the equally weighted return reduces by 0.56% in the quarter following the initial ranking, the cash flow weighted return on the investment portfolio falls by more than 2.5%, significantly underperforming the equally weighted return by nearly 1% per quarter for holding periods up to one year. If investors decide to keep their money four more quarters in the investment set, their returns will underperform even further the equal allocation strategy by a significant 1.35% per quarter. On a style-adjusted basis, as shown in Panel A of Figure 4, the differences exacerbate for short holding periods. For example, in the quarter following the ranking period, investors' returns significantly underperform the equally weighted return by 1.38%, and also the style index by 1.13%. These figures 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.

[31] Recall that our sample period contains 22 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 21 quarters, until 1999Q4. Similarly, for a holding period of eight quarters, we can conduct this procedure along 14 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 1999Q4 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 raw 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 cash flows above the median (the "investment portfolio") and below the median (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 above-median portfolio against the return of the below-median 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
CashFlow Weighted	0.0546	0.0291	0.0280	0.0288	0.0266	0.0270	0.0234	0.0212	0.0210
Equally Weighted	0.0439	0.0383	0.0383	0.0369	0.0357	0.0349	0.0346	0.0338	0.0345
Difference	0.0107	-0.0093	-0.0103	-0.0081	-0.0091	-0.0079	-0.0112	-0.0125	-0.0135
Standard error	(0.0051)	(0.0051)	(0.0049)	(0.006)	(0.0075)	(0.0088)	(0.0068)	(0.0066)	(0.0067)

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
CashFlow Weighted	0.0217	0.0311	0.0340	0.0336	0.0346	0.0392	0.0417	0.0406	0.0426
Equally Weighted	0.0279	0.0359	0.0356	0.0346	0.0362	0.0363	0.0354	0.0333	0.0342
Difference	-0.0062	-0.0048	-0.0017	-0.0009	-0.0016	0.0030	0.0064	0.0073	0.0083
Standard error	(0.0062)	(0.0049)	(0.0061)	(0.0061)	(0.0081)	(0.0086)	(0.0112)	(0.0128)	(0.0158)

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
CashFlow Weighted	0.0329	-0.0021	-0.0060	-0.0049	-0.0080	-0.0122	-0.0184	-0.0194	-0.0216
	(0.0085)	(0.0082)	(0.0095)	(0.0107)	(0.0111)	(0.0119)	(0.0141)	(0.0149)	(0.0162)
Equally Weighted	0.0159	0.0024	0.0027	0.0023	-0.0005	-0.0013	-0.0008	0.0005	0.0003
	(0.0044)	(0.0035)	(0.0036)	(0.0042)	(0.0046)	(0.0061)	(0.0054)	(0.0041)	(0.0036)

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[32]. Moreover, given liquidity restrictions, it seems unlikely that hedge fund investors can benefit from the short-lived high returns occurring contemporaneously to flows.

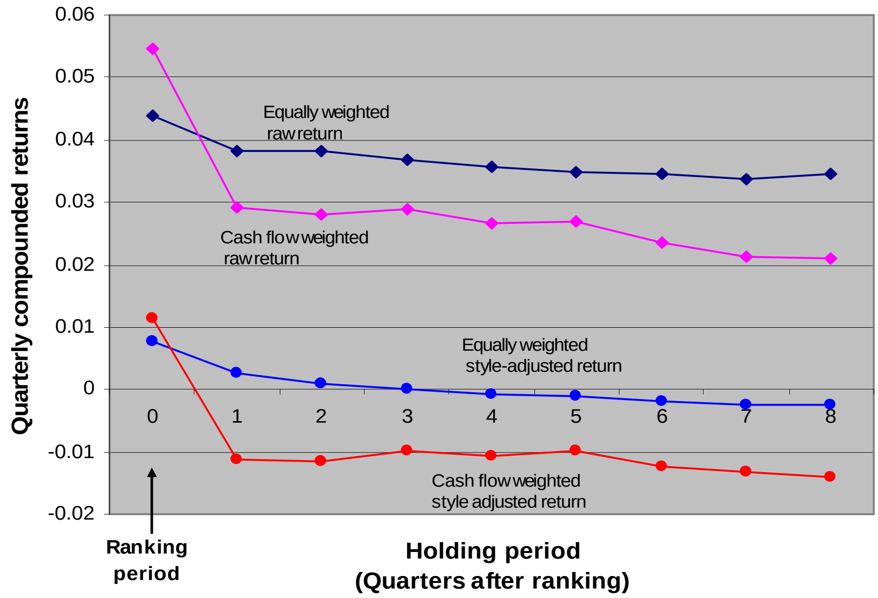
[32] A likely explanation is that fund managers cannot maintain those high returns for long periods of time, not even for one more quarter, as profitable investment opportunities are scarce. Thus, the huge inflows of money attracted by short-lived high returns end up allocated in less attractive investment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

Figure 4

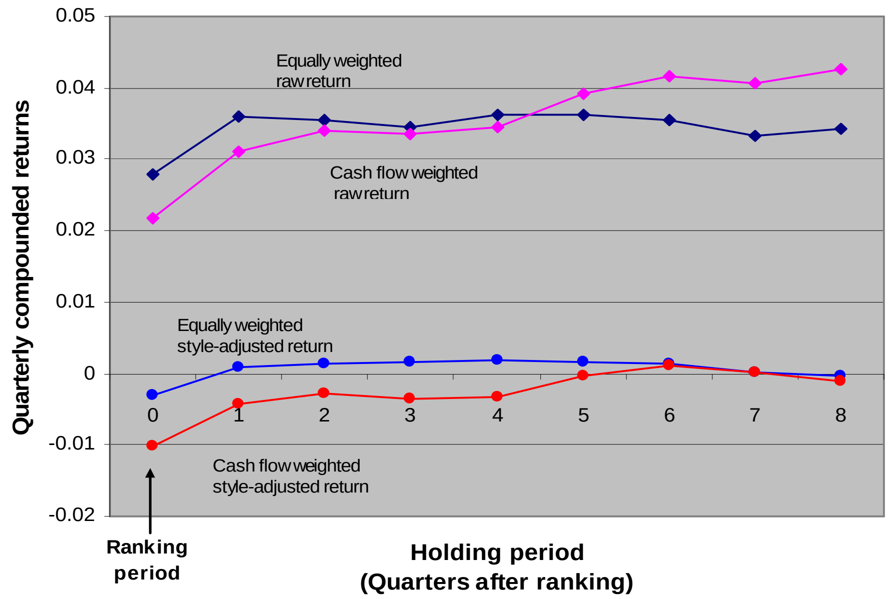
Time-series Averages of Cash Flow Weighted Returns and Equally Weighted Returns for Different Holding Periods

Hedge funds are ranked every quarter from 1994Q4 to 1999Q4 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 cash flows above the median (the “investment portfolio”) and below the median (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



On the other hand, the divestment allocations work pretty well by allowing investors to reduce to some extent the return they give up by divesting. In the ranking period the cash flow weighted return for the divestment portfolio is somewhat reduced compared to the equally weighted return, although the difference is statistically insignificant (Panel B, in Table IX and Figure 4). In the quarters subsequent to ranking, there are no significant differences between the actual investors' allocation strategy and the equally weighted strategy, although the cash flow weighted return is somewhat lower up to holding periods of 5 quarters. Furthermore, on a style-adjusted basis, both are not statistically distinguishable from the style index (Panel B, Figure 4).

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 1.6% and 1.1% in terms of absolute returns and style-adjusted returns respectively. Furthermore, if we look at cash flow weighted returns, this difference is considerably magnified, becoming 3.29% in terms of raw returns and 2.17% on a style-adjusted basis, twice as much as the difference for the equally weighted 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"[33].

However, we do not find evidence of smart money, defined by the extent to which returns of the above-median portfolio outperform the below-median 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, suggesting that hedge fund performance is unrelated to historical cash flows. Furthermore, for holding periods longer than four quarters, below-median funds increasingly outperform the above-median funds.[34]

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 1.14 million

[33] 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.

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

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 1999Q4. 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	1138672	0.1102	0.0426	7899256	0.0546	0.0291
Below-median funds	-420882	-0.0397	0.0316	-7385571	0.0217	0.0311
Difference		0.1499 (0.0105)	0.0110 (0.0086)		0.0329 (0.0085)	-0.0021 (0.0082)

US$ while below-median funds experience outflows of about –420000 US$ on average. These figures are in absolute value far below the averages obtained in Panel B for the investment and divestment portfolios (of about 7.9 and -7.4 million US$, respectively), indicating that only few investors are able to exploit positive persistence. The Spearman rank correlation coefficient between the two strategies is on average 0.082, 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). Conversely, the repeat-winner strategy predicts losers better. We find the opposite results for hedge funds. The investment portfolio performs substantially worse than above-median funds in the repeat-winner strategy (2.91% against 4.26%), while the cash flow weighted return on the divestment portfolio in the subsequent quarter after ranking is about 3.11%, slightly worse than the repeat-winner strategy, meaning that it 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 32 million US$ of net inflows for the top decile, which is around 81% 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 4.82% per quarter (fifth column), performing better than most of above-median portfolios, but do not significantly outperform the style index. In contrast, funds in the second and third above-median deciles outperform their style index by 1.5% and 1.1% respectively. Most importantly however, in the first quarter after ranking (sixth column), the average raw return of funds in the top decile falls to 2.44%, underperforming 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. The style-adjusted return also falls to –1.3%, significantly underperforming the style index, in contrast again to the performance of the second and third deciles.

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, experiencing proportionally larger dollar inflows and outflows. Funds in the top and bottom portfolios have on average 270 million and 304 million dollars in assets under management, respectively, together accounting for almost 70% 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 32 million US$ from the bottom decile, corresponding to 86% of all net outflows on average in below-median portfolios. Funds in the bottom portfolio are significantly older than funds in the top decile (63 months vs. 53 months old, not reported), although both figures are above the average life of a hedge fund in our sample (around 46 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).[35]

[35] 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 16% for some of the below-median portfolios after 8 quarters, while only 10.8% of funds in the bottom decile and 5.8% 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.

Table XI

Results from Sorting Funds in Deciles Based on Cash Flow Information

In each quarter, from 1994Q4 until 2000Q1, 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 22 quarters when we evaluate the performance at the end of the ranking period. We average over 21 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	31990875	270335775	0.0361	0.0482	0.0244	0.0083	(0.0057)	-0.0129	(0.0037)
2	5220235	64937770	0.0413	0.0548	0.0415	0.0150	(0.0053)	0.0056	(0.0050)
3	1677148	42277500	0.0498	0.0479	0.0483	0.0113	(0.0041)	0.0080	(0.0045)
4	511681	22030993	0.0568	0.0356	0.0372	-0.0010	(0.0059)	0.0043	(0.0053)
5	96343	13827815	0.0636	0.0385	0.0421	0.0067	(0.0068)	0.0117	(0.0061)
6	-62963	13769655	0.0668	0.0146	0.0377	-0.0117	(0.0064)	0.0060	(0.0077)
7	-339940	16451894	0.0645	0.0248	0.0293	-0.0010	(0.0079)	-0.0048	(0.0071)
8	-1166137	28250860	0.0565	0.0349	0.0385	0.0034	(0.0060)	0.0006	(0.0053)
9	-3783236	64065157	0.0473	0.0331	0.0311	-0.0008	(0.0047)	-0.0045	(0.0060)
Low 10	-31575580	303904259	0.0426	0.0265	0.0411	-0.0070	(0.0046)	0.0022	(0.0055)
High-Low	63566455	-33568484	-0.0065	0.0217	-0.0166	0.0153	(0.0063)	-0.0152	(0.0062)
			(0.0018)	(0.0077)	(0.0074)				

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	0.5869	39470274	0.0488	0.0651	0.0389	0.0263	(0.0079)	0.0023	(0.0058)
2	0.1454	74105656	0.0480	0.0459	0.0369	0.0101	(0.0046)	0.0004	(0.0044)
3	0.0707	102757397	0.0468	0.0425	0.0354	0.0047	(0.0054)	-0.0013	(0.0043)
4	0.0296	127072190	0.0469	0.0331	0.0392	-0.0017	(0.0058)	0.0010	(0.0069)
5	0.0078	91574826	0.0582	0.0325	0.0413	-0.0009	(0.0047)	0.0097	(0.0054)
6	-0.0067	69821320	0.0587	0.0188	0.0385	-0.0122	(0.0056)	0.0031	(0.0060)
7	-0.0262	93245734	0.0583	0.0204	0.0347	-0.0092	(0.0066)	-0.0002	(0.0069)
8	-0.0588	88237750	0.0561	0.0242	0.0331	-0.0053	(0.0068)	-0.0028	(0.0057)
9	-0.1259	99617725	0.0513	0.0310	0.0372	-0.0008	(0.0059)	0.0014	(0.0060)
Low 10	-0.3557	51232233	0.0526	0.0457	0.0358	0.0121	(0.0076)	0.0025	(0.0066)
High-Low	0.9426	-11761959	-0.0038	0.0194	0.0031	0.0142	(0.0106)	-0.0001	(0.0060)
			(0.0022)	(0.0120)	(0.0067)				

The above results help to improve our understanding of one of the main conclusions from the switching regression model in Section 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.

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 90 million dollars or more on average[36]. Funds in the top decile experience huge average growth rates of nearly 59% and exhibit the highest rates of return in the ranking period, of about 6.5% (2.63% on a style-adjusted basis). However, in the quarter subsequent to ranking, the equally weighted raw return on the top portfolio falls by 2.63% towards levels around 3.9%, underperforming several other above-median deciles. Results not reported reveal that the cash flow weighted return underperforms the equal allocation strategy by 1.25% and also the style index by about 1%. 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 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 X, deserves a separate analysis. Funds in the bottom portfolio shrink at an average rate of nearly –36%. 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

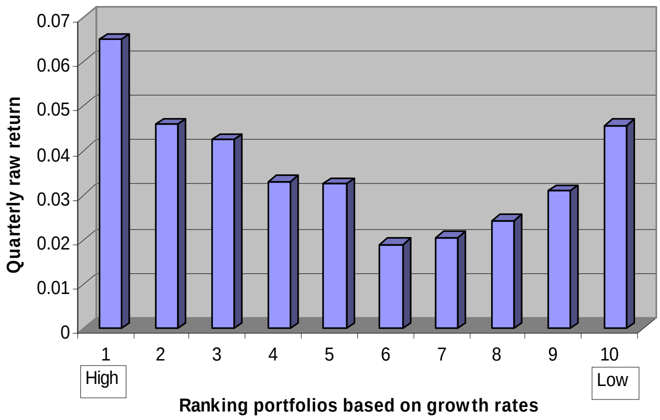
[36] Extreme growth rates are likely to be associated with small funds. Both positive and negative growth rates tend to be magnified when the total net assets at the beginning of a quarter – the denominator in equation (1) – is small. Conversely, large funds in the middle deciles experience very small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

deciles. In fact, the quarterly average raw return on the portfolio that received the highest cash flows exceeds the return on the bottom portfolio by 1.94%, but this difference is only marginally significant. However, the return on the top portfolio exceeds the return on any other below-median portfolio by at least 3.41%, which is economically and statistically significant. The results are similar in terms of style adjusted returns.[37]

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 2000Q1. 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 22 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[38]. The extreme outflow rates of funds in the bottom 10% are the result of persistent poor performance. If managers of these funds cannot make up losses to surpass the water-

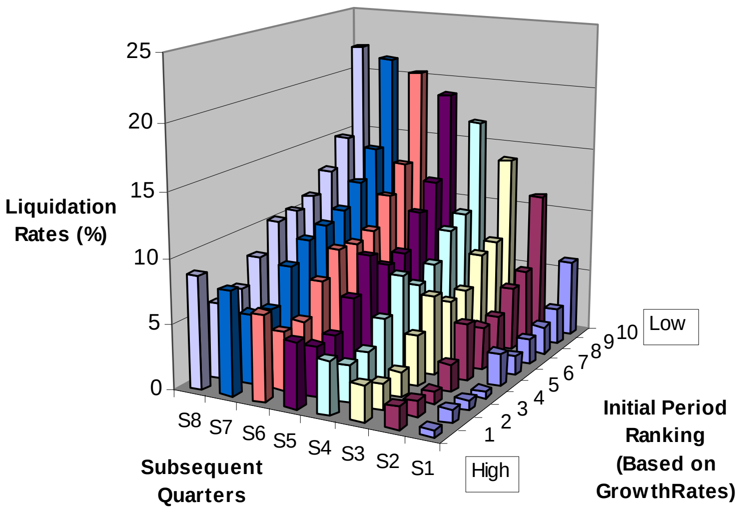
[37] Along our entire investigation we have excluded the very young funds, with less than 6 quarters of historical returns, as explained in Section 2. However, if we do take them into account in our ranking exercise based upon growth rates, most of them end up allocated in the top decile. The return on the top decile increases significantly towards 7.24% (3.28% style adjusted) and the average growth rate becomes 126%. 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 3.01% (2.35% style adjusted).

[38] 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 51 million dollars on total net assets, significantly higher than the 39.5 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 50 months old on average, compared to 40 months old for the top decile (not reported), while still considerably young compared to funds in the middle deciles (ages between 57 to 63 months). Funds in the top decile have not even reached the average life of a hedge fund in our sample, of about 46 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

Figure 6

Liquidation Rates across Deciles over Subsequent Quarters after Ranking

Hedge funds are sorted every quarter from 1994Q4 to 1999Q4 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.



mark threshold, they are likely to become reluctant to accept new investors, and eventually, will close down the fund.[39] 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 6% of funds in the bottom decile liquidate compared to 0.5% 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 10% of funds liquidate from any above-median

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.

[39] 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 difference of nearly 7%, marginally significant, in column 4, Panel B).

decile.[40] 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 behavior 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 4. Thus, the quick and sustained response of investors penalizing poor performing funds seems to be the mechanism that ensures the effectiveness of reputation costs in mitigating the gambling behavior of hedge fund managers when their option contract is out of the money, as argued by Brown, Goetzmann and Park [2001].

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.

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.

[40] Liquidation rates have a concave pattern over time and tend to stabilize after 16 quarters at levels just below 30% and 15% for the bottom and top portfolio respectively. We do not find cross-sectional differences over time for self-selection rates, either by ranking upon growth rates or dollar flows. In the quarter subsequent to the ranking period, nearly 8% of funds self-select out of the sample in any decile. Over the subsequent four quarters after ranking, the self-selection rate is nearly 29%, while it reaches 50% over a period of eight quarters after ranking.

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 behavior 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 35% of the total long run effect. This response, however, is substantially reduced by 40% 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. They invest mostly in funds that subsequently perform poorly. On average, these funds underperform the style index by more than 1% per quarter. 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 in 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.

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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 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 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, upside potential based on the entire past history of the fund and calculated with respect to the return on the US 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 21 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	-0.3662	(-1.64)	1.72E+08	(4.45)	-1.08E+08	(-6.77)
Rank lag 1 Unrestricted	0.7536	(13.23)	4.03E+07	(2.19)	6590339	(1.98)
Rank lag 2 Unrestricted	0.5598	(9.72)	3.04E+07	(2.20)	5426213	(1.80)
Rank lag 3 Unrestricted	0.5180	(8.99)	2.85E+07	(2.14)	5584452	(2.00)
Rank lag 4 Unrestricted	0.3028	(5.26)	1.59E+07	(1.83)	1201116	(0.75)
Rank lag 5 Unrestricted	0.2051	(3.57)	9794417	(1.81)	424263.4	(0.32)
Rank lag 6	0.0362	(0.65)	-152195.4	(-0.06)	-805582	(-0.49)
Rank lag 1 Restricted	0.5934	(3.75)	5.69E+07	(1.80)	8552889	(1.31)
Rank lag 2 Restricted	0.4953	(3.15)	4.70E+07	(2.42)	5223314	(1.41)
Rank lag 3 Restricted	0.8069	(4.92)	2.44E+07	(0.65)	3948526	(0.50)
Rank lag 4 Restricted	0.4891	(2.84)	2.61E+07	(1.75)	6302608	(1.33)
Rank lag 5 Restricted	0.1184	(0.70)	-3.82E+07	(-1.23)	-475042	(-0.07)
Ln(TNA)	-0.0166	(-1.59)	-8276557	(-6.33)	5885517	(11.63)
Ln(AGE)	-0.1763	(-5.78)	-1.14E+07	(-2.43)	4630.765	(0.01)
Flows lag 1	0.3083	(4.27)	1.61E+07	(2.08)	3711229	(2.53)
Flows lag 2	0.2600	(4.40)	1.35E+07	(2.12)	1908088	(1.85)
Flows lag 3	0.1201	(2.74)	6632757	(2.24)	1079340	(1.74)
Flows lag 4	0.0753	(1.82)	4255506	(2.37)	-5732.07	(-0.01)
Offshore	-0.1338	(-3.67)	-1.18E+07	(-3.37)	4229067	(4.99)
Incentive Fees	-0.0040	(-1.63)	-276637.3	(-1.87)	-71851	(-0.96)
Management Fees	-0.0154	(-0.85)	577071.9	(1.19)	-1044255	(-2.85)
Personal Capital	-0.0492	(-1.31)	-4049285	(-2.67)	545982.8	(0.75)
Upside Potential Ratio	0.0078	(1.62)	581888.4	(2.34)	22082.7	(1.92)
Emerging Markets	-0.1521	(-2.27)	-1713674	(-0.57)	-5901578	(-2.87)
Event Driven	0.1626	(2.74)	1.21E+07	(2.84)	-6431604	(-4.05)
Fixed Income Arbitrage.	-0.2611	(-1.86)	-3395466	(-0.68)	-8111029	(-4.50)
Long/Short Equity	-0.0356	(-0.71)	-644901.1	(-0.34)	-5532231	(-3.69)
Managed Futures	-0.1129	(-1.99)	-1.17E+07	(-3.09)	692341.8	(0.47)
Generalized Residual from Probit Model			7.41E+07	(2.01)	9495942	(1.47)
R^2	0.1037		0.1902		0.2125	
Number of observations	7195		3542		3653	

APPENDIX A2
The Impact of Money Flows on Hedge Fund Performance

Our results in Section 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) :

$$Rnk_{it} = a + b_1.Flow_{it}^{-} + b_2.Flow_{it}^{+} + \sum_{j=0}^{4} b_{3j}.Flow_{it-j}^{-} + \sum_{j=0}^{4} b_{4j}.Flow_{it-j}^{+} + \sum_{j=1}^{6} b_{5j}.Rnk_{it-j} +$$
$$+ b_6.\ln(TNA_{it-1}) + b_7.\ln(AGE_{it-1}) + b_8.StDev_{it-1} + b_9.(StDev_{it-1})^2 + g'.X_{it} + e_{it} \quad (5)$$

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[41]. $Flow_{it-j}$ 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 flows are not statistically significant, although they are overall negative, confirming our results in section 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

[41] $Flow_{it}^{-}$ 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 752 open-end hedge funds for the period 1994 Q4 till 2000 Q1. 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, upside potential based on the entire past history of the fund and calculated with respect to the return on the US 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	-0.2452	(-1.01)	-0.2779	(-1.12)	-0.0639	(-0.21)
Negative Cash Flows (contemp.)			-0.1077	(-3.65)	-0.6396	(-2.70)
Positive Cash Flows (contemp.)			0.0583	(3.28)	0.0102	(0.06)
Negative Cash Flows lag 1	-0.0150	(-0.48)	0.0032	(0.10)	0.0625	(1.27)
Positive Cash Flows lag 1	-0.0131	(-1.03)	-0.0162	(-1.27)	-0.0142	(-0.83)
Negative Cash Flows lag 2	-0.0328	(-1.01)	-0.0210	(-0.65)	0.0330	(0.77)
Positive Cash Flows lag 2	0.0003	(0.03)	-0.0012	(-0.10)	0.0027	(0.20)
Negative Cash Flows lag 3	-0.0383	(-1.17)	-0.0326	(-1.00)	-0.0074	(-0.20)
Positive Cash Flows lag 3	-0.0057	(-0.65)	-0.0075	(-0.82)	-0.0066	(-0.61)
Negative Cash Flows lag 4	-0.0340	(-1.05)	-0.0216	(-0.67)	0.0171	(0.42)
Positive Cash Flows lag 4	-0.0005	(-0.07)	-0.0011	(-0.17)	0.0007	(0.10)
Rnk lag 1	0.0340	(2.61)	0.0357	(2.70)	0.0692	(3.49)
Rnk lag 2	0.0221	(1.67)	0.0238	(1.79)	0.0482	(2.83)
Rnk lag 3	0.0799	(6.08)	0.0776	(5.90)	0.0940	(5.15)
Rnk lag 4	0.0193	(1.46)	0.0183	(1.39)	0.0286	(1.87)
Rnk lag 5	-0.0374	(-2.85)	-0.0378	(-2.87)	-0.0314	(-2.27)
Rnk lag 6	-0.0163	(-1.25)	-0.0163	(-1.25)	-0.0159	(-1.20)
Ln(TNA)	0.0773	(2.68)	0.0788	(2.68)	0.0478	(1.38)
$Ln(TNA)^2$	-0.0023	(-2.63)	-0.0023	(-2.61)	-0.0014	(-1.43)
Ln(AGE)	-0.0116	(-1.74)	-0.0093	(-1.40)	-0.0071	(-0.83)
Offshore	-0.0220	(-2.82)	-0.0244	(-3.12)	-0.0307	(-3.31)
Incentive Fees	0.0004	(0.81)	0.0004	(0.72)	0.0000	(-0.04)
Management Fees	-0.0046	(-1.14)	-0.0045	(-1.13)	-0.0056	(-1.34)
Personal Capital	-0.0038	(-0.46)	-0.0035	(-0.43)	-0.0012	(-0.14)
Leverage	0.0288	(3.32)	0.0290	(3.36)	0.0314	(3.56)
St.Dev.	0.8062	(4.52)	0.8047	(4.53)	0.7656	(4.23)
$St.Dev^2$	-1.4112	(-2.70)	-1.4105	(-2.71)	-1.3219	(-2.54)
Upside Potential Ratio	0.0037	(6.30)	0.0037	(6.40)	0.0040	(6.32)
$(Upside Pot Ratio)^2$	-0.00001	(-5.12)	-0.00001	(-5.23)	-0.00001	(-5.25)
R^2	0.0569		0.0610			
Number of observations	7425		7425		7425	

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)

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 significant.[42] In other words, money flowing out of a fund along a quarter and motivated by an exogenous shock appears to have an 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 three 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 5. If a fund in decline that 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 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]).[43]

[42] 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.

[43] 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 substantially larger by a non-negligible 60% compared to the OLS coefficients. The statistical significance is also greatly enhanced and the long-run impact of historical performance becomes more clear. 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. Another result to highlight is the non-linear impact of size upon relative performance when endogeneity is not taken into consideration (column B). 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. When endogeneity is taken into account, however, the effect is not significant. Apparently, size affects in some way performance through its impact on money flows. This is a complex relation that is worth of further study. 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.