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

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Abstract

Using quarterly data of 752 open-end hedge funds from the Tass Database for the period 1994-2000, we explore the flow-performance interrelation at short-term horizons by explicitly separating the investment and divestment decisions. Using a switching regression model explaining positive and negative flows and incorporating the effect of liquidity restrictions, we find significant asymmetries between the decisions of investing and divesting, especially concerning the evaluation horizons. While divestment decisions are highly sensitive to past performance in the short run, presumably as a result of an active monitoring of investors, inflows are more sensitive to past long-run performance. We interpret this last result as a consequence of high searching costs that slow down the reaction of new investors. These results provide evidence of a weaker flow-performance relation for winning funds in short-term horizons compared to annual horizons which, following Berk and Green [2004], may explain why short-run 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, they are fast and successful in de-allocating from the persistent losers, ensuring a disciplining mechanism for low-quality funds. Further, our findings provide weak support for the existence of smart money.

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

JEL code: G2

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 flow-performance relationship.

For the mutual fund industry, Berk and Green's argument is supported by empirical evidence of a positive correlation between flows and past performance, 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. In a simple definition, a hedge fund is a private investment portfolio with limited regulation, which combines both long and short positions in a leveraged basis, charging an incentive fee and managed by a general partner. Relevant features are the limited transparency, implying increased searching costs for investors, and the limited liquidity offered to clients through long lock-up periods and redemption notice periods. Given that flows of money into and out of hedge funds are restricted and searching costs are high, the question of interest is whether or not this implies a weaker relation between asset flows and past performance that could explain persistence in this industry. This paper provides an answer to this question by empirically exploring the short-term dynamics of hedge fund flows and performance and their interrelationship.

The evidence of the relation between money flows and past performance in the mutual fund industry has been documented in a number of empirical papers, 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 pension fund industry, however, Del Guercio and Tkac [2002] report a more linear and symmetric relationship. This implies that investors reward good performance with inflows as much as they punish bad performance by withdrawing their money. Furthermore, the l0% largest pension funds appear to lose assets on average, suggesting that diminishing returns to scale may be present. In the hedge fund industry, a similar result is reported by Goetzmann, Ingersoll and Ross [2003], who also document that money tends to flow out of the recent top performing funds.[3] In a recent paper, 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).

An important issue in the hedge fund industry that might affect the relation between asset flows and performance is that flows of money into and out of hedge funds are restricted. There are typically lock-up periods (i.e. minimum initial investment periods) and redemption notice periods restricting withdrawals. There are also subscription periods limiting inflows. Additionally, if a fund has reached the maximum limit of 500 investors it might be closed to new investors, while it may also be the case that given diminishing returns to scale in this industry, hedge fund managers are unwilling to accept new money before reaching the critical size. Thus, while in the mutual fund industry investors' decisions in supplying capital ultimately drive the flow-performance relationship, in the hedge fund industry liquidity restrictions and other organizational aspects on the demand side for capital are likely to have some influence on the shape of the relation.

Hedge fund investors also face high searching costs along their allocation process. Given advertising restrictions imposed by many countries and the little transparency characterizing the hedge fund industry, investors engage in a long and complex process of information gathering and evaluation, through hedge fund conferences, hedge fund databases, industry newsletters, consultants, prime broker capital introduction groups and direct contact with managers. Hedge fund selection includes quantitative and qualitative screening, followed by a thorough manager due diligence process, where manager attributes are especially taken into consideration. This selection procedure is likely to lengthen the decision of purchasing shares in hedge funds. Furthermore, while the decision to hire a hedge fund manager for the first time may take place at relatively low frequencies compared to other investment pools as mutual funds, the post-investment behavior of hedge fund investors is instead characterized by a regular monitoring, especially for style drift, on a monthly or a quarterly basis[4]. Searching costs and active monitoring are also likely to have an impact on the response of money flows to past performance.[5]

[3] This has been interpreted as a result of the unwillingness of managers to increase the fund size because of diminishing returns to scale.

[4] 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.

[5] 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.

All together, these functional aspects of the hedge fund industry motivate the main argument of this paper. On the one hand, investors' decisions to invest and divest are bounded by the organizational structure of hedge funds that constrains money flows and increases searching costs for investors. On the other hand, given these constraints, investors' decisions are the result of an extended procedure to select managers and an active post-investment monitoring. We claim that these conditions create multiple asymmetries between the decisions to invest and divest of hedge fund investors, most notably concerning the evaluation horizons. 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. Therefore, the present investigation addresses such mutual effects by providing an in-depth characterization of a typical investor in hedge funds, that is, what her evaluation horizons are, what determines her decisions to allocate and de-allocate money in hedge funds, and how these decisions affect investors' wealth?

Our paper extends the existing literature in several directions and makes a number of empirical contributions. First, we focus on the short run and use quarterly data instead of annual data, which allows us to explore the dynamics of hedge fund flows and the impact of liquidity restrictions upon the flow-performance relationship. The effect of liquidity restrictions can only be captured at short horizons, since most restrictions are defined on a monthly or quarterly basis. Furthermore, survey evidence (e.g. Bekier [1996]) suggests that investors pay attention to performance published monthly or quarterly to take their decisions. By using quarterly data we can capture the important amount of trade that takes place within a year, which is probably smoothed enormously by annual data[6]. Our empirical results reveal that the response of flows to quarterly past performance, especially outflows, occurs most significantly during the first quarter and disappears gradually over the subsequent three or four quarters. A third important consideration to study the determinants of money flows while looking at the short run is that stronger patterns of persistence have been identified at quarterly horizons compared to annual horizons (see for example Agarwal and Naik [2000], Baquero, Ter Horst and Verbeek [2004]). If persistence is indeed a consequence of a limited competition in the provision of capital, as suggested by Berk and Green [2004], we should expect a weaker flow-performance relation with quarterly data than with annual data. Our results indicate that important differences exist depending 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, where investors display a higher sensitivity to good performance and almost no sensitivity to poor performance.

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

[6] The short run in mutual fund flows would be more difficult to capture because of noise due to liquidity needs of clients, who can invest or divest on a daily basis without restrictions. This effect is of less importance in the hedge fund industry given that money flows are restricted.

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. 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, although we show that the estimation of the smart money effect in the case of hedge funds is hampered by a serious survival condition.

Overall, our findings support our claim that the investment and divestment decisions of hedge fund investors are determined by distinct factors over different time horizons. Consequently, they also differ in their implications concerning subsequent performance. The remainder of this paper is organized as follows. The next section provides a description of our sample of hedge funds, variables and hypotheses. Then, 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 [2004], 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.

[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 [2004]), 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 dataset 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.

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[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] The 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]

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

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

We refer to the first definition as *normalized cash flows* or *growth rates* and to the second as *absolute* or *dollar cash flows*. The definition of flows in dollar terms presents a

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

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

Hedge funds invest in different asset classes, with different geographical focus and using a variety of investment techniques and trading strategies. Brown and Goetzmann [2001] find that differences in style account for 20% of the cross-sectional variation in performance as well as for a significant proportion of cross-sectional differences in risk. This suggests that, from an investor's perspective, a careful assessment of style is crucial. There is no consensus in the hedge fund industry, however, on the use of a unique style classification. TASS provides a style classification of mutually exclusive styles based on manager survey responses and information from fund disclosure documents. Although self-reported styles may suffer from a self-selection bias, they constitute the most readily available source of information concerning styles for any investor. Therefore, we expect they are an important determinant of hedge fund investors' preferences, which is the focus of our study. Furthermore the TASS classification matches closely the definitions of CSFB/Tremont

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

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 [2004]).

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 that takes value one if the managers invests from her own wealth in the fund. We include 7 dummies for investment styles defined on the basis of CSFB/Tremont indices.

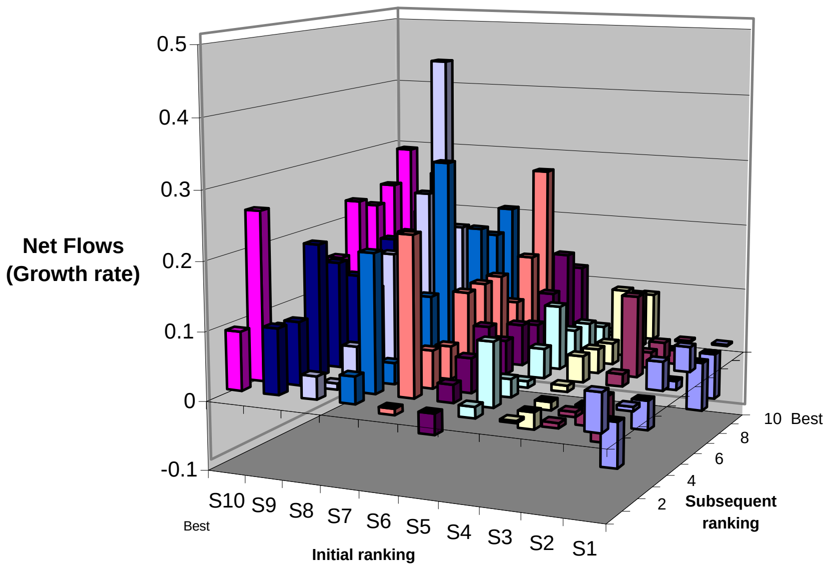
Variable	Mean	Std. Dev.	Min	Max
Cash Flows (growth rate)	0.0295	0.3215	-1.4303	8.1577
Cash Flows>0 (3676 obs)	0.1751	0.3792	0.0001	8.1577
Cash Flows<0 (3551 obs)	-0.1193	0.1549	-1.4303	-0.0001
Cash Flows=0 (407 obs)				
Cash Flows (dollars)	235008.8	3.70E+07	-1.41E+09	6.87E+08
ln(TNA)	16.7296	1.8298	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 shows 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 that was 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 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 effects of past performance on the flow of investments into a fund we take into account the impact of other variables that may affect cash flows as well, like size of a fund, age, incentive fees and investment styles. We control for these variables using a linear regression framework. Consider the following model:

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

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. The data period consists of 22 quarters, from 1994Q4 to 2001Q1. We control for time effects by including 21 time dummies, denoted by λ_t, to capture economy wide shocks conducing to different average flows across quarters, as suggested by Table I**.**

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

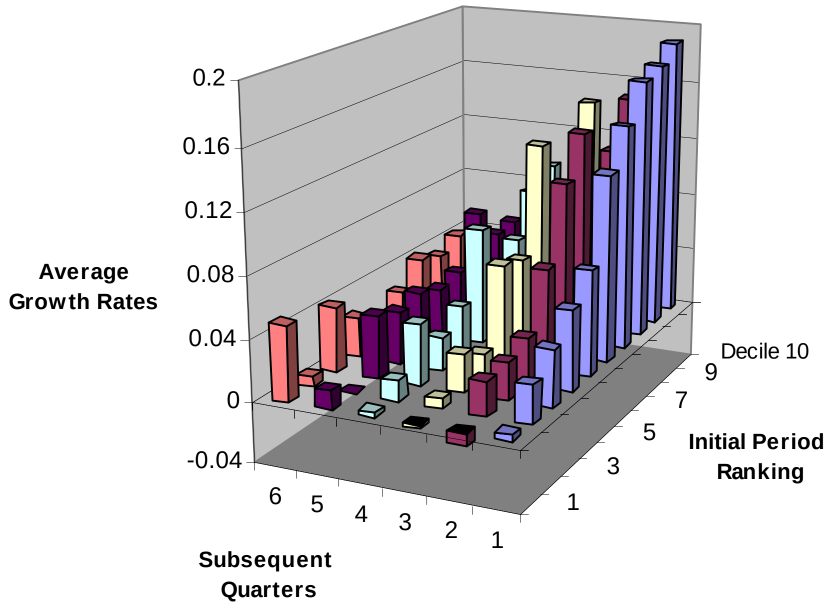
Figure 2 also highlights the importance of considering both measures of cash flows in the analysis, as each of them may reveal distinctive features of flows behavior.

Figure 2

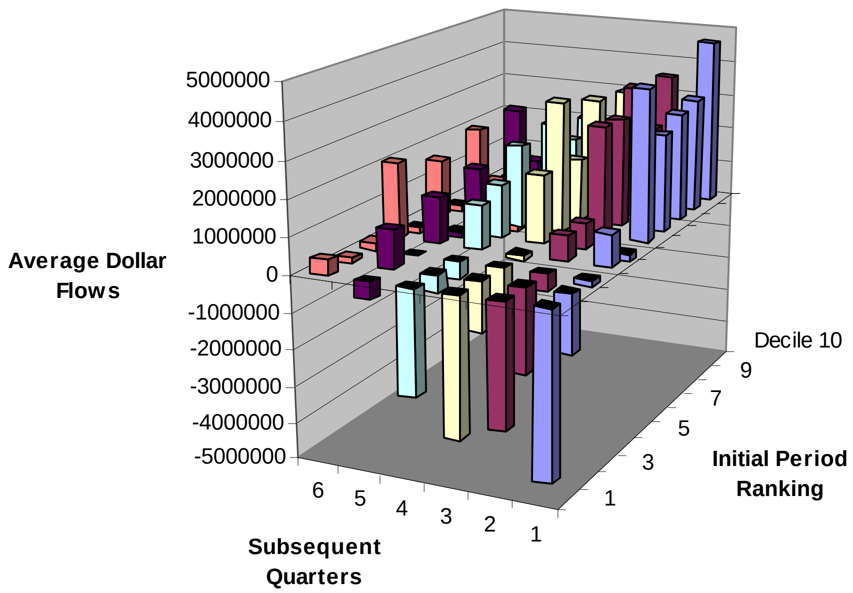
Average Flows across Deciles
Over Subsequent Quarters after Ranking

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 25th to the 75th percentile in the previous quarter, this is associated with an economically and 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 25th to the 75th 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 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

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[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]

Some 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 of return as a consequence, investors are more sensitive to the level of costs involved and the concomitant increase on 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, negative growth rates. 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.

Also the dynamics of flows appears to be economically significant and highly robust to the alternative specifications discussed above. Hedge fund flows tend to persist in the short run. 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

[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.

out at longer time horizons, suggesting once again the existence of short-run factors conditioning money flows. We defer the discussion of this issue to Section 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 last 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, although they capture well risk preferences when we model separately inflows and outflows in Section 4. 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-sample of survivors and the sub-sample of 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. 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

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[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.

is proportional among bad and good performers. This result differs from the general findings at annual horizons for both the hedge fund and mutual fund industries, where flows of money are directed mostly to the best performers the prior year. Put differently, in short horizons hedge fund investors are as sensitive to good performance as to bad 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.

[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.

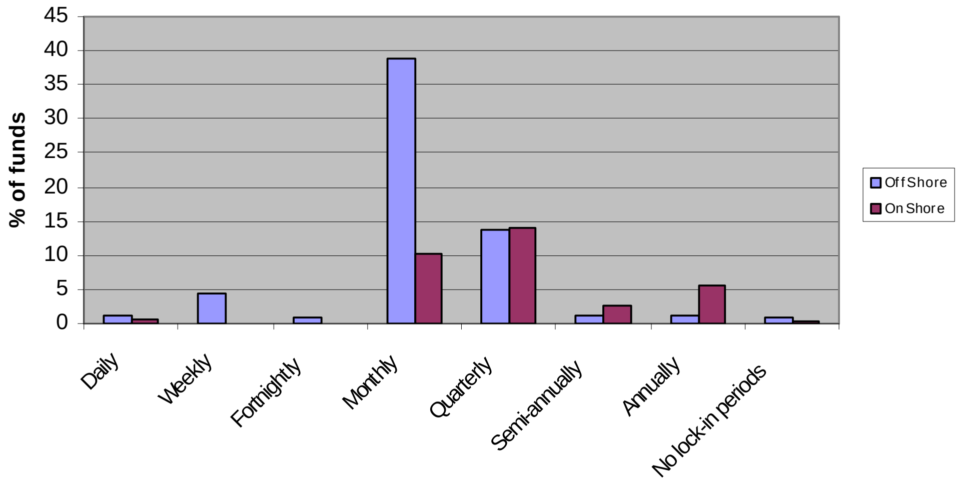
[25] See Bekier [1996] for evidence and for a detailed description of the buying process and the post-investment behaviour of hedge fund investors. Bekier quotes a hedge fund institutional investor who acknowledges that their standard process of investment may take up to 18 months, from the identification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

Restricted flows enable a hedge fund to minimize cash holdings and reduce administrative work. Subscription periods generally match the redemption periods of a fund or are somewhat shorter, depending on the trading strategies, i.e. the liquidity of the markets and instruments traded. Nearly 75% of the funds in our dataset have monthly subscription periods and 15% have subscription periods of 90 days. Regarding redemption restrictions, Figure 3 shows the distribution of redemption frequencies for the cross-section of funds from the TASS database. 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 1st 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 dataset 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 computed the maximum delay that an investor

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	

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 have an effective impact on flows. For each quarter and for every fund, we construct five dummy variables corresponding to each of the five lagged quarters, taking the value 1 if liquidity restrictions do not prevent outflows in response to the lagged performance measure.

We modify our model of flows to allow for interactions between lagged ranks and dummies accounting for limits to liquidity.[26] Estimates of our modified model are shown in Table VI. Clearly, 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 effect of the control variables remains 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. In other words, 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,

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

$$\textit{Rank Unrestricted}_{i,t-j} = \textit{Rank}_{i,t-j} * (\textit{REDR}_{i,t-j})$$
$$\text{and} \quad \textit{Rank Restricted}_{i,t-j} = \textit{Rank}_{i,t-j} * (1-\textit{REDR}_{i,t-j})$$

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 $Rank_{i,t-j}$.

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	

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 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. To do so, we specify a set of two truncated regression models that explain net money flows, conditional upon their sign.[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 style, age and size. The easiest way to interpret the model is by considering the last two equations as censored regression models (censored at zero), where a common binary choice model explains the censoring. As a result, the two flow equations contain an additional term that captures the censoring. This term is based on the generalized residual of the binary model, while its coefficient depends upon the covariance between the two 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:

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

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

The second stage is an 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

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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).

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.

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

$$E [\varepsilon_{i,t} | S_{it}=1] = cov(?_{i,t}, \varepsilon_{i,t}).E[?_{i,t} | S_{it} =1]$$

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 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 models for the truncated variables of flows. 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 entire sample. 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. Moreover, outflows of money for less restricted funds are clearly more sensitive to the most recent historical performance. The impact gradually disappears with lags, in contrast with more restricted funds, for which differences across lags are reduced.

[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	

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 of fund's size and age. In contrast, the impact of the dynamics of flows, incentive fees and the offshore dummy variable is 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 estimating the model using the entire sample, the coefficient for the offshore dummy is not significant. But when taking explicitly into account the regime of flows, the impact of this variable becomes highly significant while having opposite direction in both regimes. 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 previously from 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 positively and significantly both regimes, although the impact upon positive cash flows is substantially lower.

Estimating our truncated regression model 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 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

[30] An explanation for the momentum in outflows captured by our model lies in the fact that hedge funds have few but large investors. As pointed out by Brown, Goetzmann and Park [2001], this poses a serious threat of withdrawals, not only because one only 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 showed by our model could be the reflection of certain herd behaviour 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]).

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 evidence in favor of diseconomies of scale playing a role. Section 6 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 at short horizons a clear response of positive flows, 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

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)

Panel 1 we regress quarterly cash flows upon yearly ranks constructed on the basis of the previous one-year raw return. We report only estimates for past performance and size.

Aggregating relative performance over longer horizons does not change our previous results; quarterly outflows remain strongly sensitive to past year performance, in contrast to quarterly inflows. In Panel 2 we regress annual cash flows upon yearly ranks of the previous year. In this case, observations of four-quarter cash flows are overlapping, which introduces an autocorrelation problem and we report *t*-tests 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 investors.

5. Economic implications: is money to hedge funds smart?

In this section we show that the differential response of money inflows and outflows to past performance documented above implies several differential effects concerning subsequent performance. The recent literature on smart money has investigated the performance of the portfolio 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 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 data. Finally, the fast response of outflows to bad performance suggests an effective punishing mechanism in place. Therefore, the third 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

To answer the first question, we 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 intend to assess the performance of investors' allocations in both the investment and the divestment sets, compared to an equally weighted allocation as a benchmark. An equally weighted average of funds' returns represents an allocation of money without making any distinction across funds. However, investors do make a distinction. The returns on both investors' portfolios (i.e. the investment and the divestment sets) can be assessed by calculating a cash flow-weighted average return. If investors are successful in discriminating funds *within their investment set* with higher expected returns from those with lower expected returns, we should observe for the above-median portfolio that the cash flow weighted return *outperforms* the equally weighted return. Conversely, if investors are successful in identifying funds *within their divestment set* with lower expected returns from those with higher expected returns, we should observe for the below-median portfolio that the cash flow weighted return *underperforms* the equally weighted return.

We first evaluate the returns during the ranking period. Panel A in Table IX reports the time series averages of the equally weighted returns in each quarter of our sample period for both the above and below-median portfolios. Here the ranking is based upon growth rates, but our results differ only slightly when ranks are based upon dollar flows. We refer to the above and below-median portfolios as the *investment portfolio* and the *divestment portfolio,* respectively. Before discussing our main results, two points are worth noticing. First, both the investment and divestment portfolios on average underperform the S&P500 index in the ranking period; the latter by a statistically significant 3.5% per quarter. Second, the above-median funds significantly outperform their style index by nearly 0.8% per quarter, while there is no significant difference between the index and the return on below-median funds. This may indicate that hedge fund investors are focusing on different benchmarks to evaluate their investment and divestment options.

In panel A of Table IX we observe that in terms of absolute returns and style-adjusted returns, the investment portfolio significantly outperforms the divestment portfolio in the ranking period by 1.6% and 1.1% per quarter, respectively. Clearly, cash flows to hedge funds appear to have a strong sorting capacity of contemporaneous performance. In a way,

Table IX

The Performance of Investors' Portfolios

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, although in reality they may take place along the quarter. Above-median funds correspond to those funds that experienced the highest cash flows and approximate the portfolio of funds with positive cash flows. In panel A, we look at the performance of both above-median and below-median portfolios at the end of the ranking period. In each quarter, we compute an equally weighted return of all funds belonging to each portfolio in that quarter. Then we average over 22 quarters. We use three definitions of a fund's returns: a) raw returns, b) excess return with respect to the S&P500 index, and c) style-adjusted returns. The standard error of the time series average is reported in parentheses. Following the same approach, in panel B we look at the performance of both portfolios subsequent to ranking, measured as a compounded raw return over different holding periods. 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. Besides the equally weighted return, we also report the cash flow weighted return that takes into account investors' allocations, and the difference between both. We include the performance in the ranking period for comparison. Panel C compares the return of the above-median portfolio against the return of the below-median portfolio. We adjust for autocorrelation using Newey-West standard errors.

Panel A : The performance of investors' portfolios in the ranking period

Portfolio	Average Dollar Flows	Average Size (TNA)	Raw return		Excess return over S&P500		Style-adjusted return	
Above-median	7899256	86996069	0.0439	(0.0089)	-0.0192	(0.0136)	0.0077	(0.0035)
Below-median	-7385571	80430952	0.0279	(0.0084)	-0.0351	(0.0127)	-0.0031	(0.0049)
Difference	513685	6565117	0.0159	(0.0044)	0.0159	(0.0044)	0.0109	(0.0046)

Panel B : The performance of investors' portfolios over time (raw returns)

	Ranking period	Holding period							
	0	1	2	3	4	5	6	7	8
Above-median portfolio (the "investment" set)									
CashFlow Weighted	0.0546	0.0293	0.0282	0.0295	0.0276	0.0281	0.0247	0.0223	0.0222
Equally Weighted	0.0439	0.0386	0.039	0.0384	0.0379	0.0379	0.0379	0.0374	0.0386
Difference	0.0107	-0.0093	-0.0108	-0.0089	-0.0103	-0.0098	-0.0133	-0.0150	-0.0164
Standard error	(0.0051)	(0.0052)	(0.0035)	(0.0036)	(0.0039)	(0.0042)	(0.0029)	(0.0027)	(0.0025)
Below- median portfolio (the "divestment" set)									
CashFlow Weighted	0.0217	0.0311	0.0349	0.0347	0.0357	0.0409	0.0444	0.0432	0.0454
Equally Weighted	0.0279	0.0363	0.0373	0.037	0.0399	0.0409	0.0411	0.0399	0.0415
Difference	-0.0062	-0.0053	-0.0024	-0.0023	-0.0043	0.0000	0.0033	0.0033	0.0039
Standard error	(0.0062)	(0.0051)	(0.0045)	(0.0036)	(0.0042)	(0.0040)	(0.0051)	(0.0056)	(0.0066)

Panel C : Above-median minus below-median portfolios' performance

	Ranking period	Holding period							
	0	1	2	3	4	5	6	7	8
CashFlow Weighted	0.0329	-0.0018	-0.0066	-0.0051	-0.0080	-0.0128	-0.0198	-0.0209	-0.0231
	(0.0085)	(0.0084)	(0.0069)	(0.0065)	(0.0061)	(0.0058)	(0.0063)	(0.0062)	(0.0066)
Equally Weighted	0.0159	0.0022	0.0017	0.0014	-0.0020	-0.0030	-0.0032	-0.0025	-0.0029
	(0.0044)	(0.0036)	(0.0026)	(0.0027)	(0.0025)	(0.0030)	(0.0025)	(0.0019)	(0.0015)

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"[31].

[31] This poses an obvious endogeneity problem. It may be the case 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 may also be the case that we are capturing a causal effect of contemporaneous flows upon performance. The next sub-section gives further details on the

It is less clear, however, whether hedge fund investors actually benefit from this. They would be able to make a profit from these high returns occurring contemporaneously only in case both investments and divestments take place early in the quarter. Yet, up to now we have made the opposite extreme assumption, namely that cash flows take place at the end of a quarter. Our interest lies, therefore, in assessing the returns on cash flows over subsequent quarters after the ranking period.

We continue our analysis by computing compounded returns for all funds in the investment and divestment portfolios for different holding periods, from one to eight quarters after the ranking period. Then we compute both an equally weighted average and a cash flow weighted average return for the two portfolios and for each holding period. Finally we average both cash flow weighted and equally weighted returns over time.[32] Panel B in Table IX summarizes our results when we consider raw returns. For comparison, we also include the returns in the ranking period. Figure 4 presents the results for both raw returns and style-adjusted returns[33].

By computing cash flow weighted average returns, we take into account the actual investors' allocations across funds. Doing so affects the returns of both the investment and divestment portfolios in the ranking period. The cash flow weighted return significantly outperforms the equally weighted return for the investment portfolio by 1.07%, while the cash flow weighted return for the divestment portfolio is somewhat reduced compared to the equally weighted return, although the difference is statistically insignificant. The main point is that the difference between the investment and divestment portfolios is considerably magnified as a result of investors' allocations, becoming 3.29% in terms of raw returns (Panel C) and 2.17% on a style-adjusted basis, twice as much as the difference for the equally weighted returns discussed above. Put differently, the set of investment opportunities appears much more attractive to investors when they discriminate between funds, while there are more incentives to divest from funds in the divestment set.

We turn now our attention to the performance of the investment and divestment portfolios for different holding periods. Surprisingly, the situation reverses in the quarters after the

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contemporaneous relation. In the appendix, we make an attempt to correct for endogeneity in a more formal model.

[32] 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.

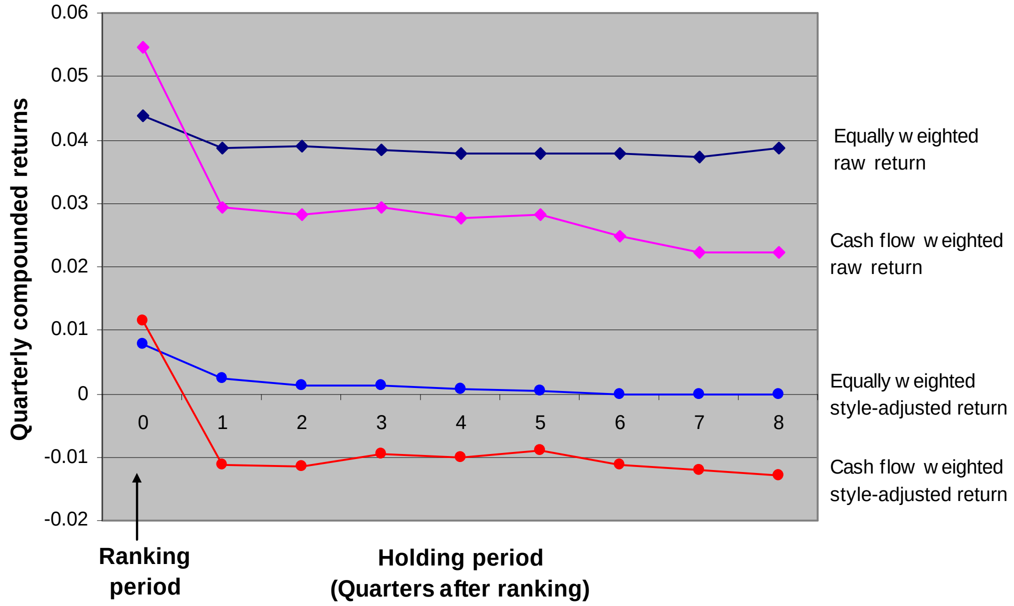
[33] This methodology follows closely the one implemented by Zheng [1999] for mutual funds. However, Zheng's study focuses upon the monthly returns over the holding period. Here we focus on the quarterly return, in order to later compare investors' allocation with the allocation based on quarterly performance, which exhibits a persistence pattern. Additionally, we are also interested in the contemporaneous flow-performance relation, that is the performance of the above-median and below median funds in the ranking period, to better understand the investors' allocations in light of our results in previous sections. Further, the second part of this section extends Zheng's approach by sorting funds into deciles to look more in detail at investors' allocations. Here the distinction between rankings based upon growth rates or dollar flows is essential.

Figure 4

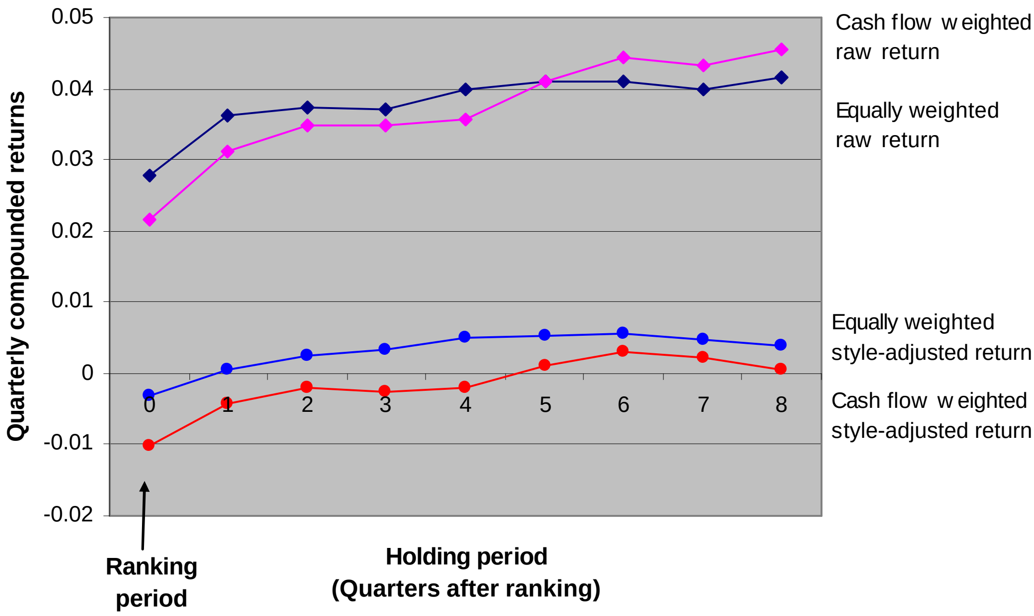
Time-series Averages of Cash Flow Weighted Returns and Equally Weighted Returns for Different Holding Periods

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. (i.e. normalized cash flows). 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



ranking period. The cash flow weighted return on the investment portfolio significantly underperforms 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 highly significant 1.64% 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 not only the equally weighted return by 1.37%, but also the style index by 1.1%. Compare these figures with 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.

Concerning the divestment set, 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).

If we look again at the performance of the investment portfolio, the equally weighted return reduces by 0.5% in the quarter subsequent to the initial ranking, while on a style-adjusted basis it does not decrease enough to underperform the index. Remarkably, however, the cash flow weighted return falls by more than 2.5%. Further, in terms of style-adjusted returns, it falls to levels significantly lower than the style index, as noticed previously. Manifestly, investors' allocations fail to appropriately discriminate funds' expected returns. That is, they invest more in some funds than is justified by subsequent returns. As a result, the opportunity cost is substantial, had they equally allocated their money across all funds in the investment set[34]. 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.

Notice in Panel C, Table X, that we do not find evidence of smart money, defined by the extent to which the above-median portfolio outperforms the below-median portfolio (see Gruber [1996] and Zheng [1999]). In fact, there are no significant differences between both portfolios after the ranking period up to holding periods of four quarters, suggesting that hedge fund performance is unrelated to historical cash flows. Furthermore, for longer holding periods, below-median funds tend to outperform the above-median funds.[35] As we will see later, the comparison between both portfolios might be affected by a survival conditioning bias.

[34] 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.

[35] Zheng [1999] also documents a mean-reversion phenomenon for mutual funds, but it takes place much later: the portfolio of mutual funds with negative money flows outperforms the portfolio with positive money flows after month 30.

B. Investors' Allocations and Persistence

In the discussion that follows, we intend to improve our understanding of the nature of investors' allocations among funds in the investment and divestment sets by characterizing the funds in both portfolios more accurately. Accordingly, 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. While the allocation of funds between the investment and divestment portfolios differs only slightly whether we rank upon growth rates or dollar flows, a subsequent allocation of funds across the five top deciles and the five bottom deciles, is likely to differ substantially. Table X summarizes our results.

Nearly 83% of dollars moved per quarter (both inflows and outflows) are concentrated in the two extreme deciles. 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. Moreover, on average these funds exhibit raw returns of 4.82% per quarter, outperforming the bottom decile by a significant 2.17%. On a style-adjusted basis, these numbers are 0.83% and 1.53% per quarter, respectively. Yet, in the first quarter after ranking, the average raw return of this group of funds falls to 2.42%, 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. 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. While the top portfolio is a good performer during the ranking period, it does not significantly outperform the style index. In contrast, the second and third above-median deciles outperform their style index by 1.5% and 1.1% per quarter, respectively, while their performance in subsequent quarters does not fall so sharply as the top decile. Actually, the third decile still significantly outperforms the style index by at least 0.5% for holding periods of two and three quarters after ranking. Obviously, most of investors' money is not directed towards the very best. This is consistent with our regression results in Section 4, which showed a non-significant response of money inflows to recent past performance.

Next, we rank and sort funds into deciles on the basis of their raw returns in a given quarter. [36] Baquero, Ter Horst and Verbeek [2004] showed that the top three deciles of this

[36] The results documented here are not reported (available upon request).

Table X

Results From Sorting Funds in Deciles Based on Contemporaneous 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. The standard error of the time series average is reported in parentheses.

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	0.0242	0.0083	(0.0057)	-0.0130	(0.0037)
2	5220235	64937770	0.0413	0.0548	0.0418	0.0150	(0.0053)	0.0057	(0.0051)
3	1677148	42277500	0.0498	0.0479	0.0491	0.0113	(0.0041)	0.0082	(0.0046)
4	511681	22030993	0.0568	0.0356	0.0375	-0.0010	(0.0059)	0.0044	(0.0053)
5	96343	13827815	0.0636	0.0385	0.0428	0.0067	(0.0068)	0.0122	(0.0062)
6	-62963	13769655	0.0668	0.0146	0.0375	-0.0117	(0.0064)	0.0056	(0.0080)
7	-339940	16451894	0.0645	0.0248	0.0299	-0.0010	(0.0079)	-0.0051	(0.0075)
8	-1166137	28250860	0.0565	0.0349	0.0383	0.0034	(0.0060)	0.0003	(0.0055)
9	-3783236	64065157	0.0473	0.0331	0.0314	-0.0008	(0.0047)	-0.0048	(0.0062)
Low 10	-31575580	303904259	0.0426	0.0265	0.0417	-0.0070	(0.0046)	0.0023	(0.0056)
High-Low	63566455	-33568484	-0.0065	0.0217	-0.0175	0.0153	(0.0063)	-0.0153	(0.0078)
			(0.0018)	(0.0077)	(0.0078)				

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	0.0388	0.0263	(0.0079)	0.0023	(0.0059)
2	0.1454	74105656	0.0480	0.0459	0.0373	0.0101	(0.0046)	0.0006	(0.0045)
3	0.0707	102757397	0.0468	0.0425	0.0357	0.0047	(0.0054)	-0.0012	(0.0044)
4	0.0296	127072190	0.0469	0.0331	0.0391	-0.0017	(0.0058)	0.0009	(0.0070)
5	0.0078	91574826	0.0582	0.0325	0.0418	-0.0009	(0.0047)	0.0100	(0.0055)
6	-0.0067	69821320	0.0587	0.0188	0.0383	-0.0122	(0.0056)	0.0028	(0.0061)
7	-0.0262	93245734	0.0583	0.0204	0.0358	-0.0092	(0.0066)	-0.0004	(0.0071)
8	-0.0588	88237750	0.0561	0.0242	0.0333	-0.0053	(0.0068)	-0.0030	(0.0060)
9	-0.1259	99617725	0.0513	0.0310	0.0383	-0.0008	(0.0059)	0.0014	(0.0062)
Low 10	-0.3557	51232233	0.0526	0.0457	0.0357	0.0121	(0.0076)	0.0022	(0.0070)
High-Low	0.9426	-11761959	-0.0038	0.0194	0.0030	0.0142	(0.0106)	0.0002	(0.0069)
			(0.0022)	(0.0120)	(0.0069)				

ranking are expected to again provide above average returns in the subsequent quarter, consistent with short-run persistence in raw returns. In the ranking period, above-median funds exhibit average raw returns of around 11% per quarter, (6.2% on a style-adjusted basis), while their return in the subsequent quarter is around 4.28% (0.5% style-adjusted). Conversely, the below-median funds exhibit average returns of –3.97% (-5.86% style-adjusted) in the ranking period, and 3.17% (-0.2% style-adjusted) in the subsequent quarter, conditional upon survival. These figures are dramatically different from the average returns discussed above in this section under the investors' allocation. Furthermore, by ranking funds upon performance, above-median funds receive on average 1.14 million US$ (with the top portfolio receiving 3.01 million US$) while below-median funds experience outflows of about –420000 US$ on average. These figures are in absolute value far below the averages obtained above for the investment and divestment portfolios, indicating that only few investors are actually able to exploit positive persistence. Obviously the two allocations are very different, while for mutual funds, Zheng [1999] documented that both allocations are not the same but are somewhat related. 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. Clearly, we find the opposite results for hedge funds. The investment portfolio performs substantially worse than above-median funds in the repeat-winner strategy, while the cash flow weighted return on the divestment portfolio in the subsequent quarter after ranking is about 3.11% (-0.4% style-adjusted), slightly worse than the repeat-winner strategy, meaning that it predicts losers somewhat better.

We can conclude that hedge fund investors are unable to chase the winners at short horizons. By the same token, they are unable to exploit persistence, which is largely a feature in the short run, while Baquero, Ter Horst and Verbeek [2004] showed that the persistent winners are not closed to new investors, meaning that persistence is susceptible of exploitation. These results reinforce one of our main arguments, namely that given the length of the evaluation procedures, investors are limited in their allocation process, and are unable to rapidly assess many good performers, while they are forced to focus on long term performance. 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. 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].

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), although both figures are far above the average life of a hedge fund in our sample. 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).

The above results help to improve our understanding of one of the main conclusions from the switching regression model in Section 4 (see Table A1). Let us state again our findings. Large funds experience more extreme variations of money flows in dollar terms than small funds. 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.[37] On the other hand, our evidence also indicates that in quarterly horizons, many large funds with good enough and consistent performance are willing to accept new money, and in fact they attract the bulk of all money inflows, but perform very poorly in the subsequent quarter.

Finally, we turn our attention to Panel B in Table X, where we used a different ranking criterion, based on growth rates. The third column of Panel B reports the time series averages of the mean size of funds per decile. A comparison with our previous results shows an opposite picture concerning the size distribution across deciles. Indeed, ranking upon growth rates is likely to assemble small funds in the extreme deciles, since 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. Instead, the middle deciles assemble large funds, with assets under management of around 90 million dollars or more on average[38]. Remarkably, funds in the top decile experience huge growth rates, with an average of nearly 59%, considerably higher than any other above-median portfolio. Further, on average these funds exhibit the highest rates of return in the ranking period, of about 6.5% (2.63% in a style-adjusted basis). Actually, only the two top portfolios significantly outperform the style index. 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. In terms of style adjusted returns it falls by 2.4%, but not enough to underperform the style index. While we did not find significant differences between the cash flow weighted return and the equally weighted return for the top decile when ranking funds upon dollar flows, the results are remarkably different when ranking funds upon growth rates. The cash flow weighted return significantly underperforms the equal allocation strategy by 1.1% in the subsequent quarter (not reported). The difference reduces slightly to 80 basis points or so for holding periods of 4 quarters or more, but still significant. The situation worsens in style adjusted terms. The investors' allocation strategy underperforms not only the equal allocation strategy by 1.25% but also the style index by about 1%. Thus, also among the subset of young, small and successful funds, most of money flows are not directed to funds that persist, failing

[37] 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 rather 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 [2004]: young funds are much more likely than old to be terminated for poor performance.

[38] These 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.

patently to discriminate funds' expected returns and incurring in important opportunity costs.

C. Investors' Allocations and Liquidation Rates of Hedge Funds

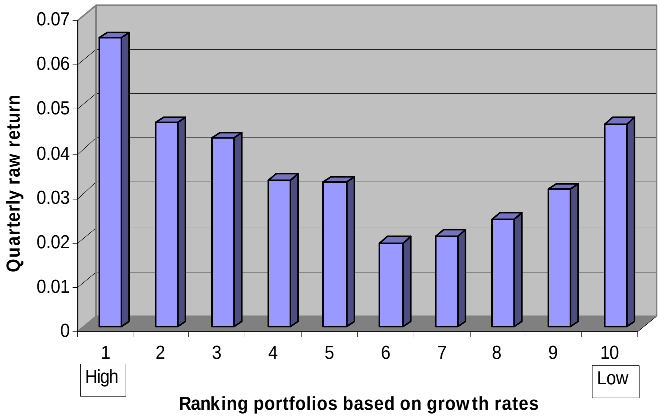
The performance of the bottom portfolio in Panel B, Table X, deserves a separate analysis. Funds in the bottom portfolio shrink at an average rate of nearly –36%. Notice in the fourth column, however, that the bottom portfolio is not the worst performer in terms of raw returns in the ranking period. Moreover, it does not underperform the style index, contrary to the rest of below median portfolios. The distribution reported in the fourth column is depicted in Figure 5, which shows a *J*-shape distribution of average raw returns across 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.[39]

The portfolio with the lowest cash flows has markedly different performance characteristics than other below-median portfolios. A closer examination of 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

Figure 5

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

In each quarter, from 1994Q4 until 2000Q1, we rank hedge funds based on the net cash flows they experienced during that quarter. Cash flows are measured as growth rates. We assume that flows take place at the end of the period. Then we sort funds in 10 portfolios and 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.



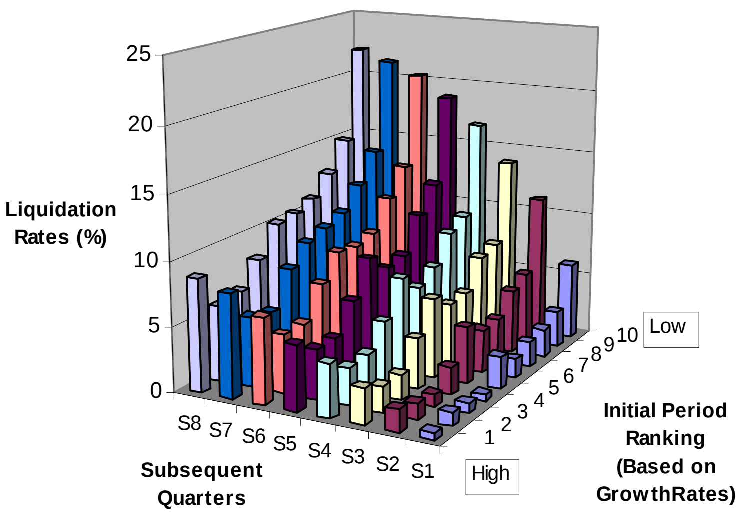
[39] Along our entire investigation we have excluded the very young funds, with less than 6 quarters of historical returns, as explained in Section 2. However, if we do take them into account in our ranking exercise based upon growth rates, the return on the top decile increases significantly towards 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).

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 maturity phase. These funds have faced important outflows probably due to a persistently poor performance, and as a consequence they have seen their asset base shrinking. These funds are declining prematurely. If managers of these funds cannot make up losses to surpass the watermark threshold, they are likely to become reluctant to accept new investors, and eventually, will close down the fund.[40] 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

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.



[40] 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 line with this, 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 (Panel B, Table X).

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 the four quarters subsequent to ranking, the liquidation rate reaches 16.6% for the bottom portfolio, a rate certainly higher than for any other decile. Finally, 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 decile.[41] 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]. Clearly, 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 fast 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].

It is worth noticeable in Table X that the performance of the bottom decile falls initially from 4.57% to 3.6% in the quarter subsequent to ranking. However, it increases steadily with the holding period thereafter (not reported), significantly outperforming the top portfolio by 1.1% (in terms of compounded returns) after 4 quarters and by 1.5% after 8 quarters. On a style adjusted basis, the bottom decile outperforms both the top decile and the index by 1.2% after holding funds for more than four quarters. This pattern is likely the result of many bad performers liquidating while the remaining survivors outperforming. This also explains the upward slope of the pattern of returns of below-median funds for different holding periods, depicted in Panel B, Figure 4, affecting the comparison between above and below-median funds and the assessment of smart money. 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 [2004]. Finally, results not reported show that the cash flow weighted return for the bottom portfolio does not differ significantly from the equally weighted return in the subsequent quarter after ranking. However it does perform worse, by 90 basis points for a holding period of four quarters, and by 1.3% after 8 quarters. In other words, not only investors successfully and rapidly identify funds in decline and likely to liquidate, but also their divestment allocations allow them to reduce even further the opportunity costs involved in their redemption decision.

[41] 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.

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 subtle 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 winners. Nor persistence is 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

Using quarterly data from a sample of open-end hedge funds, we have demonstrated that the investment and divestment decisions of hedge fund investors are driven by different determinants and operate over different time horizons. As a consequence, the two decisions also differ in their effects upon subsequent performance of both hedge funds and investors. The first part of our investigation related money flows to past performance. We have documented a strong 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 funds 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. Thus, we model separately positive and negative net cash flows using a regime switching model with endogenous switching while incorporating the combined impact of redemption and notice periods. Our results indicate that historical relative performance strongly determines whether investors invest or divest in a fund. More particularly, when funds perform poorly, we find an immediate and lasting response of money outflows that gradually disappears over four quarters or so. This effect, however, is substantially reduced 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]. These results confirm indeed that different evaluation horizons underlie investment and divestment decisions. Additionally, our model unmasks important asymmetries between the decisions of investing and divesting. Specifically, size and age play a significant role only for positive growth rates, while lagged flows, incentive fees and the fact that a fund operates offshore determine mostly negative growth rates. Very importantly, our model explaining flows in dollar terms shows that conditional to the regime of positive flows, large funds experience more important amounts of dollar flows than small funds, while conditional to the regime of negative flows, large funds are subject to larger dollar outflows than small funds. These effects remain hidden if positive and negative flows are not modeled separately. Finally, there is strong evidence that investors in hedge funds look for upside potential while minimizing downside risk, as shown by the highly significant coefficient for upside potential ratio.

The second part of our investigation relates money flows to subsequent performance and explores the implications that our previous results have for hedge funds and for investors. By looking into detail at investors' allocations across funds, we have demonstrated that investors are limited in identifying and directing their capital towards the best performers in the short run. This is consistent with our interpretation that searching costs slow down the response of investors to past good performance. In fact, investors fail patently in their investment allocation, by investing mostly in funds that subsequently perform poorly, especially large funds experiencing limits to scale. But also their allocations to small, young and fast growing funds fail to discriminate funds' expected performance. Consequently, most investors appear to be unable to exploit the persistence of the winners. It can also be argued that persistence in quarterly horizons is not competed away, following the argument from Berk and Green [2004]. 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. This is in line with Ippolito [1992]'s idea that investors' reaction has the effect of a disciplining mechanism for low-quality funds. Summing up, our findings suggest that only few investors are able to exploit the persistence of 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[42]. $Flow_{it-j}$ 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 A and B. 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

[42] $Flow_{it}^{-}$ 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.[43] 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 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 results 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 redemption and subscription dates characterizing hedge funds in comparison to mutual funds reduce hidden costs associated to liquidity-motivated trading (see Edelen [1998]).[44]

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[43] 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.

[44] 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 [2004]). 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. 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, which was also reflected in our estimates of our model in Section 4.