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Abstract

Believers in the law of small numbers tend to overinfer the outcome of a random process after a small series of observations. They believe that small samples replicate the probability distribution properties of the population. We provide empirical evidence indicating that investors are mistakenly driven by this psychological bias when hiring or firing a fund manager. Using quarterly data between 1994 and 2000 of 752 hedge funds, we look at investment and divestment decisions of investors after a successful (or losing) streak of a fund manager. Apparently, sophisticated investors exhibit a "hot-hand" bias that may seriously harm their wealth.

Keywords: law of small numbers, performance persistence, overreaction, hedge fund investors, hot-hand bias.

JEL-Classification: G11, G14, G23

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1 Introduction

Empirical studies that focus on the response of investors to past performance of fund managers are clear in one point: investors chase the winners. A convex flow-performance relationship has been documented in annual horizons for both mutual funds and hedge funds, meaning that flows of money are massively directed to the best performers in the previous year (see e.g. Ippolito [1992], Sirri and Tufano [1998], Agarwal, Daniel and Naik [2003])[3]. Chasing the winners, or momentum investing, is often seen as an expression of investors' overreaction and has been attributed to the representativeness heuristic: people rely too much on recent past performance signals as representative of future performance[4]. The hypothesis that investors overreact has almost been taken for granted on the grounds that there is little or no evidence that fund managers' performance can be predicted from past performance. Recent theoretical developments based on rational choice (see Berk and Green [2004]) suggest, however, that chasing the winners is not necessarily inconsistent with the lack of predictability in managers' performance[5]. Whether chasing the winners among fund managers is the result of a psychological bias and reflects investors' overreaction or whether it is a rational response, remains an open question that has not been empirically addressed so far.

In a recent paper, Rabin [2002] presents a theoretical model that shows how momentum investing could in fact be the result of a cognitive bias and the manifestation of investors' overreaction. Further, he derives predictions concerning the behavior of an investor who hires or fires a fund manager depending on her beliefs about dispersion in managerial talent, providing us with an attractive frame for an empirical test. Rabin's model is to a great extent motivated by the results of experiments in which subjects are asked to reproduce a series resembling a binary random process, e.g. tossing a coin. The common tendency is to

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

[4] The assessment of how likely an observed pattern is replicable in the future is often evaluated by how stereotypical or how "representative" of a more general process is such a pattern (Tversky and Kahneman [1974, 1982]). Harless and Peterson [1998] investigate several implications of the representativeness heuristic in the response of investors to past performance of mutual funds, particularly to bad performance. Also Shefrin [2000, Chapter 12] describes the inadequacy of the probability heuristic of investors, who incorrectly frame the problem of picking a talented fund manager, attributing her past performance too much to skill rather than to luck, a bias enhanced by representativeness. A few studies have investigated other psychological biases potentially affecting mutual fund investors' response to past performance, like the endowment effect, the disposition effect and cognitive dissonance, partly accounting for the reluctance of investors to divest from bad performers (see e.g Shefrin and Statman [1985], Goetzmann and Peles[1997]).

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

reproduce series with some degree of negative autocorrelation, alternating between heads and tails too often compared to a truly random series. Rapoport and Budescu [1997] refer to this tendency as the "alternation bias". One explanation widely cited for this bias is the concept of "local representativeness", proposed by Kahneman and Tversky [1972]: apparently, people's perception is that short sequences should have the same proportions of heads and tails, which in fact is a distribution property of large sequences.[6] More generally, people's perception that small samples replicate the probability distribution properties of the parent population, as much as large samples, is a cognitive phenomenon known as *the law of small numbers* or *sample-size neglect* (see Tversky and Kahneman [1971]).

Rabin [2002]'s model is a theoretical description of how local representativeness conduces to the alternation bias.[7] It applies to specific situations where samples are drawn from a binary process, as for instance a series of coin tosses, or a series of signals indicating good or bad performance over time of a manager, a firm or a basketball player. Further, it is formally derived from the model that belief in the law of small numbers leads to two well known biases in pattern recognition: the *gambler's fallacy* and the *hot-hand fallacy*. When people observe a streak of signals and they are certain that the process is purely random (i.e. a fair coin, a lucky manager), in general they expect a reversal given their belief in frequent alternations. This mistaken belief in mean reversion is known as the "gambler's fallacy". On the other hand, if people *do not know* whether the process is entirely random, they may infer (mistakenly) that the series is too long to be random, attributing a causal significance to the streak of signals (i.e. the coin is not fair, the manager is talented, the player has hot hand). In that case, people expect continuation. It follows from Rabin [2002]'s model that the larger the observed streak, the larger the expected probability of continuation will be. [8] This is the rationale behind the so called "hot-hand fallacy", first documented by Gilovich, Vallone and

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

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

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

Tversky [1985] in the context of basketball players' shots.[9] Contrarian investment strategies (trading against the trend) are often attributed to the gambler's fallacy (see De Bondt [1991], Shefrin [2000]), while momentum strategies (e.g. trend-chasing or feed-back trading) are often attributed to the hot-hand bias[10].

In the present paper we empirically investigate investors' momentum strategies in selecting fund managers and the extent to which they relate to the law of small numbers. To this end, we analyze actual money flows to and from hedge funds and their relationship with the length of past (winning and losing) performance streaks. This allows us to test the predictions of the model of Rabin [2002] concerning investors' overinference of managers' talent, as revealed by their observed actions, viz. their investments *in* and divestments *from* a hedge fund. Specifically, we test the hypothesis that overinference is positively related to the length of the streak. The extent to which investors' decisions are determined by persistence patterns of winning and losing streaks and whether or not investors display a hot-hand bias are specific questions that have not been addressed so far in the empirical literature. One reason is that all studies on the flow-performance relationship mentioned above use annual data, and thus an investigation of the responsiveness of money flows to the length of winning or losing streaks is necessarily limited by the time periods available, persistence horizons and the survival of funds.[11]

To overcome these limitations, we use quarterly data of hedge funds which allows us to identify relatively long performance streaks. The advantages of using a database of hedge funds for the purposes of this investigation will be discussed in Section 3. The typical hedge fund investor has arguably more financial expertise than the average client of mutual funds. Actually, the magnitude of the minimum investments required in this industry is meant to limit participation in hedge funds to highly sophisticated investors.[12] We could therefore

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

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

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

[12] Investments in hedge funds are limited to "accredited investors" and "sophisticated investors" (Investment Company Act, 1940). A person is a "sophisticated investor," if the investor either alone or with the investor's

expect a hedge fund investor to pay attention to appropriate benchmarks, styles, risk adjusted measures of performance and tracking error and to make sound performance analyses. Thus, by studying hedge fund investors' decisions we can separate misperceptions due to the lack of experience or the lack of understanding of financial markets from a psychological bias, if any. As suggested by De Bondt [1991], especially experts may be prone to distinguish patterns where there are none.

The contribution of this paper is twofold. We first provide a model that explains relative performance of a hedge fund from historical performance streaks while controlling for size, age, style and other fund characteristics. We find that the length of the streak is to some extent indicative of future relative performance, which confirms previous findings of multi-period performance persistence of hedge funds (see Agarwal and Naik [2000]). Second and most importantly, we investigate the response of money flows to the length of the streak, while controlling for expected performance and several variables accounting for the riskiness of a fund. Our results indicate that the length of the streak of a hedge fund manager has a statistically and economically significant impact on flows, beyond what is justified by expected future performance of the fund, suggesting that investors overinfer the likelihood of performance persistence. Our findings are in line with the predictions of Rabin [2002]'s model and with previous experimental and empirical evidence of the hot-hand bias in other domains.

The remainder of this article is organized as follows. In Section 2 we discuss some relevant characteristics specific to the process of investing in hedge funds. In Section 3 we describe our dataset and variables. Section 4 presents stylized evidence of momentum investing of hedge fund investors in response to multi-period performance persistence. In Section 5 we provide a model that disentangles a rational response of investors to past performance streaks from a response presumably induced by the law of small numbers. Section 6 presents some robustness checks, while Section 7 concludes.

2 The process of selecting a hedge fund manager

This section describes some of the key aspects of investing in hedge funds that are necessary to understand how potential psychological factors might affect investors' decisions. Simply stated, a hedge fund is a private investment portfolio with limited regulation that combines

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purchaser representative(s) has such knowledge and experience in financial and business matters that the investor is capable of evaluating the merits and risks of an investment in the hedge fund. An "accredited investor" is either an individual with a net worth of $1 million or more or an annual income of $200000 or more, either an entity with total assets above $5 million.

both long and short positions on a leveraged basis.[13] The manager is usually a general partner and charges a performance-based incentive fee in addition to management fees that cover operation and administrative expenses. Relevant features are the limited transparency, implying increased searching costs for investors, and the limited liquidity offered to clients through lock-up periods and redemption restrictions. The attractiveness of hedge funds for both private and institutional investors lies in two key features. First, given the structure of managerial incentives, hedge funds seek absolute returns instead of relative returns with respect to a benchmark, as it is the case for the more traditional mutual funds.[14] Second, the limited regulation they enjoy allows them to make active use of short selling and derivatives and to dynamically trade in a wide array of assets, which explains the low historical correlations between hedge funds and traditional asset classes. These features make hedge funds attractive for diversification and hedging purposes in a variety of ways, depending on the specific risk and return targets of an investor's portfolio.

Any considerations about investing in hedge funds are usually preceded by a clear definition of investors' own objectives. Investors often set a target return for their portfolio with a given exposure to markets. Given these investment objectives, investors seek the most appropriate hedge fund strategy that helps diversify their portfolio and achieve their investment goals. Once the appropriate strategy has been identified, investors strive to find the most talented manager(s) in that strategy. The following is a schematic picture of the process of selecting a hedge fund manager. In a first stage, investors identify potential talented managers by their performance track records.[15] Given the information hurdles faced by investors (i.e. limited transparency and restricted advertising imposed by regulatory authorities), the track record of a manager plays a major role as the most readily available information indicative of his potential skill. It also gives the means for a screening procedure, to identify the potential targets among a large number of managers in a database that are worth a more careful analysis later. In a second stage, a quantitative and qualitative due diligence process follows, in order to determine whether the observed track record was generated by a lucky manager or by a truly skilled manager. In a quantitative analysis, return and risk characteristics and other variables are assessed over time, like the amount of leverage, the amount of capital managed,

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

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

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

money flows, the investment strategies employed, downside deviations, upside potential ratios and expense ratios. Besides, the alignment incentive mechanisms are taken into account, like the level of incentive fees and the amount of the manager's personal wealth invested in the fund. Finally information contained in the offering memorandum, especially regarding redemption conditions, is essential. The qualitative analysis pays attention to manager's integrity and personality, his investment ideas, the quality of the organization and personnel. This is carried out through frequent personal meetings and references from former colleagues of the manager or peers in the industry. Finally, a third stage corresponds to the post-investment phase. After hiring a manager, an ongoing due diligence is crucial. Frequent monitoring and quantitative and qualitative evaluations are necessary to detect changes in investment style or major changes in the organization.[16]

From this brief account of the steps usually undertaken by investors, it should remain clear that, regardless of whether the main purpose of investing in a hedge fund is diversification or the pursuit of absolute returns or both, the first task for an investor is to find a talented manager within the strategy that better suits the investor's objectives. Notice that a primary assumption from investing in a hedge fund is that the manager *has* talent. In fact, the entire hedge fund industry is marketed on the grounds of managerial skill and defines itself as a skilled-driven industry. This is a feature with special relevance for our study. If investor's perception of a manager's track record is indeed biased due to local representativeness (i.e. the law of small numbers), it is precisely the belief or not in talent what determines, in theory, the direction of the bias. This is formally captured by the model of Rabin [2002]. Investors who are fully skeptical about managerial talent are certain about the probability of success of any manager (i.e. 50%), but also they believe in no variation in quality among managers (i.e. all managers have the same probability of success). Skeptical investors will be prone to the gambler's fallacy and will tend to underestimate the probability of performance persistence[17]. Hedge fund investors, on the contrary, firmly believe that talented managers exist.[18] Thus, by definition, they believe in quality dispersion. In theory, when investors are uncertain about the probability of success of a given manager, they will be prone to overinfer

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

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

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

his talent from an observed performance streak and exaggerate the probability of continuation. Further, the longer the streak, the larger the overinference will be, which is precisely the feature we focus on and we test in the present paper. Curiously, an important additional result derived from the model of Rabin is that the belief in local representativeness results in an illusory belief in wider differential ability than actually exists. Further, investors' overinference of the likelihood that a manager is talented exacerbates in turn his beliefs about how talented he is.

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

3 Data

We use a survivorship-free data of open-end hedge funds from TASS Management Limited, a private advisory company and provider of information services. We focus on individual open-end funds reporting in US$, and exclude funds-of-funds (i.e. portfolios of hedge funds). Our sample contains 752 funds and a total of 7457 fund-period observations between the fourth quarter of 1994 and the first quarter of 2000. The funds that liquidated amount to 163, while 86 funds self-selected out of the database for different reasons. [19]

Along this paper we argue that investors are sensitive to the precise pattern of performance signals they observe. In the hedge fund industry, information on total net assets under management (TNA) and raw returns of individual funds and style indices is released periodically, typically on a quarterly basis for monitoring purposes.[20] The financial press and industry newsletters also emphasize quarterly figures. Further, most redemption restrictions take place quarterly, which imposes an implicit frame for investors' decisions. We study,

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

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

therefore, the response of investors to sequences of quarterly performance signals. Returns are net of all management and incentive fees. Following a standard definition, assuming that flows take place at the end of period *t+1*, flows are measured as the growth rate in total assets under management 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.

$$CashFlow_{t+1} = \frac{Assets_{t+1} - Assets_{t}}{Assets_{t}} - r_{t+1}$$

This definition is also referred to as *normalized cash flows*. Alternatively, a measure of absolute cash flows, in dollar terms, is computed as a net change in assets minus internal growth.[21]

$$DollarFlow_{t+1} = Assets_{t+1} - Assets_{t}(1 + r_{t+1})$$

Table I shows some descriptive statistics for normalized cash flows, dollar flows and assets under management. Notice that the distribution of cash flows appears to be relatively symmetric, in sharp contrast with the distributions found for mutual funds.[22] This is a feature that we exploit later in our investigation, as we are interested in both investments and divestments decisions as proxies for investors' beliefs.

Table I

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

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

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

[21] See Ippolito [1992], Gruber [1996], Zheng [1998], Del Guercio and Tkac [2002] for a discussion about the assumptions underlying these definitions of flows.

[22] 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%.

Table A1 in the appendix shows descriptive statistics for several fund-specific characteristics as well as some performance and risk metrics of the funds in our dataset. A brief description of each variable is also provided.[23] Using data on hedge funds presents several advantages for the purposes of our study. First, given the persistence patterns of hedge funds in quarterly and annual horizons, it is more likely to identify relatively long series of successive wins and losses with quarterly data than for mutual funds. In fact, we could identify streaks from one up to twelve successive gains or failures. Second, mutual fund flows are subject to noise in short horizons due to the liquidity needs of investors, for whom daily withdrawals and subscriptions are possible, while hedge funds impose restrictions to both withdrawals and subscriptions, typically monthly or quarterly[24]. This makes money flows to hedge funds less subject to noise or to large variations and more suitable to be studied in horizons shorter than one year. Third, in quarterly horizons there appears to be a response of money outflows to poor performance in the previous quarter, contrary to annual horizons where investors display little sensitivity to previous year poor performance. Therefore, with quarterly data we can also assess a "cold-hand" phenomenon whereby investors expect continuation from observed losing streaks. [25]

4 The response of money flows to persistence patterns

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

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

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

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

Table II

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

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

Panel A : Winner Streaks

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

Panel B : Loser Streaks

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

According to Panel A in Table II, for instance, we identified 687 three-quarter winning streaks between 1994Q4 and 1999Q4. In the quarter that followed the series, 0.44% of funds liquidated and 0.58% self-selected. Also, 57.5% of funds remained winners (i.e. persistent funds) while 70.89% received positive net flows of money. The average money flows that investors directed towards these funds after a successful three–quarters history amounts to nearly 6.2 million US dollars per fund (considering both positive and negative net flows). We interpret net flows of money as a measure reflecting the average opinion of investors about a given fund. If net flows of money are positive (i.e. inflows outweigh outflows), it means that a majority of investors expect an above-median performance of a fund in that quarter and they invest accordingly.[26]

Panel A indicates that, in general, a fund is more likely to persist after longer winning streaks (see column five). While 52.77% of funds remained winners after two successful quarters, almost 70% of funds were winners after displaying a six-quarter winning streak. The pattern becomes somewhat erratic for streaks longer than six quarters, probably due to the reduced number of observations. These figures, however, favor the idea that managerial skill exists in the hedge fund industry and that hedge fund performance is to some extent predictable. We do observe a concomitant reaction of investors, who appear to pour larger amounts of money as the length of the streak increases. The average money flow that a fund experiences after a two-quarter winning streak is around 2.1 million US dollars, while a fund receives on average above 9 million US dollars after six successful quarters. For a given streak length, however, investors do not invest in 100% of funds, an indication of their effort to distinguish the lucky from the truly skilled managers. Noticeably, the percentage of funds receiving positive net flows of money also increases monotonically with the length of the streak, as indicated in column six. Distinguishing between luck and skill is a notoriously difficult task and a certain percentage of error is expected. The mismatch is shown in the last column of Table II. For streaks of two quarters length, positive money flows were actually directed to subsequent loser funds in 41.26% of the cases. This percentage reduces with streak length as the probabilities for a fund to remain a winner increase. However, for 6 quarters of streak length, the likelihood of an over-forecast is still a substantial 25.58%. If we repeat this exercise separately for large and small funds, the patterns remain the same and percentages do not change substantially[27]. The question of interest is how much of this forecast error is

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

[27] According to Baquero and Verbeek [2005], there is a non linear impact of size upon quarterly relative performance of hedge funds, which presumably reflects decreasing returns to scale in this industry. There seems to be a turning point around US$ 25 million of total net assets under management. Above this level, an increase

due to over-optimism, presumably induced by the length of the streak as the law of small numbers suggests?

Panel B of Table II shows the results for losing streaks. The likelihood for a fund to remain a loser after a series of successive failures increases with the length of the streak. For instance, if a fund has been ranked below the median for six quarters on a row, there is a 60.76% probability that the fund persists as a loser in the subsequent quarter, while only 47.72% of funds are persistent losers after two quarters of poor performance. These figures are likely to be underestimates given the large percentage of funds liquidating, especially for long streaks. If a fund survived after an extended period of bad performance, it is likely that it performed better than average so as to recover past losses and surpass the high watermark.[28] Given these patterns of negative persistence, or "cold hand", investors react accordingly by withdrawing increasing amounts of money as funds persist below the median for longer periods. After two quarters on a row of bad performance, a fund experiences average outflows of around 1.8 million dollars. If bad performance persists up to five quarters, a fund will face further withdrawals of nearly 11 million dollars on average. Again, these figures are likely to be affected downwards by the high attrition rates of persistent losers. On the other hand, several factors might reduce the responsiveness of investors to losing streaks compared to winning streaks. For example, restrictions imposed to withdrawals are more important than restrictions to subscriptions. Further, investors often face switching costs relative to closing and opening accounts. Finally, several psychological biases may inhibit investors from divesting, like the endowment effect, the disposition effect or cognitive dissonance as suggested by Goetzmann and Peles [1997].

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

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in size results in a loss of ranking position. Therefore we used this amount of assets to separate small from large funds. This threshold is slightly above the cross sectional mean of about US$18 million.

[28] Remember that the typical incentive contract aims at enhancing managerial effort by paying hedge fund managers a percentage of annual profits if returns are above some hurdle rate and provided the fund value is above a high watermark.

Table III

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

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

Panel A : Winner Streaks

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

Panel B : Loser Streaks

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

longer persistence patterns (columns 6 and 7), although long streaks have less predictive ability of future relative performance. The dispersion in money flows is less pronounced than in the previous table, consistent with the findings from Baquero and Verbeek [2005] that money flows are more responsive to ranks based on raw returns than on style-adjusted returns.[29]

Intuitively, the belief on a manager's skills is eroded with very long streaks and the increasing skepticism would lead eventually to commit gambler's fallacy. This idea is also formally captured in Rabin's model.[30] The key question is for how long an investor believes talent will last. The hot-hand bias and the gambler's fallacy are obviously two related biases and compete with each other. The stylized evidence presented in Tables II and III shows a monotonic pattern in money flows as the streak length increases, up to six quarters or so. As indicated above, for longer streaks the pattern becomes less clear. It is difficult, however, to conclude from our data whether the change in pattern is the result of emergence of the gambler's fallacy, since the number of observations considerably reduces with streak length. Moreover, money inflows might be increasingly restricted as funds grow in size.

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

5 A model explaining money flows from the length of streaks

Our results in the previous section show that money flows are increasingly directed towards funds that successfully performed for longer periods of time. In this section we investigate to what extent this seemingly overwhelming response of investors is rationally justified. Is there

[29] This might be an indication of an insufficient adjustment of investors to style as a source of risk.

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

any component in that response that is beyond a rational expectation of future performance and risk?

In order to disentangle these two components of the response of investors to past performance, namely a sensible reaction from one presumably induced by a psychological bias, we first determine what an investor can rationally expect of future relative performance of a fund given a number of informative variables, including historical persistence patterns. Our previous analysis did not consider several factors that can also be driving performance, such as size, age, style and other fund-specific features. Arguably, investors, especially sophisticated investors, pay attention to these characteristics, as well as variables accounting for risk. Consider the following model predicting relative performance of a fund (i.e. relative to its peers):[31]

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

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

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

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

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

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

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

Table V provides an answer to these questions. In column A, we report the estimates of a probit model explaining the sign of cash flows from the expected rank, as obtained from our previous model, but we explicitly include the persistence dummies in order to identify any

Table IV

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

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

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

Table V

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

The table reports estimates of a probit model explaining positive and negative flows. The sample includes 752 open-end hedge funds for the period 1994 Q4 till 2000 Q1. We measure cash flows as a quarterly growth rate corrected for reinvestments. The independent variable takes value 1 if cash flows are positive. Otherwise it takes value 0. The independent variables include 12 mutually exclusive dummies accounting for the length of winner and losing streaks and we control for expected rank (obtained from our model reported in Table IV, Panel C). The model reported in Panel B also controls for fund specific characteristics including the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows, upside potential based on the entire past history of the fund and calculated with respect to the return on the 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 (estimates not reported). The model also includes 21 time dummies (estimates not reported). We estimate each model by pooling all fund-period observations. z-statistics are provided in parentheses.

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

additional effect that the pattern of persistence might have on investors' decisions. The impact of the predicted rank upon flows is positive and highly significant, as can be expected. The higher the predicted rank, the more likely a fund will experience positive money flows. Besides, we find a remarkable pattern for the coefficients of the dummies. All the estimated coefficients for winning and losing streaks are highly significant, while in absolute value they increase monotonically as the length of the streak increases. The longer the winner streak, the more likely is a fund to attract further inflows of money, regardless of what is rationally justified given expected relative performance. Conversely, the longer the losing streak, ceteris paribus, the more likely that a fund experiences further outflows. In column B we provide an extended model that considers the fact that investors' decisions are also affected by their expectations about risk. If we include several control variables like age, size, style, standard deviation of historical returns, downside risk, that are informative of the fund's riskiness besides expected rank, the explanatory power of the model enhances substantially, as indicated by the value of the pseudo R^2. Several of these added variables have indeed economically and statistically significant coefficients. Statistically, the impact of expected rank upon flows reduces slightly but remains significant. However, the pattern and magnitude of coefficients for the persistence dummies remains essentially unchanged, clearly showing that flows are directed much more towards persistently winning funds and out of persistently losing funds than is justified by expected future performance.[32]

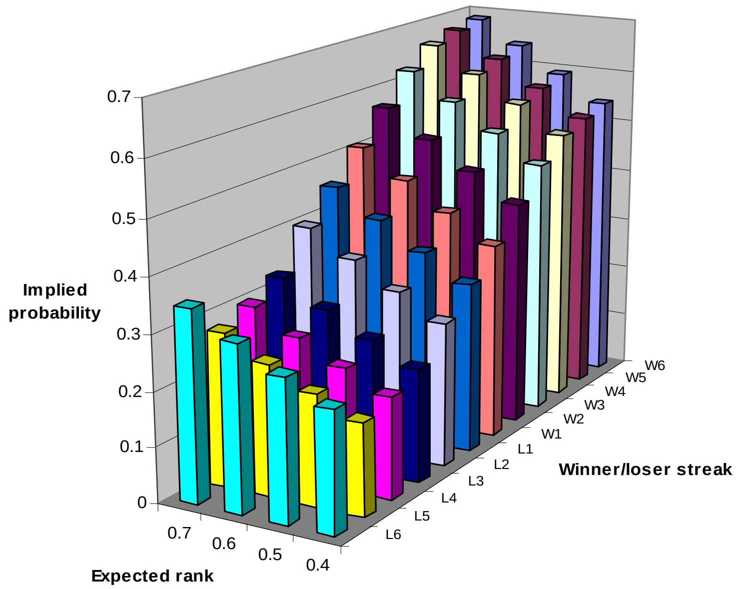
To have an idea of the economic significance of our findings, we use the coefficients of the persistence dummies in the previous model to compute the implied probability that investors invest in a fund (as indicated by a positive sign of cash flows) given a certain streak length, for different values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

Consider a fund which is rationally expected to be in the 70th percentile of the distribution in the next period according to our model (i.e. rank=0.70). The likelihood that investors direct their money towards this fund differs across streak lengths, although the information content of a streak is already accounted for in the expected rank. This likelihood is 69% after a winning streak of six quarters, compared to 51% after a winning streak of one quarter. Similarly, if a fund is expected to be ranked in the 40th percentile, the likelihood that investors redeem is 78% after a losing streak of six quarters, compared to 69% after a losing streak of one quarter. Interestingly, there is a non negligible probability of 35% that investors invest in a fund after six losing quarters when the expected rank equals 0.7, while in 46% of cases investors will divest from a fund after six winning quarters if the fund's expected rank equals 0.4.

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

Figure 1

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



The results so far indicate that hedge fund investors are directing their money flows in response to winner and losing streaks much more than is justified by the expected future performance of the funds. To further investigate this issue, we consider three different investment strategies. The first one is a naïve strategy that prescribes to invest in all persistent winners and to divest from all persistent losers. The second strategy is the one followed by the average investor, as indicated by the sign of money flows. That is, this strategy invests in funds with a positive money flow (equally weighted) and divests from funds with a negative money flow. The third strategy is based on our model explaining ranks reported in Table IV, Panel C, and prescribes to invest (divest) in a fund if the model predicts that subsequent rank is above (below) the median.[33] In Table VI, Panel A, we report raw returns obtained from these three strategies, where we also decompose the returns across subsets of funds with a given (winner or losing) streak length. The investment strategy based upon the model provides an average return of 6.31% per quarter, outperforming the funds with positive money flows by 1.72%, especially the funds with losing streaks. The divestment strategy based upon the model prescribes to divest from funds that subsequently performed worse than the funds from which investors actually redeemed (1.81% against

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

Table VI

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

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

Panel A: Subsequent quarter raw returns

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

Panel B: Subsequent quarter style-adjusted returns

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

2.98% on average)[34]. Assuming that divestments finance investments, the zero-investment strategy prescribed by the model provides an excess return of 4.5% per quarter, against 1.61% obtained by the zero-investment strategy followed by investors[35]. Panel B shows similar results in terms of style adjusted returns. We can conclude that the excessive importance that investors attribute to the length of performance streaks as indicative of future performance, is detrimental to investors' wealth. On the other hand, investors directed money inflows towards funds with winning streaks that outperformed the naïve strategy (5.27% against 4.46% on average). Conversely, investors redeemed from funds with losing streaks that underperformed, on average, the naïve divestment strategy (2.76% against 3.14%). These figures indicate that investors strive to discriminate between skilled and lucky managers in spite of a given performance streak. However, it seems that many investors follow contrarian strategies more actively than what the model prescribes, often investing in previous losers and divesting from previous winners, which offsets to a large extent the gains from momentum investing. As a result, investors do not perform overall much better than the naïve strategy. In fact, in terms of style adjusted returns, the naïve strategy provides slightly higher returns from investments (0.59% against 0.52%) and slightly worse returns from divestments (-0.34% against -0.28%).

Our previous analysis indicates that investors' allocations are potentially suboptimal. The opportunity costs involved appear sizeable, suggesting that investors take decisions that are not adequately grounded. On the other hand, we did not take into account transaction costs or liquidity restrictions that may prevent investors from taking timely decisions or from shifting their capital as the model prescribes. The next section analyzes the impact of liquidity restrictions in the estimation of our model and discusses several additional robustness tests.

6 Robustness checks

In this section, we consider a large number of alternative model specifications and assumptions to analyze the sensitivity of our main results. First, we investigate a model that explains growth rates of cash flows rather than just their sign. Second, we experiment with different thresholds to define winners and losers. Third, we consider specifications where we use ranks and persistence dummies based on style-adjusted returns instead of raw returns.

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

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

Fourth, we include expected performance over the coming year rather than just the next quarter in the model. And finally, we explore the potential effects of liquidity restrictions.

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

This main result is robust to a number of alternative specifications. We have experimented with different thresholds to define winners and losers other than the median (see Tables A4, A5, A6, A7 in the appendix). Also, we have estimated our models using ranks and persistence dummies based on style-adjusted returns instead of raw returns[36] (see Tables A2 and A3). In all these specifications we obtain similar results as before: the longer the streak, the more important is its impact on investors' decisions.

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

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

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

Table VII

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

The table reports OLS estimates of a model explaining money flows. The sample includes 752 open-end hedge funds for the period 1994 Q4 till 2000 Q1. We measure cash flows as a quarterly growth rate corrected for reinvestments. The independent variables include 12 mutually exclusive dummies accounting for winner and losing streaks. We control for expected rank (obtained from our model estimated in Table IV, Panel C) and for fund specific characteristics like the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows, upside potential based on the entire past history of the fund and calculated with respect to the return on the 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 (estimates not reported). The model also includes 21 time dummies (estimates not reported). We estimate each model by pooling all fund-period observations (t-statistics are provided in parentheses).

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

interactions between the persistence dummies and dummies accounting for the combined impact of redemption and notice periods.[37] Table VIII reports our results. Notice first that the impact of winning streaks on money flows is indeed magnified when liquidity restrictions are in place, especially for streaks of 4 and 5 quarters length, while the response of money flows to losing streaks is virtually non-existent, as could have been expected. As a consequence, the response of unrestricted money flows to winning streaks reduces slightly compared to our results in Table V, while the response to losing streaks is enhanced. Removing the effect of restrictions, however, does not change the main result of this paper. We still find a significant and increasingly positive (negative) response of unrestricted money flows to the length of winning (losing) streaks.

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

7 Concluding remarks

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

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

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

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

Table VIII

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

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

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

hedge funds and we present a model that disentangles a rational component from a heuristic-driven component in momentum investing.

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

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

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

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

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APPENDIX

Table A1

Cross-Sectional Characteristics of the Hedge Fund Sample

This table presents summary statistics on cross-sectional characteristics of our sample of 752 hedge funds for the period 1994Q4 till 2000Q1. Cash flows are the change in total net assets (TNA) between consecutive quarters corrected for reinvestments. Returns are net of all management and incentive fees. Age is the number of months a fund has been in operation since its inception. In each quarter, the historical standard deviation of monthly returns, semi deviation and upside potential have been computed based on the entire past history of the fund. Semi deviation and upside potential are calculated with respect to the return on the 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 the value one if the managers invests from her own wealth in the fund. The dummy leverage takes the value one if the fund makes substantial use of borrowing. We include 10 mutually exclusive dummies for investment styles defined on the basis of CSFB/Tremont indices. The dummy labeled *hedge fund index* takes value 1 whenever a fund could not be categorized in a specific investment style.

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

Table A2

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

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

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

Table A3

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

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

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

Table A4

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

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

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

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

Table A5

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

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

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

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

Table A6

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

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

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

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

Table A7

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

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

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

Table A8

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

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

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

Table A9

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

The table reports estimates of a probit model explaining positive and negative flows. The sample includes 752 open-end hedge funds for the period 1994 Q4 till 2000 Q1. We measure cash flows as a quarterly growth rate corrected for reinvestments. The independent variable takes value 1 if cash flows are positive. Otherwise it takes value 0. The independent variables include the previous annual rank and 12 mutually exclusive dummies accounting for winner and losing streaks. Independent variables accounting for fund specific characteristics include the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows, upside potential based on the entire past history of the fund and calculated with respect to the return on the 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 (estimates not reported). The model also includes 21 time dummies (estimates not reported). We estimate each model by pooling all fund-period observations. z-statistics are provided in parentheses.

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