HEDGE FUND FLOWS AND PERFORMANCE STREAKS: HOW INVESTORS WEIGH INFORMATION*

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January 28th, 2015

ESMT Working Paper Nº 15-01

Abstract

We examine the relative weights hedge fund investors attach to past information in the fund selection process. The weighting scheme appears inconsistent with econometric forecasting models that predict fund returns, alphas or Sharpe ratios. In particular, investor flows are highly sensitive to performance streaks despite their limited predictive power regarding fund performance. Further, allocations based on forecast models' out-of-sample predictions beat investor allocations by a significant margin, which suggests that the latter are suboptimal and reflect overreaction to certain types of information. Our findings do not support the notion that sophisticated investors have superior information or superior information processing abilities.

Keywords: hedge funds, money flows, extrapolative expectations, law of small numbers, performance streaks, relative weights, smart money.

JEL-Classification: G11, G12, G14, G23

ISSN 1866-3494

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* The authors benefited from extensive discussions with Francis de Vericourt, Ben Jacobsen, Yaakov Kareev, Anthony Lynch, Dimitri Vayanos and Georg Weizsäcker. We are also grateful to Frank de Jong, Alberta Di Giuli, Simone Kohnz, Ignacio Palacios-Huerta, Tarun Ramadorai, Zheng Sun, Ashley Wang, and three anonymous referees for valuable and constructive comments. Early versions of this manuscript were circulated under the title "Do Sophisticated Investors Believe in the Law of Small Numbers?"

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1. Introduction

Investor decisions to allocate wealth among the large numbers of hedge funds reflect an elaborate process of collecting, processing, and interpreting many sources of information, both qualitative and quantitative. Previous studies have shown past performance, summarized in many different measures, to play a significant role in hedge fund investors' capital allocation (see, for example, Aragon et al., 2014, Ding et al., 2009, and Li et al., 2011). We further explore in this paper the role of information in this allocation process. We examine the relative weights hedge fund investors attach to performance measures and other variables, and how this weighting scheme affects their choices and subsequent performance. We identify an additional important signal related to past performance that hedge fund investors weigh heavily, namely, the length of past performance streaks. We find the lengths of winning and losing streak patterns (the number of subsequent quarters a fund performs above or below a given benchmark) to have an economically and statistically significant impact on net flows, and to be among the most important predictors of investor decisions relative to other performance metrics. That the information content of such streaks relative to future hedge fund performance is quite limited, however, leads to one of the main findings of our study: on average, hedge fund investors weigh information signals suboptimally, and thus make poor investment and divestment decisions, their performance easily being beaten by data-driven allocation decisions based on recursive out-of-sample forecasts from simple linear regressions.

Our results relate closely to recent findings in the literature from psychology and economics that document the tendency of investors to identify, and expect continuation of, trends in prices. This behavior reflects extrapolative expectations that appear to be inconsistent with models of rational expectations (see, for example, Greenwood and Shleifer, 2014). Investors may attach disproportionate importance to streak length because performance streaks are easily observable and may be perceived to be more informative than is justified by the data. People's biased tendency to respond to streak patterns has been widely documented in the psychological literature (see, for example, Gilovich, Vallone and Tversky, 1985). Recent theoretical papers that attempt to explain investors' perception of streaks assume agents to have a mistaken belief about the underlying process by which these signals are generated. Barberis, Schleifer and Vishny's (1998) model of investor sentiment, based on the behavioral heuristics of representativeness and conservatism, generates under-reaction to signals that revert frequently and overreaction to signals that trend. Rabin (2002) describes a model based on representativeness and the law of small numbers (Tversky and Kahneman, 1971, 1972), which implies that the longer the observed series, the greater the expected probability of continuation. Belief in the law of small numbers in the latter model leads to two well-known biases in pattern recognition: the "gambler's fallacy" and "hot-hand fallacy." The belief in frequent alternations leads those certain that the process by which a series of signals is generated is purely random (i.e., a fair coin, a lucky manager) to generally expect a reversal. This mistaken belief in mean reversion is termed the "gambler's fallacy." Those, on the other hand, who attribute causal significance to a series of signals inferred (mistakenly) to be too long to be random (i.e., the coin is not fair, the manager is talented, the player has a hot hand), expect continuation. This is the rationale for the so-called "hot-hand fallacy."[3] In the context of hedge funds, investors who believe that, say, six consecutive quarters of fund performance above a given benchmark likely reflects managerial skill expect the fund to outperform in the future, even in cases in which winning streaks are completely driven by randomness.[4] Rabin and Vayanos' (2010) model, which also examines the links between the gambler's and hot-hand fallacies, hinges on a mistaken belief by economic agents that the true series of signals exhibits reversals. Their model also predicts that individuals overreact to long streaks, but may underreact to very long streaks, and possibly to short ones as well. Durham, Hertzel and Martin's (2005) evidence of overreaction to short streaks and under-reaction to long streaks in the college football betting market is to some degree in line with these predictions. Asparouhova et al.'s (2009) and Loh and Warachka's (2012) recent evidence of investor response to streaks of earnings surprises is in line with gambler's fallacy and Rabin's (2002) model.

In the asset management industry, alternative explanations why investors may attend to specific sequences or patterns of performance signals generated by funds over time are that performance streaks may signal stability, reduced exposure to risk factors, reduced variance of performance forecasts or reduced operational risk, all of which would increase investor confidence. In this sense, streak length likely

[3] The "hot-hand" phenomenon was first documented by Gilovich, Vallone, and Tversky (1985) for basketball players' shots. A player who successively scores several times is perceived to have a "hot hand" and expected to continue to score. Gilovich et al. (1985) demonstrate there to be no such phenomenon, and basketball players' shots to be largely random. Evidence from the market for organized gambling in basketball games is provided by Camerer (1989), who finds that teams with winning (losing) streaks are believed to be somewhat more likely to continue winning (losing) than they actually are. An overview of psychological evidence that supports the hot hand phenomenon is provided by Gilovich (1991) and Falk and Konold (1997). See also Wagenaar's (1972) survey.

[4] Even when the probability of a winning quarter is 0.5, independently, over time, the probability of observing a winning streak of length six in any six-period-window is more than 1.5%.

correlates with past alphas or past Sharpe ratios, and may be informative about future fund performance above other metrics. To determine whether investors respond to streaks beyond this set of considerations is one of our objectives.

Our focus in this paper is on the role of performance streaks in hedge fund investors' allocation decisions from the broader perspective of how investors process information. First, we test the hypothesis that streaks matter to investors in the fund selection process. We use model selection criteria to determine a relatively parsimonious specification of a probit model that explains the decision of the average investor to invest in or divest from a hedge fund, allowing for a wide set of candidate performance-related variables on the right-hand side. The model controls for return smoothing, return volatility, skewness, share restrictions, and a number of fund-specific features. Our empirical analysis of net money flows to and from hedge funds over the period 1995-2010 shows the length of performance streaks to matter to investors in an economically and statistically significant way. Hedge funds with long streaks of winning quarters experience substantially higher inflows, funds with long streaks of losing quarters substantially higher outflows. Further, streak patterns exert a distinct impact beyond other performance measures like ranks, alphas, and Sharpe ratios as well as risk metrics. This finding is robust to the inclusion of measures of operational risk, variance of performance forecasts, managers' option delta, and choice of sample periods.

A key question with respect to improving understanding of how investors process information is the relative importance they attribute to the variables in their information set. We investigate this by complementing the model estimations with the relative weights analysis introduced by Johnson (2000), which enables us to calculate estimates of the relative importance of each set of explanatory variables in explaining the variation in flows. This analysis shows the most important predictors to be annual ranks and streaks and lagged flows, the least important, fund characteristics and styles (which are mostly time-invariant).

The previous findings motivate us to analyze the predictive power of the same set of variables with respect to fund performance. Although we confirm hedge fund returns to be to some extent predictable based on streaks and publicly available information (cf. Avramov, Barras and Kosowski, 2013), investors appear to weigh these information signals quite differently than forecast models. For example, investors attach a weight of more than 17%, the second largest, to the performance streaks relative to other information signals, while streaks appear to be one of the least important predictors of hedge fund performance relative to fund style, fund characteristics, annual ranks and the combined effect of other performance and risk metrics. This contrast could be partly explained if flows themselves affect future performance negatively, for instance, due to capacity constraints or a temporary impact on valuations in a fund's underlying securities. We test this possibility in a number of robustness checks, but, consistent with results reported by Dichev and Yu (2011) and Li et al. (2011), find no evidence in any of our models of an effect of current flows or lagged flows on subsequent performance.

Admittedly, there are potentially omitted factors in both the flows model and the forecast model that are unobservable to the econometrician but are known to investors. In the second part of this paper, we test the hypothesis that investors are better informed than the empirical forecast models, by comparing how investors perform ex post relative to the model's predictions. We first investigate the performance of (hypothetical) hedge fund investments and divestments based on forecasts derived from the set of econometric benchmark models. The models are used to generate, for each fund, out-of-sample forecasts of relative performance that translate into decisions to invest or divest in the subsequent quarter. In almost all cases, the investment portfolio based on model forecasts outperforms the divestment portfolio. In contrast, when we analyze the performance of the average investor strategy to invest or divest, the ex post performance spread between investments and divestments is in all cases insignificantly different from zero, with the exception of the raw return differential in the most recent crisis period, which is significantly negative. This shows that, on average, hedge fund investors' decisions to invest or divest are not smart, and a straightforward econometric model relatively easily beats their performance. Our results are strongly robust to tests that take into account potential restrictions to inflows and outflows, potential capacity constraints, look-ahead bias, different trading rules underlying the benchmark allocations, different investment horizons, and potential flow-induced performance as suggested by Berk and Green's (2004) model. In cases in which investors' decisions differ from the models', it is clear that, among other factors, performance streaks are highly significant, indicating that the relative weights investors attach to the set of information variables are suboptimal and impair investors' ex post performance.

Our work makes a number of important contributions to an understanding of hedge fund investors' behavior, the predictability of hedge fund returns and the extent to which investors are able to benefit from that predictability. [5] First, it documents the crucial role patterns of performance signals play in hedge fund investors' decisions to allocate their wealth. Funds with long positive performance streaks experience substantially higher inflows, those with long negative streaks larger outflows, even after controlling for a wide range of performance measures and other fund characteristics. Second, our work shows performance streaks to have little predictive value regarding future hedge fund performance. Third, we introduce a relative weights analysis that affords a novel perspective on the information processing strategies of investors and the value of information. We show that investors weigh information signals quite differently from what is justified by their information content with respect to future fund performance (as measured by raw and style-adjusted returns, fund alpha and Sharpe ratio). Fourth, we contribute from a new angle to the small but growing literature that studies hedge fund investors' ability to anticipate future fund performance (see Baquero and Verbeek, 2009, Dichev and Yu, 2011, Ding et al., 2009, Ramadorai, 2013). We document funds selected by hedge fund investors to perform economically and statistically significantly worse than those selected by simple rules based on econometric out-of-sample forecasts. This holds for both investment and divestment decisions. We further show cases in which their decisions deviate from the models' to be partly attributable to investors' sensitivity to performance streak lengths. Taken together, these findings do not provide evidence for the existence of smart money in the hedge fund industry. Our main results are at odds with the assumption that investors have superior qualitative or quantitative information, or superior information processing abilities, and consistent with the interpretation that hedge fund investors in their decisions to invest or divest attach too much weight to performance streaks.

The remainder of this article is organized as follows. In Section 2, we describe our dataset and present descriptive statistics of streaks and their correlation with flows and other performance metrics. In Section 3, we estimate the relation between streak patterns and investor decisions to invest or divest. Section 4 presents a model that evaluates the information value of performance streaks. Section 5 examines the welfare implications of our results, and includes some robustness checks. Section 6 concludes.

[5] Our findings complement both the recent literature studying the determinants of money flows to hedge funds (see e.g. Aragon, Liang and Park, 2014, Baquero and Verbeek, 2009, Ding, Getmansky, Liang and Wermers, 2009, Fung, Hsieh, Naik and Ramadorai, 2008, Goetzmann, Ingersoll, and Ross, 2003, or Li, Zhang and Zhao, 2011) and the one studying the determinants of hedge fund performance (see e.g. Agarwal, Daniel and Naik, 2009, Aggarwal and Jorion, 2010b, Aragon, 2007, Li, Zhang and Zhao, 2011, Liang and Park, 2008, Malkiel and Saha, 2005, Naik, Ramadorai and Stromqvist, 2007, Sun, Wang and Zheng, 2011 or Titman and Tiu, 2011).

2. Data and variables

2.1 Data description

We use survivorship-free data on individual hedge funds from TASS Management Limited, a private advisory company and provider of information services. Given limited regulation and disclosure requirements, hedge-fund participation in any database is voluntary. We focus on open-end funds reporting in US$, and exclude funds-of-funds (i.e., portfolios of hedge funds). Our sample covers the period 1995-2010 and contains 1,856 funds. Of these, 1,179 do not provide information through the end of 2010, for various reasons - e.g., liquidation (661 cases) or removal at the fund manager's request. We refer to the latter phenomenon as self-selection.[6] Hedge funds typically impose flow restrictions on both withdrawals and subscriptions. Whereas most subscriptions accommodate monthly frequencies, more than 50% of the funds in our sample are subject to either redemption periods or redemption notice periods of one quarter or more, and 30% impose lockups periods, most commonly of 12 months. (See Appendix E for a description of flow restrictions in our sample.)

We argue throughout this paper that investors are sensitive to the precise pattern of performance signals they observe. In the hedge fund industry, information on individual funds' raw returns (net of management and incentive fees) and assets under management (AUM) is released to investors for monitoring purposes, typically quarterly. The financial press and industry newsletters also emphasize quarterly figures. That most redemption restrictions operate quarterly imposes an implicit time frame on investor decisions. We consequently study investor response to sequences of performance signals generated over quarterly frequencies.[7]

Our data set is corrected for backfilling, or instant-history, bias, a type of selection bias that affects hedge fund databases owing to the self-reported nature of information (see, for example, Ackermann et al., 1999, and Fung and Hsieh, 2000). Backfilling occurs when a fund has already a number of periods of historical performance by the time it commences reporting. This period of incubation prior to the first

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[6] A self-selection bias might arise owing either to poor performers not wishing to make their performance known or well-performing funds that have reached a critical size having less incentive to report to data vendors to attract additional investors (see e.g. Agarwal, Fos and Jian, 2013, and Ter Horst and Verbeek, 2007).

[7] Although monthly figures are available in our database, because performance fees are deducted from fund asset value on an individual-client basis, calculation of total net assets and rates of return delays the release of monthly figures. Consequently, accurate monthly information might not be available to investors for all funds in real time.

reporting date is instantly incorporated (i.e. backfilled) when a fund begins to report to a database. The bias occurs if a manager chooses to commence reporting only after a period of good performance, in which case backfilled returns will appear systematically higher than non-backfilled returns. Because we are likely to observe relatively long winning streaks prior to the date a fund is added to a database, we attempt to allay the potential effect of backfill bias in the manner suggested by Aggarwal and Jorion (2010a, 2010b), by considering only returns reported after the date a fund was added to the TASS database.[8] The median incubation period in our sample is six quarters, the mean 9.6 quarters, with a standard deviation of 9.2 quarters.[9] We find that 70.4% of funds exhibit winning, and 29.6% losing, streaks immediately prior to the first reporting date. Corresponding figures for the non-incubation period are 60% and 40%, respectively. We find that prior to the first reporting date, the proportion of one- and two-quarter winning streaks is 30% greater during the incubation period, the proportion of losing streaks longer than two quarters nearly one quarter the proportion found in the non-incubation period.

2.2 Flows definition

Following a standard definition, assuming that they occur at the end of period $t+1$, net flows are measured as a fund's growth rate, in total assets under management, between the start and end of quarter $t+1$ in excess of internal growth r_{t+1} for the quarter, had all dividends been reinvested.

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

This definition is referred to as *normalized cash flows*.[10] We winsorize the distribution of normalized cash flows at the 0.1% level to control for the extreme outliers typically observed in cash flow data. Table 1 presents descriptive statistics for normalized cash flows, dollar flows, and assets under management. Note

[8] This screening approach also eliminates the survivorship bias occasioned by the merger of the Tremont and TASS databases between April 1999 and November 2001, documented by Fung and Hsieh (2009) and Aggarwal and Jorion (2010a).
[9] These figures are influenced to some extent by the merger period associated with the Tremont and TASS databases. If we eliminate this period from consideration, the median remains the same, but the mean reduces to 8.8 quarters.
[10] See Ippolito (1992), Gruber (1996), Sirri and Tufano (1998), Zheng (1998), and Del Guercio and Tkac (2002) for a discussion of the assumptions that underlie these definitions of flows.

that the distribution of dollar flows appears to be only slightly skewed, with a median of almost zero, in sharp contrast to the distributions observed for mutual funds.[11]

[Insert Table 1]

2.3 Performance streaks

This paper being focused on performance streaks and their implications for hedge fund flows, we show the numbers of successive signals above or below a relevant benchmark to have a major impact on flows beyond the usual sensitivity to past performance documented in previous studies (e.g., Wang and Zheng, 2008, Agarwal, Daniel and Naik, 2009, Baquero and Verbeek, 2009, and Ding et al., 2009). Table 2 summarizes the series of successive quarterly return signals above and below the quarterly US Treasury bill identified in our dataset. We refer to these, respectively, as winning and losing streaks. A winning streak commences at the point at which a return reverses from below to above the benchmark. Its length is the number of consecutive quarters in which the fund performs above the benchmark. We identify, for example, for a fund that is a loser in 1997Q1 (first quarter of 1997) but a winner in 1997Q2, 1997Q3, and 1997Q4, one-quarter (1997Q2), two-quarter (1997Q2, 1997Q3), and three-quarter (1997Q2, 1997Q3, 1997Q4) winning streaks.

[Insert Table 2]

Table 2, Panel A, for instance, identifies 2,660 three-quarter winning streaks between 1995Q1 and 2010Q3. In the quarter following the series, 1.32% of funds liquidate, 0.68% self-select out, 66% remain winners (i.e., persistent funds), and 49.36% receive positive net flows of money. Net money flows directed towards funds with a successful three-quarters history average nearly 7.7 million US$ per fund (note that subsequent performance and money flows are missing for some observations; see columns (6) and (8)). We interpret net flows of money as a measure of investors' average opinion of a fund; if net flows are positive (i.e., inflows are greater than outflows), most investors are assumed to anticipate profitable performance and invest accordingly.

Results reported in Panel A suggest that remaining above the U.S. Treasury bill is difficult for a hedge fund, only 4,182 of the 7,266 observations with a one-quarter winning streak (57.54%) persisting above the T-bill for a second consecutive quarter. The likelihood of remaining above the T-bill increases to some

[11] For example, Del Guercio and Tkac (2002) find the top 5% of dollar inflows to mutual funds to be nearly three times larger than the bottom 5% of outflows.

extent with streak length, being above 60%, on average, for winning streaks of two quarters or more (see column (5)). We observe a concomitant reaction on the part of investors, who appear to increase investment significantly as streak length increases (see column (9)). The average money flow experienced by a fund following a two-quarter winning streak is approximately 3.51 million US$, following five successful quarters, about 18.9 million US$. For longer streaks, amounts tend to stabilize, possibly because money inflows may become increasingly restricted as funds grow in size. Note that funds with streak length between two and six quarters capture approximately 87 billion US$ in aggregate, which represents nearly 89% of all net flows to winning streaks. The percentage of funds that receive positive net flows of money increases almost monotonically with streak length, as indicated in column (7), and seems to stabilize at around 56% beyond streak lengths of six quarters. That not all funds receive investment for a given streak length suggests a distinction on the part of investors between lucky and skilled managers. Separating skill from luck is a notoriously difficult task and a certain percentage of error is expected. The mismatch is reported in the last column of Table 2. For streaks two quarters in length, positive money flows were directed to subsequent loser funds in 35% of cases. This percentage diminishes to some extent with streak length.

Panel B of Table 2 shows the results for losing streaks. The likelihood that a fund will remain a loser after successive failures increases with streak length. A fund, for instance, that experiences returns below the T-bill for five consecutive quarters has a 48.28% probability of persisting as a loser in the subsequent quarter, but only 44.19% of funds are persistent losers after two consecutive quarters of poor performance.[12] These figures are likely underestimates given the large percentage of funds that liquidate, especially over long streaks (see column (3)). A fund that survives after an extended period of bad performance is likely to have performed better than average in order to recover past losses and surpass the high-water mark. Investors react to patterns of negative persistence, or the "cold hand," by withdrawing money from an increasing number of funds at an increasing rate in dollar terms, as streaks lengthen (see columns (7) and (9)). These figures are likely to be driven down by the high attrition rates of persistent losers. Dollar amounts withdrawn decline progressively for streaks longer than four quarters, in part because little money

[12] For longer streaks, the pattern becomes somewhat erratic, probably because the number of observations declines considerably with streak length.

might be left to withdraw from a fund with a long losing streak. A number of factors might reduce investor responsiveness to losing relative to winning streaks; restrictions imposed on withdrawals are more important than restrictions on subscriptions, for example, and investors often face switching costs relative to closing and opening accounts. Investors might also be inhibited from divesting by psychological biases, such as endowment and disposition effects, gambler's fallacy, or cognitive dissonance, as suggested by Goetzmann and Peles (1997)

Two patterns emerge from the stylized evidence presented in Table 2. First, it appears that funds with longer winning streaks are more likely to persist above, funds with longer losing streaks more likely to remain below, the T-bill. Second, we observe a nearly monotonic pattern in money flows as streak length increases, which suggests that investors are sensitive to the precise sequence of performance signals above or below the T-bill. The question we try to answer in the remainder of the paper is whether investors exclusively follow a trend, or whether they exploit any information value contained in performance streaks.

2.4 Correlations between streaks and other performance and risk metrics

The previous analysis does not consider other performance variables and risk metrics that may drive both money flows and subsequent performance that possibly correlate with streak length. Long streaks might result, for example, from the exposure of funds to illiquid securities and spurious serial correlation in monthly returns. If, on the other hand, it signals managerial ability, streak length may correlate with past alphas or relative performance measures like annual ranks. Long winning streaks might also signal that a fund is well above the high-water mark, or be indicative of lower return variance, lower operational risk, and lower liquidation probabilities, all attractive features to investors.

Correlation patterns between streaks and various performance and risk metrics are analyzed in Table 3, which presents averages per streak length for a number of performance metrics (e.g., alphas, Sharpe ratios, raw ranks, under-water dummy) and risk metrics (standard deviation of monthly returns, downside-potential ratio, ω-score) as well as measures of return smoothing. We obtain alphas from Fung and Hsieh's (2004) seven-factor model, augmented by an emerging markets factor. The under-water dummy indicates whether cumulative returns over a period of eight quarters are negative (see Brown et al., 2001). The ω-score developed by Brown et al. (2008) is a proxy for operational risk.[13] Return smoothing is proxied by the monthly first-order serial correlation coefficient and the coefficients from Getmansky et al.'s (2004) model of return smoothing. How we estimated these performance and risk metrics is detailed in Appendix E.

Table 3 shows that alphas, Sharpe ratios, and raw ranks evaluated over the previous two years increase monotonically as the length of past winning performance streaks increases. Funds with eight-quarter winning streaks, for instance, exhibit alphas four times larger than funds with one-quarter winning streaks, which is a statistically significant difference. We also observe a six-fold difference in Sharpe ratios. In terms of risk metrics, the average under-water dummy indicates that 22% of funds with a one-quarter winning streak have negative cumulative returns over the last eight quarters. Funds with longer winning streaks exhibit a diminished incidence of being under water, smaller standard deviations of raw returns, smaller downside-upside potential ratios, but also greater smoothing (smaller θ coefficients). These results are generally mirrored for losing streaks. Alphas, Sharpe ratios, and raw ranks decrease monotonically, downside-upside potential ratio, ω-score, and under-water incidence increase, as streak length increases. A fund's standard deviation, however, generally decreases with the length of losing streaks.

[Insert Table 3]

These correlation patterns demonstrate that the lengths of performance streaks capture, to some extent, information about funds' past risk and performance. A long winning streak is associated with lower risk and superior risk adjusted performance over the previous two years; a long losing streak indicates the opposite. That this does not necessarily mean that streaks are informative about future performance and risk is investigated in subsequent sections. The results in Table 3 highlight the importance of controlling for various performance and risk metrics when estimating the effect of streaks on flows and subsequent performance in an econometric model.

3. A model of investor choice

The results reported in the previous section show money flows to be increasingly directed towards funds that perform successfully above the U.S. Treasury bill over longer periods of time. The analysis presented in Table 2 did not consider such other factors that might be driving investor decisions as size, age, style, and

[13] Their study exploits a short time window in 2006 when hedge fund managers were required to file Form ADV with the SEC (see also Brown et al, 2012). We are grateful to Bing Liang for facilitating the ω-score for the year 2005.

other fund-specific features. Sophisticated investors, especially, attend to these characteristics as well as to other performance measures and variables that account for risk. Consider the following model that describes the probability that the average investor in fund *i* chooses to invest (S_{it} =1) such that the fund experiences net inflows if an underlying latent variable S_{it}^* is positive,

$$
\begin{aligned}
S_{it}^* = \alpha + \sum_{j=2}^{8} \beta_{1j} W_{jit-1} + \sum_{j=1}^{8} \beta_{2j} L_{jit-1} + \sum_{j=1}^{6} \beta_{3j} Count_{jit-1} \\
+ [\beta_4 AnnualRnk_{it-1} + \beta_4^B Bottom30_{it-1} + \beta_4^T Top30_{it-1}] \\
+ [\beta_5 AnnualRnk_{it-5} + \beta_5^B Bottom30_{it-5} + \beta_5^T Top30_{it-5}] + \beta_6 Rnk\_alpha_{it-1}^{2y} \\
+ \beta_7 Rnk\_Sharpe_{it-1}^{2y} + \beta_8 Under_{it-1}^{2y} + \beta_9 \sigma_{it-1} + \beta_{10} DWUP_{it-1} + \beta_{11} Corr_{it-1}^{2y} \\
+ \beta_{12} ShareR_{it} + \beta_{13} ln(AUM_{it-1}) + \beta_{14} \ln(AGE_{it-1}) + \sum_{j=1}^{8} \beta_{15j} Flow_{it-j} + \gamma' \mathrm{X}_i + \lambda_t \\
+ \varepsilon_{it} \qquad (1)
\end{aligned}
$$

$$
S_{it} = \begin{cases} 0 \ \ if\ a\ fund\ i\ experiences\ net\ outflows\ (S_{it}^* < 0) \\ 1\ if\ a\ fund\ experiences\ net\ inflows\ (S_{it}^* \geq 0) \end{cases}
$$

where S_{it} is a dummy that indicates the sign of money flows for fund *i* in quarter *t* (S_{it} =1 if *Net Flows*$_{it}$ >0) and W_{jit-1} and L_{jit-1} (*j* = 1 …8) are 16 mutually exclusive dummies that indicate a past winning or losing streak of length *j* quarters ending in quarter *t-1* for fund *i*. W_{jit-1}=1 if fund *i* is a winner in the previous *j* quarters *only*, and is zero otherwise. Likewise, L_{jit-1}=1 if fund *i* is a loser in the previous *j* quarters *only*, and is zero otherwise. By leaving out W_{1it-1}, funds with only a one-quarter winning streak act as the reference category. We capture the effects of streaks of eight quarters length or more with dummies W_{8it-1} and L_{8it-1}, the number of observations for long streaks being quite small. It could be that what matters to investors is not the specific sequence of signals or length of the streak, but only the total number of winning periods over a two-year horizon independent of the sequence. We purge streaks of this potential effect by counting the total number of winning quarters (i.e., when the return is above the T-bill) over the two-year period that precedes each observation, and defining a set of mutually exclusive dummies, $Count_1$ to $Count_8$, each of which corresponds to a given number of winning quarters within the previous eight-quarter period. We avoid multicollinearity by including only $Count_1$ to $Count_6$. [14]

Two lagged annual performance ranks ($AnnualRnk_{it-j}$ is the j[th] lagged rank based on raw returns) are included, and we allow for a non-linear response using a piece-wise linear specification with three segments, the lower segment accounting for the bottom 30%, the upper segment for the top 30%, of funds in terms of annual ranking.[15] We also control for such other performance measures commonly used by sophisticated investors as alphas from Fung and Hsieh's (2004) eight-factor model estimated over the preceding 24 months and Sharpe ratios calculated from monthly returns over the preceding 24-month period (alternatively, we use the information ratio, calculated by dividing alpha by the standard deviation of residuals). Our main specification uses ranks based on Sharpe ratios and alphas ($Rnk\_Sharpe^{2y}_{it-1}$ and $Rnk\_alpha^{2y}_{it-1}$). Using absolute Sharpe ratios and alphas does not affect our main results. In alternative specifications, we use alphas obtained from the CAPM model as well as Sharpe ratios and alphas estimated over a 36-month window preceding each observation. $Under^{2y}_{t-1}$, a dummy that indicates whether two-year cumulative returns are negative or positive, is used as a proxy for a fund being deep under the water mark. $Corr^{2y}_{it-1}$, the first-order serial correlation coefficient of monthly returns estimated over a rolling window of 24 months, is used as a proxy for return smoothing. Alternatively, we use the coefficients from the time-series model of smoothing from Getmansky et al. (2004). $ShareR_{it}$ is a dummy that represents fund share restrictions that apply at time t as a result of redemption frequencies combined with redemption notice periods. We assume an investor at the beginning of quarter t who decides to redeem in response to performance of fund i reported in quarter $t-1$. For each fund i and quarter t we compute the maximum time for her redeeming decision to become effective. If that delay is longer than one quarter, we classify net

[14] In a separate specification, we tested instead the effect of the number of reversals between winning and losing quarters over the previous eight-quarter period. The models of Barberis, Shleifer and Vishny (1998) and Rabin and Vayanos (2010), for instance, suggest that the frequency of reversals determines whether investors overreact or underreact to past information. However we do not find a statistically significant effect of reversals frequency on the sign of flows.

[15] The piece-wise linear specification is defined as follows:

$$Bottom30_{it-j} = \min(0.3, AnnualRnk_{t-j});$$
$$Top30_{t-j} = \max(0, AnnualRnk_{t-j} - 0.7).$$

Therefore, the coefficient β_4 in equation (1) represents the slope of the middle segment; $\beta_4+\beta_4^B$ is the slope of the lower segment and $\beta_4+\beta_4^T$ is the slope of the upper segment.

flows for fund i in quarter t as *restricted* (dummy variable $ShareR_{it}$ = 1). The standard deviation of monthly returns, σ_{it-1}, and downside-upside potential ratio, $DWUP_{it-1}$, are computed over the previous 24 months (alternatively, we use a fund's entire past history of monthly returns). $Flow_{it-j}$ is the j^{th} lagged flow measured as a growth rate. The model controls for the log of size (total assets under management) and age of the fund in the previous period, $\ln(AUM_{i,t-1})$ and $\ln(AGE_{i,t-1})$, and includes a set of time dummies, λ_t, and vector X_i of fund-specific, time-invariant characteristics like management and incentive fees, lockup periods, and managerial ownership and style.

Table 4 presents descriptive statistics for several fund-specific characteristics of, as well as some performance and risk metrics for, the funds in our dataset. A brief description of each variable is provided in Table E2 in the Appendix E. Average fund age in our final sample is nearly seven years and assets under management USD 52.7 million. The average incentive fee is 18.88%, the average management fee about 1.4%. Offshore funds account for 64.3%, and capital is invested by the manager in 57%, of the funds in our sample. The most common investment style is long-short equity (38.8% of our sample), followed by event driven (13.8%), emerging markets (13.2%), and managed futures (9.6%).

3.1 Specification search

We use maximum likelihood to estimate (1) as a probit model, for which the preferred specification is chosen on the basis of a number of model selection criteria, and a rigorous search process that attends, in particular, to three issues. The first is how to define "winning" and "losing" in the streak variables, the second is how to measure relative fund performance, and the third relates to the evaluation horizon (length of the evaluation window). We explore a wide range of alternative benchmarks and define winning and losing relative to the Treasury bill, zero, the S&P 500 return, median raw return or median return within a fund style, and, lastly, a style-specific and an overall hedge fund index. In Table 5, Panel A, we investigate the explanatory power of the probit models explaining the sign of flows with these alternative streak definitions (to facilitate comparison, all models are estimated using the same number of observations). In terms of pseudo R^2, loglikelihood value, and the Akaike (AIC) and Schwartz Bayesian Information Criteria (BIC), the models that use winning and losing streaks relative to the T-bill rate and zero beat all other specifications. That is, these two models provide a better description of investors' aggregate decisions to invest in or divest from a fund with the same number of parameters. The model that uses streaks defined relative to the S&P 500 return yields the poorest fit. The specification using the T-bill return as a benchmark performs slightly better than the one using zero as a benchmark. Economically, we believe the Treasury bill return to provide a more natural benchmark to hedge fund performance, constituting a salient reference point often used as the hurdle rate in managers' contracts and a benchmark for calculating such risk and performance measures as alphas and the downside-upside potential ratio. Accordingly, our analysis defines winning and losing streaks relative to the T-bill return.

[Insert Table 5]

In the previous exercise we controlled for lagged annual ranks over the previous two years based on raw returns (i.e. $AnnualRnk_{lagj}$). It being possible, however, that investors attend to quarterly rather than annual ranks, or compare funds based on style-adjusted returns rather than raw returns, we conduct a second specification search to select the most powerful set of rank variables based on a fund's past performance. Results are reported in Table 5, Panel B. We experiment, in particular, with including annual or quarterly performance ranks over the previous two years based on raw returns or style-adjusted returns, where the latter is combined with style ranks based on the style index returns in the same period. Moreover, we consider ranks within a fund's style combined with the style ranks. We also experiment with including annual or quarterly raw returns instead of ranks. Because the number of explanatory variables varies widely across the different specifications, we pay particular attention to the Akaike and Schwartz Information Criterion, as these are developed to quantify the trade-off between a model's goodness-of-fit and parsimony (measured as the number of parameters). Typically, the latter criterion favors more parsimonious models. Note that the worst performing are the models that include lagged annual (Model 4) and lagged quarterly (Model 8) returns. Raw (as well as style-adjusted) returns are mostly insignificant in explaining flows. In additional specifications in which we include lagged ranks and lagged returns together, lagged ranks overwhelmingly capture the effect of past performance on flows. In terms of explanatory power (pseudo R^2, loglikelihood value) we see little difference between the models that use annual ranks and those that use quarterly ranks based on the same underlying performance variables. Because the models with lagged annual performance ranks are more parsimonious, we prefer to continue with them.[16] Relatively similar

[16] A separate specification that includes both annual ranks and quarterly ranks together shows annual ranks to capture most of the effect.

performance being observed for the model that uses annual raw ranks and the one that uses annual style ranks combined with within-style ranks, we use the first specification due to its substantially lower BIC value. A wide range of robustness tests suggests that our main conclusions are not strongly affected by choice of control variables.

The third choice we face is over which horizon historical performance metrics are important in explaining flows. The foregoing estimations being based on lagged performance over a two-year horizon, we conduct a further specification search and perform a wide range of tests using one-, two- and three-year horizons. The three-year horizon specification includes three lagged annual ranks, 12 lagged quarterly flows, alphas and Sharpe ratios computed over 36 months, and the under-water dummy is computed on the basis of compounded returns over 12 quarters. Results are reported in Table 5, Panel C. We facilitate comparison by estimating the three specifications using the same number of observations (N=17461), corresponding to the three-year horizon specification. In terms of explanatory power (pseudo R^2, loglikelihood value) the two-year horizon model performs substantially better than the other two specifications. It also exhibits substantially lower AIC and BIC values. A series of tests reveals that including 36-month instead of 24-month alphas, or adding a third lagged annual rank does not significantly improve the explanatory power of the two-year horizon model. Including 36-month instead of 24-month Sharpe ratios, in fact, reduces both the model's explanatory power and its AIC and BIC values. Our results strongly suggesting that hedge fund investors attend most closely to historical performance over a two-year horizon, we use this time frame in our final specification.

3.2 Base model estimation

[Insert Table 6]

The estimation results of equation (1) based on the preferred model from the above specification search are reported in Table 6. Following Petersen's (2009) recommendations, we employ panel-robust standard errors throughout the paper. The estimation results of our full specification, which includes the full set of streak dummies, are reported in column D. Both losing and winning streaks up to five or six quarters in length have a statistically significant impact on the sign of cash flows, and the magnitude of the coefficients exhibits a clear monotonic pattern as streak length increases. Ceteris paribus, the longer the winning streak, the greater the likelihood of investment, and the longer the losing streak, the greater the likelihood of divestment. Our results show streaks to have an impact on flows beyond the effect both of annual ranks documented in studies of the flow-performance relation, and of other performance metrics like alphas and Sharpe ratios, which are all statistically significant. A joint test on the inclusion of the streak dummies (reported in Table 5) strongly rejects the null. Thus the full specification significantly increases the explanatory power of the model compared to the specification reported in column E, in which performance streaks are not included. The economic significance of this effect is analyzed in Figure 1, which depicts, for each performance streak and a range of annual ranks, with the rest of variables fixed at their sample average, implied probabilities obtained from the model reported in column D, Table 6. A fund with an annual performance rank equal to 0.5 in each of the previous two years will experience subsequent quarterly inflows with an estimated probability of 55.5% if the previous six-quarters returns are all above the T-bill (i.e., a six-quarter winning streak), compared to 44.4% if only the previous quarter return is above the T-bill (i.e., a one-quarter winning streak). The same fund will have only a 41% probability of experiencing subsequently quarterly inflows if the previous quarter return is below the T-bill (i.e., a one-quarter losing streak), 36% if the previous three quarters are below the T-Bill (i.e., a three-quarter losing streak).

[Insert Figure 1]

The impact of lagged annual ranks is also statistically and economically significant. Flows appear sensitive to the first, but not to the second, lagged annual rank. If, for any performance streak in Figure 1, a fund's annual rank improves from 0.3 to 0.7, the likelihood of net inflows increases by approximately 20%. Note that our piece-wise linear specification captures a non-linear relation between flows and ranks. The response of flows is positive and more prominent in the mid range of ranks, and decreases for funds ranked above the 70^{th}, or below the 30^{th}, percentile. A joint test on the inclusion of annual ranks indicates that the full specification reported in Column D performs significantly better than the specification that does not include annual ranks (reported in Column C). Both performance streaks and annual ranks thus appear to be major determinants of hedge fund investors' decision to invest or divest. Note that the effect of streaks appears to be independent of the dummies $Count_1$ to $Count_6$, which capture the total number of winning quarters in a two-year horizon. Other performance measures like Sharpe ratios and alphas calculated from monthly returns over a 24-month window also have significant effects on flows. We shall analyze later in this section the relative importance investors attribute to each of these performance metrics.

Our control variables reveal a number of effects. We find, for example, that investors are insensitive to return smoothing, proxied by either the monthly first-order serial correlation coefficient, $Corr(R_t^0, R_{t-1}^0)$, or the coefficients from Getmansky et al.'s (2004) time-series model of smoothing. Our results further indicate that the under-water indicator, high-water mark dummy, and level of incentive and management fees play no role in explaining the sign of flows.[17] Neither does the existence of lockup periods affect investors' decisions to invest or divest. The coefficient of the dummy for share restrictions, on the other hand, indicates that redemption frequencies combined with redemption notice periods have a positive and statistically significant impact on the signs of flows. Naturally, liquidity restrictions reduce outflows and thus they increase the likelihood of observing net inflows. An alternative specification includes the interaction between the dummy for share restrictions and the streak dummies.[18] Share restrictions, by reducing the response of outflows to losing streaks, increase the probability of net inflows by 5%, on average, across losing streak dummies. Share restrictions also increase the probability of net inflows in response to winning streaks of up to three quarters. When we interact the lockup period with performance streaks we find that long lockups (12 months or more) significantly reduce the response of outflows to losing streaks. Among other results, we find smaller, younger funds to be more likely than larger, older funds to experience net inflows.[19] Lastly, the coefficients of lagged flows are statistically significant and reveal an interesting pattern: the larger previous quarterly flows, the more likely net inflows will subsequently be observed. The effect gradually wanes and is no longer significant after five or six quarters.

Overall, our results support the notion that investors' decisions are determined not only by aggregate measures of past performance, but also by specific sequences or patterns of information signals generated over time. Even after controlling for a wide variety of other performance related variables, the performance streak dummies are statistically and economically significant in a model that explains the sign of net money flows to hedge funds. Apparently, investors respond strongly and positively to long winning streaks and

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[17] It is possible that the impact of the under-water indicator is observed mostly when high-water marks are in place. No significant effects are observed, however, when the high-water mark dummy is interacted with the underwater dummy.

[18] In each quarter, t, we define for each streak dummy $W_{ji,t-1}$, and for each fund i :

$$W\_Restricted_{ji,t-1} = W_{ji,t-1} * (ShareR_{i,t}) \quad \text{and} \quad W\_Unrestricted_{ji,t-1} = W_{ji,t-1} * (1\text{-}ShareR_{i,t})$$

where $ShareR_{i,t}$ is a dummy variable that takes value 1 if the combination of redemption restrictions and notice periods prevent outflows in quarter t in response to a winning streak of length j ending in $t-1$. Idem for losing streaks.

[19] In a series of tests we interacted fund-specific characteristics with streaks. Though we found slightly different responses of flows depending on size and age, the effects of streaks are robust to all the interactions we tested.

negatively to long losing streaks because they are driven either by behavioral biases like the hot hand fallacy or by their belief that performance streaks help to forecast future fund returns. A detailed investigation of the information value of performance streaks is reported in Section 4.

3.3 Robustness tests.

Our results thus far are consistent with the notion that investors' decisions are partly determined by specific sequences of performance signals. We present here the results of a number of tests meant to rule out the possibility that streaks may capture other effects.

We consider first, in an unreported alternative specification, the possibility that operational risk proxied by the ω-score developed by Brown et al. (2008) explains part of the impact of streaks on flows. As described in the previous section, the ω-score is available only for 2005. We thus re-estimate our main specification including the ω-score for the period 2004 to 2006, which contains 5,546 observations. The ω-score coefficient is only marginally significant at the 10% significance level and does not alter the pattern of the coefficients of streak dummies described above. Although the effect is small, the negative coefficient suggests that inflows are less likely as operational risk increases.

We next consider the possibility that the length of winning (losing) streaks signals lower (higher) liquidation probabilities, and that this may partly explain the investor preference for longer streaks. In Appendix C we report the estimation results of a liquidation model for hedge funds. When we test the liquidation model for the inclusion of streak dummies, none of the coefficients is statistically significant. The joint F-test for inclusion of all streak dummies does not reject the null that all streaks coefficients are zero.

This paper focuses on the aggregate decision to invest or divest following a given performance streak. But the question remains whether streaks have an impact not only on the sign, but also on the level, of flows. Estimating an OLS regression that explains net flows with the same set of variables in the right hand side as equation (1), we find that streaks do, indeed, determine not only the direction, but also, in terms of growth rate, the amount of net flows. The coefficients of streak dummies are all significant up to six or seven quarters length, and generally increase in magnitude with streak length. For instance, ceteris paribus, a fund with a previous seven-quarter winning streak will subsequently experience an estimated growth rate of 9.4%, compared to 2.7% for a fund with a four-quarter winning streak. A fund with a six-quarter losing streak will subsequently experience outflows at a rate of 4.2%, a fund with a three-quarter losing streak at a rate of 2.6%. Our results show streaks to have an impact on flows beyond the effect of annual ranks documented in the flow-performance relation literature, as well as beyond alphas, Sharpe ratios, and other performance and risk metrics accounted for in our model.

We consider as well the possibility that the streak length correlates with forecast precision. That more precise forecasts may intuitively be generated from funds with longer streaks could partly explain investor preference for longer streaks. In the next section, we will present estimation results of different forecast models over different investment horizons. We obtain out-of-sample forecasts from these models, and calculate for each fund-period observation, as a measure of forecast accuracy, the root mean squared error (RMSE) of the eight lagged forecasts.[20] Our results suggest that the RMSE has a negative impact on the sign of flows, but the effect is small and not significant in the full specification (see Section 5 and Table 11, Column 3, for further details).

Provided returns are above a hurdle rate (usually the T-bill) and past losses have been recouped, the typical asymmetric compensation contract in the hedge fund industry affords managers options on investors' assets under management. Because longer winning streaks likely increase, and longer losing streaks decrease, the value of managers' portfolios of option-like incentive contracts, investors may perceive streak length as a proxy for managers' dollar incentives, which could partly explain the impact of streaks on flows. To test this possibility, we re-estimate our main specification by including a measure of managerial dollar incentives, namely managers' option delta, calculated following Agarwal, Daniel and Naik's (2009) algorithm (details of this calculation are provided in Appendix E). The delta variable captures the sensitivity of the manager's total dollar compensation to performance. The portfolio of options from all incentive contracts not being observable, calculation of the delta requires a set of assumptions about the amount and timing of investor inflows and outflows. It also assumes that managers reinvest all after-tax incentive fees, thereby increasing their stakes. Our results (not tabulated) indicate that the delta of managers' option contracts has, unlike incentive fees, a positive and highly statistically significant effect on the sign of flows. We find the delta from the managers' stakes, on the other hand, to have a negative, albeit

[20] More specifically, if we denote the ex post realizations by y_h and the series of predictions by $\widehat{y_h}$, h=t-1,t-2,…,t-8, where t is the current quarter, then the RMSE of the eight lagged forecasts is defined as $RMSE_t = \sqrt{\frac{1}{8}\sum_{h=1}^{8}(\widehat{y_h} - y_h)^2}$.

only marginally significant, effect on flows. Yet, including both managers' option delta and the delta from managers' stakes has a negligible effect on the coefficients of streak dummies and other performance variables. Although investors appear to be aware of total dollar incentives, the impact of streaks on flows remains strongly robust to this alternative specification.

[Insert Table 7]

Lastly, we test the robustness of our results to the choice of sample period. We compare, in particular, the period 1995Q1-2007Q3 and the financial crisis period from 2007Q4 to 2010Q3.[21] Our results for both periods, presented in Table 7, remain unaltered, the coefficients of streaks exhibiting a monotonic pattern as streak length increases and being statistically significant. However, the response of flows to streaks, both winning and losing, and to other performance variables like annual ranks appears much stronger in the period prior to the crisis. Nearly all coefficients of streaks are larger (5% on average) in magnitude compared to the crisis period, and the effect is strongly significant even for quite long streaks (up to six quarters length for losing streaks, and eight quarters or more for winning streaks). During the crisis period, losing streaks are significant only up to three quarters. Note that the response of outflows to streak dummy L_1 is particularly strong compared to the non-crisis period, consistent with the idea that investors are more sensitive to the first bad news as a preemptive response to potential share illiquidity at times of crisis (see Ben-David et al., 2011). Results are equally robust to testing our model for other sub periods.

3.4 Relative importance of predictors

As described above, several performance and risk metrics in our model have a significant impact on investor decisions to hire or fire a hedge fund manager. Understanding of investor behavior might be deepened by evaluating the relative importance attributed to each of these variables in investors' information processing strategies. We analyze the relative importance of predictors in our model in terms of their contribution to the R^2. To estimate the proportion of explained variance that can be attributed to each predictor, we implement a *relative weights analysis* (see, for example, Johnson, 2000, Johnson and LeBreton, 2004, and Tonidandel and LeBreton, 2011). Results are similar to those produced by *dominance*

[21] August 9, 2007 is the generally accepted start date of the financial crisis, which manifested initially as a liquidity crisis that forced BNP Paribas to suspend withdrawals from three hedge funds specialized in US mortgage debt, triggering a sharp rise in the cost of credit in August and September 2007. In our empirical model, the first response of quarterly flows to these events occurring in 2007Q3 can only occur in 2007Q4.

analysis (Budescu, 1993), but relative weights analysis is a more efficient alternative when the number of predictors is large.[22] Partition of the R^2 is straightforward when predictors are uncorrelated, as each predictor's contribution is given by the squared standardized regression coefficient. When predictors are correlated, the underlying idea of *relative weights analysis* is to obtain a set $\boldsymbol{Z}$ of orthogonal predictors via a linear transformation of the original standardized predictors $\boldsymbol{X}$, as $\boldsymbol{Z} = \boldsymbol{X}\boldsymbol{\Lambda}^{-1}$, where $\boldsymbol{\Lambda}$ is the square root of the diagonal matrix containing the eigenvalues of the correlation matrix $\boldsymbol{X}'\boldsymbol{X}$ (see Johnson, 1966). The fully standardized coefficients β_s of a regression of $\boldsymbol{Y}$ on $\boldsymbol{Z}$ provide a means to obtain a partition of the R^2, in which the relative contributions are given by: $\boldsymbol{\varepsilon} = \boldsymbol{\Lambda}^2 \boldsymbol{\beta}_s^2$ (see Johnson, 2004). The sum of these contributions equaling the model's R^2, contributions are usually expressed as proportions of the R^2. In models with limited dependent variables, such as probit and logit models, the $\boldsymbol{\beta}$ coefficients can be fully standardized as follows: $\beta_{s,k} = (\sigma_k \beta_k)/\widehat{\sigma_{y^*}}$, where $\widehat{\sigma_{y^*}}$ is the estimated standard deviation of the latent variable y^*, and σ_k is the standard deviation of predictor *k* (see Long and Freese, 2001). In this case, the sum of the $\boldsymbol{\varepsilon}$ contributions equals the McKelvey and Zavoina's pseudo R^2, which is defined in terms of the variance of the latent variable y^*.[23] Technical details of the implementation of *relative weights analysis* are discussed in Appendix A.

[Insert Table 8]

Table 8 presents our estimates of relative weights, expressed as percentages of the pseudo R^2. Standard errors and confidence intervals are estimated using a bootstrap approach, as recommended by Johnson (2004) and Tonidandel, LeBreton and Johnson (2009). Specifically, standard errors are computed as the standard deviation of the relative weights obtained across 1,000 bootstrap samples, equal in size to the original dataset. The 99% confidence intervals are constructed assuming normality of the large sample distribution of relative weights. Although generally a reasonable assumption according to Johnson (2004), the distribution tends to be positively skewed when relative weights are near zero, in which case we report

[22] In dominance analysis, the relative importance of each predictor is measured by the average contribution to the R^2 when the predictor is included with each possible combination of predictors. Given *p* predictors, this method requires the estimation or $(2^P\text{-}1)$ submodels. Thus, with a large number of regressors, this method becomes computationally highly demanding. We applied dominance analysis to a simplified specification model with 25 regressors and we found very similar results to those obtained with relative weights analysis. We are grateful to Joseph N. Luchman for providing the Stata module *domin* to conduct dominance analysis.

[23] Alternatively, the $\boldsymbol{\beta}$ coefficients from models with limited dependent variables can be standardized as in Menard (2004) (see Tonidandel and LeBreton, 2010). In this case, the sum of the $\boldsymbol{\varepsilon}$ contributions is equal to Efron's R^2 (also described in Azen and Traxel, 2009). However either way of standardizing coefficients leads to the same relative weights when converted to proportions of the corresponding pseudo R^2.

the empirically observed confidence interval based on the bootstrapped percentiles (Efron and Tibshirani, 1993).[24]

Lagged annual rank is the most important predictor with the largest contribution to the model's R^2. The combined effect of the piece-wise linear specification for the first lagged annual rank explains 21.1% (second lagged annual rank less than 3%) of the predictable variance in the sign of cash flows. Remarkably, the combined contribution of streak dummies is the second largest among the performance variables, explaining 17.2% of the predictable variance (winning streaks explain 9.0%, losing streaks explain 8.2%). Other performance metrics explain a significantly lower proportion of the predictable variance, 24-month Sharpe ratios and alphas, for instance, 8.9% and 4.7%, respectively, the under-water dummy, 3.0%, and the combined effect of the Count dummies, 2.3%.

All estimates of relative weights for the performance variables are statistically significant.[25] Note, in particular, that the 99% confidence interval for the relative weight of the lagged annual rank ranges from 17.8% to 24.4%, and for streaks, from 13.9% to 20.5%. The overlap notwithstanding, the lagged annual rank's average differential contribution of 3.9% over streaks is statistically significant at the 5% significance level.

Of the remaining control variables in our model, the combined contribution of the four lagged quarterly flows in the previous year is the largest, accounting for 17.7% of the explained variance (lagged quarterly flows in the second year explain less than 1%). The set of time dummies also makes a large contribution to the R^2, of about 15.1%, half of which, however, is concentrated in 2008 and 2009 during period of the financial crisis. Fund characteristics, like size, age, share restrictions, incentive and management fees, return smoothing, and so forth collectively explain a significantly smaller proportion, around 3.8%, and style dummies only 2.3%, of predictable variance.

The foregoing analysis indicates lagged annual ranks, performance streaks and lagged flows to be more important predictors of investment and divestment decisions of hedge fund investors than other

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[24] That is, when the relative weights are near zero, the 99% confidence interval is constructed by taking the 0.5 percentile and 99.5 percentile of the bootstrapped distribution.

[25] We test the statistical significance of the relative weight of a predictor as in Tonidandel, LeBreton and Johnston (2009). Using the bootstrapped distributions, we compare the predictor's relative weight to the relative weight produced by a randomly generated variable included in the model, which represents a variable with zero importance in the population. We reject the null hypothesis that the predictor's relative weight is zero if it is significantly different from the relative weight for the random variable.

performance metrics like alphas and Sharpe ratios. Remarkably, hedge fund investors appear to attribute significantly less importance to style and fund specific characteristics. This ranking of the relative importance of predictors in our model offers a novel perspective on the behavior of hedge fund investors and enhances our understanding of their information processing strategies. It highlights, in particular, the prominence of performance streaks relative to other variables, supporting the notion that sequences of performance signals influence investor choices.

4. The information value of performance streaks

The model of flows described in the previous section indicates that investors find fund characteristics and performance indicators like streaks, past alphas, past raw returns, and past Sharpe ratios informative of subsequent fund performance. We investigate here whether these variables, in particular, performance streaks, are indeed able to predict subsequent performance and, if so, which are the better predictors, and over what investment horizons. We then analyze the extent to which flows are determined by, and the accuracy of, these forecasts. In Section 5, we use the selected models to determine out-of-sample forecasts, on which we base simple investment and divestment rules, and compare the performance of those forecasts with those of the aggregate investor.

We use different definitions of subsequent performance in both absolute and risk-adjusted terms. We focus first on the one-year investment horizon, natural for hedge fund investors in our sample, given that 96% of funds impose lockup periods of 12 months or less or redemption and notice periods confined within a year. We investigate later the effect of investment horizons longer than one year. Consider the following model for predicting the relative (to its peers) performance of fund i,

$$\begin{aligned} Rank^{i}_{t,t+3} = \alpha &+ \sum_{j=1}^{8} \beta_{1j}\, W_{jit-1} + \sum_{j=1}^{8} \beta_{2j}\, L_{jit-1} + \sum_{j=1}^{6} \beta_{3j}\, Count_{jit-1} \\ &+ [\,\beta_4 AnnualRnk_{t-1} + \beta_4^B Bottom30_{t-1} + \beta_4^T Top30_{t-1}] \\ &+ [\beta_5 AnnualRnk_{t-5} + \beta_5^B Bottom30_{t-5} + \beta_5^T Top30_{t-5}] \\ &+ \beta_6 Rnk\_alpha^{2y}_{t-1} + \beta_7 Rnk\_Sharpe^{2y}_{t-1} + \beta_8 Under^{2y}_{t-1} + \beta_9^A \sigma_{it-1} + \beta_9^B \sigma_{it-1}{}^2 \\ &+ \beta_{10}\, DWUP_{it-1} + \beta_{11} Corr^{2y}_{t-1} + \beta_{12} ShareR_{it} + \beta_{13} ln(AUM_{it-1}) + \beta_{14} \ln(AGE_{it-1}) \\ &+ \sum_{j=1}^{8} \beta_{15j}\, Flow_{it-j} + \gamma'\, \mathrm{X}_i + \varepsilon_{it} \end{aligned} \qquad (2)$$

where $Rank_{t,t+3}^{i}$ is the relative performance of fund i evaluated over the four-quarter-ahead period, from quarter t to quarter $t+3$, measured by the fund's cross sectional rank based on the following four criteria: raw returns (Model 1), style-adjusted returns (Model 2), alphas (Model 3), and Sharpe Ratios (Model 4).[26] The main explanatory variables are the 15 mutually exclusive streak dummies, seven of which account for winning, and eight for losing, streaks. The set of control variables is the same as in equation (1), except that equation (2) includes the squared standard deviation of returns and does not include time dummies (see the variable definitions in Table E2).

4.1 Model estimation

We estimate equation (2) using OLS pooling all quarterly observations (N=16,498). The dependent variable in all four models being measured over four quarters, which is longer than the data frequency, we report Newey-West (HAC) standard errors to account for autocorrelation in the error terms.

[Insert Tables 9 and 10]

Our estimation results are reported in Table 9, and a comparison of the goodness-of-fit of all four models is provided in Table 10, Panel A. For this set of information variables, the predictability of relative Sharpe ratios (Model 4) exceeds that of the other three performance measures. Model 4, which exhibits the highest adjusted R^2 and lowest AIC, BIC, and loglikelihood ratio, explains about 9% of the total variance of the Sharpe ratio ranks. The coefficients of most winning and losing streaks in Model 4 are statistically significant, winning streaks (particularly streaks eight quarters or more in length) predict superior four-quarter-ahead Sharpe ratios, losing streaks (up to four quarters in length), the opposite.

The explanatory power of the first three models is substantially lower. Although Model 2 explains only 4.3% of the total variance of style-adjusted return ranks, it performs well in terms of AIC, BIC, and loglikelihood ratio. The impact of winning and losing streaks is less clear in the first three models than in Model 4. Although most coefficients of winning streaks are not statistically significant, some coefficients for losing streaks, particularly in Models 1 and 2, show a significant effect. Table 10, Panel B reports the F-tests for including winning and losing streaks in each model. The F-tests yield the highest values in Models

[26] More specifically, we compound quarterly raw and style-adjusted returns from quarter t to quarter $t+3$. Alphas are computed from a time series regression of monthly returns on Fung and Hsieh (2004) risk factors over the 12-month period between the beginning of quarter t and end of quarter $t+3$. Sharpe ratios are obtained by dividing the average excess monthly return by the monthly standard deviation over the 12-month period between the beginning of quarter t and end of quarter $t+3$.

1 and 4, and reject, at the 0.1% significance level, the null that the joint effect of all winning and losing streaks is zero. Whereas these results indicate that winning and losing streaks have some predictive ability with respect to one-year-ahead raw returns and Sharpe ratios, we find limited evidence that streaks are able to predict one-year-ahead alphas or style-adjusted returns. In Model 3, in particular, the F-test does not reject, at the 5% significance level, the null that the joint impact of all *losing* streaks is zero, whereas in Model 2 the null that all *winning* streaks have zero coefficients is not rejected at the 1% significance level.

Of the variables that control for fund performance, two-year Sharpe ratios positively predict subsequent performance in all models. Remarkably, the under-water dummy is also associated with subsequent positive performance.[27] Higher volatility (as measured by the standard deviation of monthly returns) is positively related to subsequent returns and style-adjusted returns, and, as expected, negatively related to subsequent Sharpe ratios. Two-year alphas have no predictive ability with respect to subsequent annual performance in any of the models. Lagged yearly returns predict subsequent yearly returns, style-adjusted returns, and Sharpe ratios. The piece-wise linear specification reveals a convex kink in the bottom 30th percentile.

Except for Model 2, fund-specific characteristics like short-term share restrictions, lockup periods, high-water marks, management fees, and managers' personal capital have a positive and statistically significant effect on subsequent performance. [28] The coefficient of return smoothing is also positive and significant, but the level of incentive fees has a negative impact. We find no effects associated with fund age or size or the offshore dummy. We also control in all models for eight lagged quarterly flows (not reported); none of the coefficients is statistically significant (in contrast to the evidence of capacity limits from Ramadorai, 2013).

Note that a number of these covariates play a quite different role in the flows model in Table 6. For instance, return smoothing and most fund-specific characteristics (except for share restrictions) have no impact, while the coefficients of two-year alphas, age, size, and especially lagged flows have a statistically significant effect, on the sign of flows. This suggests that investors may attach differential importance to information available to them relative to an empirical model that forecasts future hedge fund performance. We return to this issue below.

[27] This is likely a result of survival; a fund deeply under the water mark must have survived thanks to significantly improved subsequent performance.
[28] These results are consistent with the findings of Agarwal, Daniel and Naik (2009) and Ding et al. (2009) for share restrictions.

In a robustness test, we include in our model quarterly flows arriving in quarter t to control for any flow-induced performance, to rule out, for instance, that in the presence of capacity constraints performance is competed away by flows chasing past performance, as in Berk and Green's (2004) equilibrium. [29] Consistent with Dichev and Yu (2011) and Li et al. (2011) we find the effect of quarterly flows on subsequent yearly performance to be negligible and not statistically significant. In further checks, where we condition this analysis to funds with various levels of quarterly flows, we obtain similar results. Interacting current flows with streaks or other performance metrics also yields insignificant results. We also test the inclusion of contemporaneous yearly flows. That the corresponding coefficient is positive and significant in all specifications most likely captures the response of yearly flows to performance contemporaneously. Including quarterly or contemporaneous yearly flows does not, however, alter our previous results.

4.2 Forecast evaluation

The foregoing results indicate that streaks have some information value and are able to predict one-year-ahead Sharpe ratios and, to a lesser extent, one-year-ahead raw returns. A number of predictors of performance, on the other hand, have no apparent impact on flows, and some predictors of flows play no role in the performance models. Our purpose here is to determine, in a way that justifies investor response to performance streaks and other performance signals, the extent to which investors are driven by the forecasts obtained from the models described above. We do so by first computing out-of-sample forecasts of one-year-ahead performance ranks for each period t to $t+3$ using the coefficients from recursive estimations of equation (2) based on $t-1$ information. The first forecast corresponds to the four-quarter period 1997Q4-1998Q3, based on prior cross-sectional information available from 1995Q1 to 1997Q3.

The accuracy of the forecasts generated by these models is evaluated in Table 10, Panel C, which compares the predictions with the ex post realizations in four ways. We report first the root mean squared error (RMSE), which punishes larger forecast errors more heavily. Second, we compute the mean absolute deviation (MAD) based on the absolute size of the forecast error. Third, we compute an out-of-sample R^2 based on the squared correlation coefficient between the forecasts and ex post realizations (see Pesaran and Timmermann, 1995). Finally, we report a hit rate defined as the proportion of times a model correctly

[29] The empirical evidence of this effect is mixed. Studies that find that flows negatively forecast subsequent performance are Fung et al., 2008 (for funds of funds) and Naik et al.,2007 (at the style level). Dichev and Yu (2011) and Li et al. (2011) find no reliable relation between fund flows and future performance of individual hedge funds.

predicts whether Expected rank≥0.5 or Expected rank<0.5. The latter measure implicitly assumes an investment strategy determined by a switching rule relative to the median rank (i.e., investing if rank forecast is above or equal to 0.5, and divesting otherwise). These four measures are conditional on fund survival. We analyze a potential survivorship bias of our models' forecasts in Section 5.

Consistent with our previous analysis, Model 4 exhibits the highest out-of-sample R^2, of about 6.9%, the other models fairly low values, below 3%. The mean rank error across models, as measured by RMSE and MAD, is as large as 25 to 30 rank percentiles, the hit rate across models above 50% (up to 59% for Model 4). These results show that past information available to investors can be optimally combined into a performance forecast via an econometric model to predict hedge fund performance, but predictability at the level of the individual fund is fairly limited (cf. Wegener, von Nitzsch and Cengiz, 2010, and Avramov, Barras and Kosowski, 2013).

[Insert Table 11]

4.3 Performance forecasts and flows

We now investigate the extent to which investor choice is determined by the performance forecasts obtained above. The out-of-sample forecasts, being based on all available information until $t-1$, constitute a realistic benchmark at the time investors make decisions regarding investment or divestment. Table 11 reports our estimates of a number of alternative specifications, similar to the probit model in Table 6 that explains investor choices, but including the expected performance obtained from the four forecast models (Panels A to D). Under the assumption that performance streaks' and other variables' relevance to future hedge fund performance is completely captured by these forecasts, behavioral arguments provide likely explanations for any additional sensitivity of investor flows to performance streaks.[30] As before, we estimate the probit model by pooling all fund-period observations including time dummies to capture cross-sectional dependence, and employing clustered-robust standard errors to account for serial correlation in the error terms for the same fund across time. In each panel, we report first the estimates of a simple specification model (column (1)) that explains the sign of cash flows from the expected rank, defined as the predicted rank from each of the models reported in Table 10. Because investors may take into account not only the rank, but also precision, of these forecasts, we control for a measure of forecast accuracy,

[30] Weizsäcker (2010) employs a similar methodology in an experimental context as a test for rational expectations.

calculated for each fund-period observation as the root mean squared error (RMSE) of the eight lagged forecasts.[31] Across models, we find Expected performance to have a positive and statistically significant impact on the sign of flows. The higher the predicted rank, the more likely a fund will experience positive money flows. That the RMSE has a negative impact on the sign of flows indicates that investors are less likely to invest as the mean forecasting error increases. The effect of RMSE is statistically significant only in Model 3, however, and only marginally significant in Model 1.[32]

It being conceivable that investors perceive a trade-off between estimated expected performance and the accuracy of the estimate, in alternative specifications (not reported) we test a potential interaction by multiplying expected performance and RMSE or computing a ratio of expected performance over RMSE. Neither interaction has a significant effect on flows. That the pseudo R^2 of the specification in column (1) is fairly low (between 0.4% and 1.4%) across models suggests that out-of-sample forecasts of one-year-ahead performance have little explanatory power with respect to the variability of flows.

In column (2) in each of the panels we report an extended specification model that includes as controls, in addition to estimated expected performance and RMSE, the streak dummies, count dummies, fund characteristics, lagged flows, and style and time dummies. We exclude the set of controls for fund performance (e.g., annual ranks, Sharpe ratios, and alphas). Although the effect of Expected Performance and RMSE diminishes considerably across models, the coefficient of Expected Performance remains statistically significant. The estimated coefficients for winning and losing streaks are all highly significant, whereas in absolute value they increase monotonically with the length of the streak, up to five or six quarters in length. The longer the winning streak, the more likely a fund will attract inflows, the longer the losing streak, ceteris paribus, the more likely a fund will experience outflows, beyond the expected relative performance. Across models, the pseudo R^2 of specification B ranges from 8.6% to 8.9%, a significant improvement with respect to the specification in column (1).

When we add, in the specification model reported in column (3), the set of controls for fund performance (i.e., annual ranks, Sharpe ratios, alphas, under-water dummy, standard deviation of historical

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[31] As before, if we denote the ex post realizations by $y_h$and the series of predictions by $\widehat{y_h}$, h=t-1,t-2,…,t-8, where t is the current quarter, then the RMSE of the eight lagged forecasts is defined as $RMSE_t = \sqrt{\frac{1}{8}\sum_{h=1}^{8}(\widehat{y_h} - y_h)^2}$.

[32] That the expected performance rank is constructed on the basis of predictions from a first-stage regression may lead to a "generated regressors" problem (see Pagan, 1984, Newey, 1984) if it is assumed that agents, unlike the econometrician, are familiar with the true values from the first stage coefficients.

returns, and downside risk), the effects of Expected Performance and RMSE become insignificant in all models. The coefficients of all other variables are similar in magnitude and statistical significance to those from the probit model of flows reported in Table 6 (Column D), even though all of these variables are included in the estimation of the performance forecast. There is no change in our main results regarding streak dummies, namely, that the coefficients of streaks exhibit a monotonic pattern as streak length increases, and are statistically significant. Including the set of performance variables as controls in column (3) considerably enhances the explanatory power of the model with respect to the specification in column (2), as indicated by the value of the pseudo R^2 (11.2% across models).

Our results show predicted rank from the different forecast models to explain only a minor portion of flows variation. Moreover, the coefficients of all variables in the flows model change little when we control for predicted rank and prediction accuracy, even though all variables are included in the performance forecast. These results suggest that investor choice is determined by a different linear combination of covariates than that estimated in any of the forecast models. To better understand how differently investors weigh past information compared to the forecast models, we pursue below a deeper analysis based on the relative importance of regressors.

4.4 Relative importance of predictors

In Section 3 we implemented a *relative weights analysis* to estimate, in terms of their contribution to the R^2, the relative importance of predictors in the flows model. We implement the same technique to estimate the proportion of explained variance that can be attributed to each predictor in the forecast models. This enables us to evaluate the information processing strategy of investors against the model's benchmark.

[Insert Table 12]

Table 12 reports our estimates of the relative weights for the four models (Panels A to D), expressed as percentages of R^2s. As above, standard errors and confidence intervals are estimated using a bootstrap approach. The 99% confidence intervals are constructed assuming normality of the large sample distribution of relative weights. Whenever relative weights are near zero, we report the empirically observed confidence interval based on the bootstrapped percentiles.[33] The combined contribution of the

[33] That is, when the relative weights are near zero, the 99% confidence interval is constructed by taking the 0.5 percentile and 99.5 percentile of the bootstrapped distribution.

streak dummies to the R^2 varies across models, explaining nearly 10% of the predictable variance in Model 1 (i.e., the raw-returns model), 6.94% in Model 2, 12.93% in Model 3, and nearly 29% in Model 4 (i.e., the Sharpe ratio model). Note, however, that the large relative weight in Model 4 is due mostly to the W8 dummy; against its exceptionally large relative weight of about 16.83%, the combined relative weight of the remaining winning streaks is only 3.66%.

Across models, the most important predictors associated with the largest contribution to the R^2 are the set of fund-specific characteristics, set of style dummies, and set of performance and risk metrics (including the combined effect of lagged annual ranks), which together account for at least 70% of explained variance. The least important predictors are the set of count dummies, set of performance streak dummies (except for W8 in Model 4), and set of lagged flows. Note, on the one hand, the remarkable contrast with the relative weights analysis in the flows model (see Table 8); the set of fund-specific characteristics and set of style dummies, although among the most important predictors of subsequent performance relative to other variables in the forecast models, have the lowest relative importance in the flows model; the set of streak dummies and set of lagged flows, although among the most important predictors relative to other variables in the flows model, have the lowest relative importance in the forecast models. On the other hand, one of the most important predictors of subsequent performance in most forecast models, namely the lagged annual rank, is the variable that investors weigh the most relative to other variables in the flows model. The evidence that annual ranks persist while strongly determining flows does not lend support to the main proposition of Berk and Green (2004) applied to hedge funds, that under decreasing returns to scale, flows chasing a certain past performance signal compete away in equilibrium the forecasting power of that signal.

The results reported in this section indicate that investors weigh past information very differently than the forecast models that predict raw or style-adjusted returns, alphas, or Sharpe ratios. Put differently, the relative importance investors attribute to predictors diverges from the relative importance of predictors in the forecast models. This does not imply that investors are uninformed or behave irrationally. There are potentially omitted factors that predict performance, such as qualitative information collected in due diligence reports, that are unobservable to the econometrician but known to investors. Admittedly, both the flows and forecast models exhibit relatively low R^2s. Our results, however, suggest that (1) the set of covariates jointly observed by investors and the econometrician have some predictive power with respect to subsequent performance, (2) this predictable component is not what drives investor choice, and (3) investors appear to attribute some value to covariates beyond expected performance or to covariates that play no role in our forecast models.

In the next section, we test the possibility that investors are better informed than our empirical forecasting models by comparing investors' ex post performance with the models' predictions.

5. Welfare implications

5.1 Performance comparison of investors' versus models' fund choices

We evaluate the ex-post performance of investors' investment and divestment allocations relative to the out-of-sample predictions of the forecast models. Based on each forecast model, we define a benchmark trading rule that prescribes investing in funds with a rank forecast above or equal to the median fund (i.e., Expected rank≥0.5), and divesting otherwise. Our timing assumption throughout this section is that both investors and the model make an allocation at the beginning of quarter t based on all past information available at the end of quarter $t-1$. We evaluate the ex-post performance of these allocations for the four-quarter period t to $t+3$ by obtaining equally weighted averages across all funds selected by each strategy of four-quarter-ahead raw returns, style-adjusted returns, alphas (annualized), and Sharpe ratios.

[Insert Table 13]

Table 13, Panel A reports our results for investments. All t-statistics (in parentheses) are based on clustered-robust standard errors to account for within-fund serial correlation. Investor strategy is shown in column (1). On average, funds that experience actual net money inflows (N=7552 observations) at the beginning of quarter t deliver a subsequent four-quarter return of 9.12%, a style-adjusted return of 1.35%, an annualized alpha of 3%, and a Sharpe ratio of 0.286. Examining the performance of investment rules based on the forecast models, the first three outperform the average investor in nearly all four accounts (columns (2), (4) and (6)). On average, raw returns differences range from 2.25% to 3.53%, all statistically significant (1.05% to 2.73% after style adjusting, also statistically significant, except for Model 3). In terms of annualized alphas, all four models outperform the average investor by from 4.2% to 4.92% (statistically significant, except for Model 1). For Sharpe ratios, we observe only small, not statistically significant, differences with respect to the first three models, but Model 4 (Column (8)) outperforms the average investor by a significant margin of 0.148.[34]

We observe a similar pessimistic picture for the divestment portfolio of the average investor reported in column (1) of Panel B. In this case, a good divestment strategy should have low returns. On average, funds that experience net outflows at the beginning of quarter t (N=8750 observations) deliver a subsequent four-quarter return of 8.95%, a style-adjusted return of 0.97%, an annualized alpha of 3.24%, and a Sharpe ratio of 0.223. Again, this is outperformed by the divestment rules based on the first three forecast models. Raw return differentials range from -2.24% to -3.63%, all statistically significant (-0.06% to -2.95% after style adjusting, statistically significant only for Model 2). In terms of annualized alphas, all four models outperform the average investor, although the differences are not statistically significant. Measured in terms of Sharpe ratios, Model 4 outperforms the average investor by a significant difference of -0.089.

Panel C reports the return spreads between the average fund invested in and average fund divested from, based on the allocations of the average investor (column (1)) and each of the forecasting models. For the actual investor allocations, the performance spreads are small and not significantly different from zero, only the differential Sharpe ratio being marginally significant at the 10% level. In contrast, the performance spreads of the investment and divestment decisions prescribed by all forecast models are nearly all positive and statistically significant. Return differences range from 1.54% to 5.77%, and alpha differences from 1.80% to 2.64% (see columns (2), (4), (6) and (8)). These performance spreads are significantly larger than those of investors in nearly all accounts, and most differences, reported in columns (3), (5), (7), and (9), are significant. When we evaluate the trading strategies with smoothing-adjusted returns and Sharpe ratios, spreads are reduced somewhat, but the statistical significance of our main results remains unaltered. In most

[34] These results abstract from several possible complications. First, investor money flows will occur at different times within the quarter, which will make the performance of our investor allocation strategy look better than actual if investors use performance during the first part to allocate their money in the second half of the quarter. There is, however, an opposing force if investors are able to optimize their timing during the quarter. Second, the analysis ignores the possibility that actual investor flows have a subsequent causal effect on performance (Fung et al., 2008). To investigate the possible importance of these effects, we included contemporaneous quarterly flows in the estimated return forecasting models and found them, in all cases, to have no significant impact on performance (see 4.1. above). In the absence of accurate information about the timing of investor flows within each quarter, we feel comfortable concluding that the economic impact of these complications is limited. Dichev and Yu (2011) and Li, Zhang and Zhao (2011) also find no reliable relation between fund flows and future returns. As a robustness check, we evaluate the performance of model-based allocations when investments are restricted to funds/periods that experience actual inflows, and divestments to funds/periods that experience actual outflows (see Appendix B1).

cases, the forecasting model's allocation rules perform relatively well when the performance metric that is predicted coincides with the evaluation criterion. For example, allocating funds on the basis of the model that predicts the Sharpe ratio ranks results in a Sharpe ratio differential between investments and divestments of 0.300, which is both economically and statistically highly significant and about three times larger than the allocations based on forecasts of style-adjusted returns or alphas. Similarly, the largest style-adjusted return spread of 4.66% is obtained for the style-adjusted return forecasting model.

These results are robust to the choice of different sample periods. We test, in particular, the performance of investment allocations in the periods prior to (1995Q1 to 2007Q3), and during (2007Q4 to 2010Q3), the financial crisis. For the pre-crisis period, we allow investments only until 2006Q4, so that the four-quarter-ahead evaluation period does not overlap with the crisis period. Prior to the crisis, all investment and divestment allocations from investors and forecast models alike deliver absolute returns significantly larger than in the crisis period. For example, the investment allocations prescribed by Model 1 deliver absolute returns of 15.66% before, and 7.21% during, the crisis, the divestment allocations, 8.03% before, and 2.96% during, the crisis. The return-spread for Model 1 (reported in Table B1, Panels A and B, in the Appendix) is thus 7.63% before (Panel A) and 4.25% during (Panel B) the crisis, exceeding the return spread of investors by a statistically significant margin in both periods. We observe a similar pattern for the investment strategies of all other models, whether evaluated in terms of returns, alphas, or Sharpe ratios.

The results in Table 13 show that, on average, funds in which investors invest do not perform better than funds from which they divest. Moreover, simple investment and divestment rules outperform the decisions of the average hedge fund investor by an economically significant margin. It is possible, though, that investors are able to identify the better funds within the investment, or poorer funds within the divestment, portfolio and take this into account in making allocations. We investigate this possibility by analyzing whether investors' cash-flow weighted returns perform significantly better than equally-weighted returns. The results (not tabulated) indicate the opposite. Funds that experience actual net money inflows at the beginning of quarter t deliver a subsequent four-quarter cash-flow weighted average return of 7.42%, an average style-adjusted return of 0.64%, an average annualized alpha of 1.92%, and a cash flow weighted average Sharpe ratio of 0.323. Funds that experience actual net outflows at the beginning of quarter t deliver a subsequent four-quarter cash-flow weighted average return of 8.02%, an average style-adjusted return of 0.22%, an average annualized alpha of 5.164%, and a Sharpe ratio of 0.276. The spread on investors' allocations thus delivers a cash flow weighted performance significantly smaller than the equally weighted performance, and often negative.

It is remarkable that simple allocation schemes based on forecast models with limited predictive ability, as discussed in the previous section (see Table 10, Panel C), outperform investors by a statistically significant margin for nearly all evaluation criteria.[35] Admittedly, our analysis does not consider the possibility that the forecast models' prescribed trading strategies invest in funds that are actually closed to new investments, or divest from funds that impose severe share restrictions or lockup periods. Our performance evaluation of all trading strategies reported in Table 13 is also conditional on fund survival. Defining the hypothetical investment strategies based on a switching rule around the median rank could also explain our results. Thus, we conduct a wide range of robustness tests, reported in Appendix B, that take into account potential restrictions to inflows and outflows, potential capacity limits, and the potential effect of a survivorship bias. We also analyze the effect of thresholds other than the median to define the switching rule that underlies the benchmark allocations. Finally, we investigate the effect of investment horizons longer than one year. Our main results in this section are strongly robust to these tests, which all indicate that performance differences between investments and divestments based on out-of-sample forecasts are positive and statistically significant and outperform investor strategies. The results also suggest a distinction among three types of funds: those commonly selected by investors and the models, those selected only by the models, and those selected only by investors. It is the latter, which seem to be characterized by extremely poor performance, that drive the differences documented in this section. Accordingly, we further analyze, below, cases in which investor allocations deviate from the model allocations.

5.2 When investors and models disagree

The following analysis, focused on funds for which the average investor allocation decision deviates from the decision implied by model forecasts, enables us to identify what drives investors to deviate and whether deviation improves their performance.

[35] Note that all investment and divestment rules ignore transaction costs, but these are likely to be comparable to the transaction costs faced by investors.

[Insert Table 14]

Table 14, Panel A reports the four-quarter-ahead performance of funds with positive net flows in quarter t conditional on Expected rank<0.5. That is, by investing in these funds the average investor diverges from the models' four-quarter-ahead forecast. Panel A shows average performance to be poor whenever investors deviate from any of the models. Investors who deviate from Model 1 in 4,233 observations (column (2)), for example, earn an annual raw return of 6.6% (0.07% style-adjusted), which is significantly below the 9.12% (1.35% style adjusted) average raw return for all investors (see column (1)). The picture is similar in all cases in which investors deviate from the models' forecasts (columns (4), (6), and (8)). Panel B reports the four-quarter-ahead performance of funds with negative net flows in quarter t conditional on Expected rank≥0.5. In this case, investors deviate from the models' positive forecast by divesting, and as a result systematically forego relatively high returns. Investors who deviate from Model 1 in 2,862 cases (column (2)), for example, forego an annual raw return of 12.93%, which is significantly higher than the average return of all funds from which investors divest (8.95%). Investors who deviate from the forecast of Model 4 forego large Sharpe ratios of approximately 0.41, on average. Panel C reports the performance spread between investments and divestments. Deviating from the models' forecasts represents a significant net cost, both economically and statistically, for investors. The spreads are negative and statistically significant in nearly all cases for raw returns, style-adjusted returns, and alphas, and are also negative for Sharpe ratios, being especially sizeable when investors deviate from Model 4.

We now investigate which factors determine that investors diverge from the model's forecasts in nearly 45% of observations.[36] First, conditional to Expected rank<0.5, we estimate a model describing the probability that the average investor in a fund i dissents from the forecast and chooses to *invest* ($d_1 = 1$), such that the fund experiences *positive net flows* if an underlying variable, d_1^* is positive. The explanatory variables are the same as in equation 1 (see Section 3). Likewise, conditional to Expected rank≥0.5, we estimate a model describing the probability that the average investor in a fund i dissents from the forecast and chooses to *divest* ($d_2 = 1$), such that the fund experiences *negative net flows* if an underlying variable, d_2^* is positive.

[36] The divergence translates in a low correlation coefficient between the dummy variable indicating investors' choice (equal to 1 if net flows>0, zero otherwise) and the one indicating the model's choice (equal to 1 if Expected rank>0.5, zero otherwise), which is 0.22 (with Model 1), 0.19 (with Model 2), 0.24 (with Model 3) and 0.23 (with Model 4).

[Insert Tables 15 and 16]

Results of the first estimation are reported in Table 15. Performance variables like annual ranks, streaks, the count dummies, and Sharpe ratios significantly determine investors' choice to invest when the forecast models prescribe divestment. The length of winning streaks increases the likelihood that investors deviate from, the length of losing streaks that they divest and thus converge towards, the models' prescription. Results of the second estimation, reported in Table 16, indicate that losing streaks (up to three quarters in length) increase the likelihood that investors divest when the model prescribes investment (the only exception being column (1), in which losing streaks have no significant impact). Conversely, the length of winning streaks makes it more likely that investors invest and thus converge towards the models' prescription.

In Section 4, we found streaks to have limited predictive ability with respect to subsequent performance. Our results in this section strongly suggest that investor focus on streak length is partly responsible for their poor investment and divestment choices.

6. CONCLUSIONS

Hedge fund investors, being arguably sophisticated, should possess some ability to interpret and analyze information pertinent to their decisions to invest or divest. Our analysis, however, reveals the average hedge fund investment and divestment to be not particularly "smart" (cf. Baquero and Verbeek, 2009, or Ramadorai, 2013); simple decision rules based on out-of-sample forecasts of linear performance models easily outperform the average investor by an economically and statistically significant margin.

In this paper, we analyze hedge fund investors' decisions to invest or divest in relation to a wide range of information variables available to them. We pay particular attention to the relevance of performance streak variables, performance streak being defined as subsequent quarters during which a fund performs above or below a benchmark. We show investor flows to react positively to winning, and negatively to losing, streaks, the strength of the reaction increasing with the length of the streak. Performance streaks are patterns that are relatively easily observed, and potentially stressed by funds or financial media in the case of good performance. Although investor response to streaks may reflect a belief in "hot hands," in which case good performance is likely to persist, our analysis shows performance streaks to have limited predictive value with respect to future fund performance. More precisely, relative weights analyses of the explanatory factors in the econometric models that explain flows and performance reveal investors to be likely to overweigh the importance of performance streaks, and, more generally, to fail to optimally weigh the information available to them. Further, investor decisions underperform, ex post, simple model allocation rules, and there is no evidence that better returns are realized in cases in which investor allocations deviate.

In summary, hedge fund investors' ability to select funds shows little sign of sophistication; they weigh information suboptimally, and their ultimate investment and divestment performance is disappointing.

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TABLES AND FIGURES

Table 1

Distributions of Flows and Assets under Management

This table shows the cross-sectional distribution of cash flows and total net assets under management in our sample of 1856 open-end hedge funds from 1995Q1 till 2010Q3. 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 AUM of the previous quarter.

Percentile	Cash Flows (growth rate)	Cash Flows (dollars)	Assets Under Management (million dollars)
99%	0.9951	1.76E+08	2500
95%	0.3446	4.63E+07	781.44
90%	0.1872	1.90E+07	425.32
75%	0.0510	2464053	151.60
50%	-0.0003	-2769.16	47.97
25%	-0.0617	-2697553	12.92
10%	-0.1956	-1.74E+07	4.00
5%	-0.3233	-4.12E+07	1.9207
1%	-0.6466	-1.60E+08	0.4489

Table 2. Summary of Winner and Loser Streaks

In each quarter we define the winners and the losers taking the US Treasury Bill as a benchmark. The table indicates the total number of streaks with consecutive winning quarters (Panel A) and consecutive losing quarters (Panel B) across all funds and all periods in our database. 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 net negative money flows).

Panel A : Winner Streaks

1	2	3	4	5	6	7	8	9	10
Streak Length	Number of observations	Subsequent Liquidation %	Subsequent Self-selection %	Subseq. Persistent Winner %	Unknown subsequent performance %	Subsequent Positive Money Flows %	Percent of missing Money Flows obs.	Average Amount of Dollar Flows Invested	Frequency of Wrong Forecasts Up %
1	7266	1.83	0.99	57.54	0.00	39.87	8.48	-1,150,593.9	37.42
2	4182	1.24	0.65	63.61	0.86	47.30	8.68	3,512,485.8	35.04
3	2660	1.32	0.68	65.98	1.17	49.36	8.46	7,756,753.0	30.85
4	1755	1.20	0.68	61.48	0.23	54.02	8.55	11,610,995.0	34.18
5	1079	1.11	0.56	62.56	0.74	56.26	8.43	18,976,586.0	29.49
6	675	1.48	0.74	57.63	3.41	57.33	8.30	15,624,994.0	34.88
7	389	1.03	0.00	54.24	10.28	53.47	6.17	14,570,951.0	36.06
8	211	0.47	0.47	61.14	3.32	59.72	6.64	18,125,440.0	33.33

Panel B : Loser Streaks

1	2	3	4	5	6	7	8	9	10
Streak Length	Number of observations	Subsequent Liquidation %	Subsequent Self-selection %	Subseq. Persistent Loser %	Unknown subsequent performance %	Subsequent Negative Money Flows %	Percent of missing Money Flows obs.	Average Amount of Dollar Flows Divested	Frequency of Wrong Forecasts Down %
1	7698	1.65	0.92	41.78	0.00	50.86	8.33	-4,197,773.5	54.84
2	3216	2.77	1.27	44.19	1.24	59.11	7.40	-11,564,070.0	51.50
3	1421	5.28	2.39	46.52	1.13	61.65	6.12	-13,967,102.0	49.43
4	661	5.14	1.82	52.65	1.21	63.09	6.66	-14,390,516.0	43.17
5	348	5.75	2.01	48.28	0.86	66.09	6.90	-11,646,918.0	49.57
6	168	5.95	4.17	46.43	3.57	59.52	6.55	-10,528,012.0	55.00
7	78	5.13	2.56	33.33	0.00	62.82	8.97	-5,254,313.5	59.18
8	26	3.85	0.00	61.54	0.00	76.92	3.85	-6,437,588.5	35.00

Table 3. Streaks and Performance Metrics

For each length j of streaks observed between $t-1$ and $t-j$, we report the sample mean of various performance metrics measured over the 8-quarter period from $\mathrm{t}-1$ till $t-8$, namely: monthly alphas, Sharpe ratios, raw return ranks, under-water dummy, downside-upside potential, standard deviation of monthly returns, the 2005 omega score calculated for the period 2004 to 2006 (5546 obs) and the three smoothing variables: Serial Correlation, Smoothing Index and Theta coefficient, calculated for the subsample of funds for which Smoothing index≤1. The last two rows in each Panel report the test of differences of means between eight-quarter streaks and one-quarter streak (except for omega score in Panel B since there is only one observation for L8).

Panel A : Winner Streaks

Streak Length	Two year Alpha	Two year Sharpe Ratio	Two year Raw Rank	Underwater dummy	Downside-Upside Potential	StDev	Omega score 2005	Autocorrel. coefficient	θ_0	HHI
1	0.0032	0.1504	0.4773	0.2178	1.2991	0.0491	-0.4296	0.0797	0.7160	0.6244
2	0.0045	0.2023	0.5187	0.1724	1.2403	0.0477	-0.4259	0.1014	0.7101	0.6112
3	0.0053	0.2534	0.5500	0.1434	1.1800	0.0459	-0.4316	0.1260	0.7008	0.6045
4	0.0053	0.3017	0.5858	0.1133	1.1382	0.0434	-0.4840	0.1422	0.6899	0.5919
5	0.0073	0.3747	0.6442	0.0570	1.0836	0.0421	-0.4974	0.1541	0.6893	0.5876
6	0.0093	0.4658	0.6848	0.0110	1.0292	0.0390	-0.5281	0.1265	0.6945	0.6034
7	0.0100	0.5554	0.7141	0.0058	0.9966	0.0345	-0.5691	0.1038	0.6840	0.5993
8	0.0130	0.8761	0.7351	0.0000	1.0268	0.0309	-0.5740	0.0257	0.6441	0.5681
W8 - W1	0.0098	0.7257	0.2578	-0.2178	-0.2722	-0.0183	-0.1444	-0.0541	-0.0719	-0.0563
t-stat	(12.04)	(25.57)	(19.10)	(-44.33)	(-5.61)	(-10.37)	(-1.86)	(-2.99)	(-4.44)	(-4.06)

Panel B : Loser Streaks

Streak Length	Two year Alpha	Two year Sharpe Ratio	Two year Raw Rank	Underwater dummy	Downside-Upside Potential	StDev	Omega score 2005	Autocorrel. coefficient	θ_0	HHI
1	0.0041	0.1657	0.4881	0.1894	1.2726	0.0484	-0.4421	0.0850	0.7091	0.6159
2	0.0017	0.0626	0.3982	0.3118	1.4200	0.0489	-0.4387	0.1150	0.7053	0.6133
3	-0.0007	-0.0512	0.3018	0.4634	1.5578	0.0520	-0.3480	0.1210	0.6956	0.6014
4	-0.0022	-0.1249	0.2238	0.6320	1.7321	0.0554	-0.2225	0.1154	0.6903	0.6001
5	-0.0033	-0.2073	0.1861	0.8139	1.8353	0.0521	-0.2932	0.1382	0.6861	0.5877
6	-0.0046	-0.2972	0.1788	0.8621	1.9497	0.0512	-0.2733	0.1967	0.6365	0.5560
7	-0.0080	-0.3788	0.1406	0.9028	2.1415	0.0502	-0.3836	0.1256	0.6456	0.5658
8	-0.0223	-0.6231	0.0922	1.0000	2.0796	0.0465	-0.3219	0.0267	0.6426	0.5283
L8 - L1	-0.0263	-0.7888	-0.3959	0.8106	0.8070	-0.0019	0.1203	-0.0583	-0.0664	-0.0876
t-stat	(-6.97)	(-20.80)	(-15.67)	(179.08)	(2.90)	(-0.30)	**	(-0.94)	(-2.03)	(-3.34)

Table 4. Cross-Sectional Characteristics of the Hedge Fund Sample

We report summary statistics on cross-sectional characteristics of our sample of 1856 hedge funds for the period 1995Q1 till 2010Q3. Cash flows are the change in assets under management between consecutive quarters corrected for reinvestments. Returns are net of all management and incentive fees. Age is the number of months a fund has been in operation since its inception. In each quarter, the historical standard deviation of monthly returns, semi deviation and upside potential have been computed based on the entire past history of the fund. Semi deviation and upside potential are calculated with respect to the return on the US Treasury bill taken as the minimum investor's target. Offshore is a dummy variable with value one for non U.S. domiciled funds. Incentive fee is a percentage of profits above a hurdle rate that is given as a reward to managers. Management fee is a percentage of the fund's net assets under management that is paid annually to managers for administering a fund. Personal capital is a dummy variable indicating that the manager invests from her own wealth in the fund. We include 10 dummies for investment styles defined on the basis of the CSFB/Tremont indices. See Appendix E for further details of variable definitions.

Variable	Obs	Mean	Std. Dev.	Min	Max
		Fund characteristics			
Ln(AUM)	20420	17.7809	1.8530	-0.0101	23.2882
Ln(Age)	20420	4.4304	0.5056	3.3322	6.0014
Offshore	20420	0.6425	0.4793	0.0000	1.0000
Incentive Fee	20420	18.8842	4.8615	0.0000	50.0000
Manager's Option Delta (USD)	20416	155,991	490,188	0.0000	11,300,000
Total Delta (USD)	20416	382,634	1,017,084	0.0000	20,100,000
Management Fees	20420	1.4135	0.6679	0.0000	8.0000
Personal Capital	20420	0.5743	0.4945	0.0000	1.0000
Leveraged	20420	0.7142	0.4518	0.0000	1.0000
High-water mark	20420	0.6117	0.4873	0.0000	1.0000
Convertible Arbitrage	20420	0.0527	0.2235	0.0000	1.0000
Dedicated Short Bias	20420	0.0090	0.0945	0.0000	1.0000
Emerging Markets	20420	0.1315	0.3379	0.0000	1.0000
Equity Market Neutral	20420	0.0496	0.2170	0.0000	1.0000
Event Driven	20420	0.1386	0.3456	0.0000	1.0000
Fixed Income Arbitrage	20420	0.0505	0.2191	0.0000	1.0000
Global Markets	20420	0.0560	0.2299	0.0000	1.0000
Long Short Equity	20420	0.3880	0.4873	0.0000	1.0000
Managed Futures	20420	0.0963	0.2950	0.0000	1.0000
Other	20420	0.0278	0.1644	0.0000	1.0000
		Cash flows			
Cash Flows (growth rate)	20420	0.0002	0.3124	-0.9653	5.7814
Cash Flows > 0	9141	0.1394	0.3932	0.0000	5.7814
Cash Flows < 0	11279	-0.1126	0.1515	-0.9653	0.0000
Dollar Flows	20420	-313,479	60,100,000	-547,000,000	559,000,000
		Performance variables			
Quarterly return	20420	0.0187	0.1091	-1.0000	1.8311
alphaCAPM_12 months (monthly)	20420	0.0035	0.0170	-0.1938	0.2034
alphaCAPM_24 months (monthly)	20420	0.0042	0.0120	-0.1012	0.1240
alphaCAPM_36 months (monthly)	19662	0.0051	0.0099	-0.0623	0.0946
alphaFung&Hsieh_12 months (monthly)	20420	0.0030	0.0274	-0.5639	0.4719
alphaFung&Hsieh_24 months (monthly)	20420	0.0032	0.0129	-0.1308	0.1841
alphaFung&Hsieh_36 months (monthly)	19662	0.0037	0.0098	-0.0641	0.1169
Sharpe ratio 12m	20420	0.2526	0.8387	-1.4406	22.2137
Sharpe ratio 24m	20420	0.2182	0.6137	-1.2034	16.8014
Sharpe ratio 36m	19662	0.2254	0.5050	-1.1093	14.4541
Under-water dummy	20420	0.2239	0.4169	0.0000	1.0000
Standard Deviation (of monthly returns)	20420	0.0464	0.0341	0.0006	0.3245
Downside potential	20420	0.0271	0.0213	0.0000	0.2140
Upside potential	20420	0.0216	0.0143	0.0013	0.1229
Downside-Upside Potential Ratio	20420	1.2613	0.6848	0.0000	11.5237
Autocorrelation Coefficient	20420	0.1100	0.2336	-0.7924	0.9738
theta0	20419	0.8854	0.5998	-0.7329	3.9193
Omega Score (2004-2006)	10486	-0.4612	0.6427	-2.6104	2.8167

Table 5. Flows Model: Specification Search

The table compares the explanatory power of different specifications of a probit model explaining the sign of net flows, as described in equation (1). The dependent variable takes value 1 if net flows>0, and zero otherwise. All specifications are estimated pooling all fund-quarter observations. The sample includes 1856 open-end hedge funds between 1995Q1 and 2010Q3. The explanatory power is compared in terms of R^2, loglikelihood value, and the Akaike (AIC) and Schwartz Bayesian Information Criteria (BIC). We also report the F-test for inclusion of the streak dummies in all specifications. In Panel A we compare various specifications in which streak dummies are defined relative to different benchmarks. Panel B compares alternative specifications where the historical performance controls are different in each specification. The first four specifications control for two annual performance lags, based on four different criteria, either: raw returns, raw return ranks, style-adjusted ranks combined with style ranks, or within-style ranks combined with style ranks. The last four specifications in Panel B control instead for eight lags of quarterly performance, based on the same four criteria. In all specifications in Panel B streaks are defined relative to the US T-bill. Panel C compares three model specifications in which all controls for historical performance are defined over different horizons, namely one year, two years, and three years. In the three specifications streaks are defined relative to the US T-bill.

Panel A

	Streaks Benchmark						
	T-Bill	SP500	Zero	Style Index	HF Index	Median Raw Ret.	Median Style Ret.
N	20157	20157	20157	20157	20157	20157	20157
Pseudo R^2	0.1024	0.0989	0.1022	0.1003	0.1005	0.1008	0.1016
AIC	25099.74	25194.36	25105.35	25156.08	25150.99	25143.13	25121.65
BIC	26001.63	26096.25	26007.23	26057.97	26052.88	26045.02	26023.54
Loglikelihood ratio	-12435.87	-12483.18	-12438.67	-12464.04	-12461.50	-12457.56	-12446.83
F-test streak dummies	142.067	46.002	139.850	74.766	88.791	100.536	100.429
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Panel B

	Two lags annual performance				Eight lags quarterly performance			
	Model 1 Style-adj. Ranks + Style Ranks	Model 2 Within-style Ranks + Style Ranks	Model 3 Raw Return Ranks	Model 4 Raw Returns	Model 5 Style-adj Ranks + Style Ranks	Model 6 Within-style Ranks + Style Ranks	Model 7 Raw Return Ranks	Model 8 Raw Returns
N	19852	19852	19852	19852	19852	19852	19852	19852
Pseudo R^2	0.0999	0.1011	0.1011	0.0954	0.0999	0.1013	0.1002	0.0959
AIC	24802.31	24768.08	24763.80	24920.29	24826.71	24787.11	24802.82	24919.47
BIC	25686.67	25652.44	25632.37	25788.85	25805.83	25766.23	25718.76	25835.41
Loglikelihood ratio	-12289.16	-12272.04	-12271.90	-12350.14	-12289.36	-12269.56	-12285.41	-12343.73
F-test streak dummies	161.23	150.04	137.59	229.93	81.16	63.04	47.57	209.88
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Panel C

	Model1 One-year lagged performance	Model2 Two-year lagged performance	Model3 Three-year lagged performance
N	17461	17461	17461
Pseudo R^2	0.0964	0.1015	0.0996
AIC	21864.03	21753.79	21807.09
BIC	22671.87	22600.47	22692.61
Loglikelihood ratio	-10828.01	-10767.90	-10789.54
F-test streaks dummies	62.80	126.00	122.59
p-value	(0.000)	(0.000)	(0.000)

Table 6. Net Inflows, Net Outflows and Performance Streaks

The table reports estimates of a probit model explaining the sign of net flows. The sample includes 1856 open-end hedge funds between 1995Q1 and 2010Q3. We measure flows as a quarterly growth rate corrected for reinvestments. The dependent variable takes value 1 if net flows>0, and zero otherwise. The independent variables are defined in Table E2 in the appendix. Style and time dummies are included (estimates not reported). We pool all fund-quarter observations. Panel-robust z-statistics are in parentheses.

	A		B		C		D		E	
Intercept	-0.1861	(-9.42)	0.2697	(0.86)	-0.4156	(-1.36)	-0.2007	(-0.60)	-0.0311	(-0.09)
W2_TBill	0.2307	(8.37)	0.2304	(7.19)	0.2029	(6.21)	0.1557	(4.65)		
W3_TBill	0.3061	(9.57)	0.3381	(9.03)	0.2906	(7.53)	0.1943	(4.88)		
W4_TBill	0.4052	(10.48)	0.4406	(10.13)	0.3765	(8.40)	0.2273	(4.83)		
W5_TBill	0.4635	(10.01)	0.4805	(9.13)	0.3868	(7.08)	0.2613	(4.62)		
W6_TBill	0.6268	(10.81)	0.5838	(8.95)	0.4569	(6.72)	0.3491	(5.01)		
W7_TBill	0.5744	(7.85)	0.4766	(5.97)	0.3313	(3.93)	0.2212	(2.59)		
W8_TBill	0.4479	(7.75)	0.4236	(7.03)	0.1534	(2.32)	0.1066	(1.64)		
L1_TBill	-0.0616	(-2.66)	-0.0845	(-3.04)	-0.0877	(-3.11)	-0.0886	(-3.10)		
L2_TBill	-0.3232	(-9.76)	-0.3112	(-8.29)	-0.2555	(-6.65)	-0.1893	(-4.84)		
L3_TBill	-0.4708	(-10.08)	-0.4774	(-9.15)	-0.3807	(-7.05)	-0.2780	(-5.09)		
L4_TBill	-0.4884	(-7.35)	-0.4089	(-5.70)	-0.2806	(-3.76)	-0.1885	(-2.46)		
L5_TBill	-0.7081	(-7.90)	-0.5986	(-6.08)	-0.4471	(-4.28)	-0.3507	(-3.29)		
L6_TBill	-0.4820	(-3.93)	-0.2988	(-2.25)	-0.1729	(-1.21)	-0.0750	(-0.52)		
L7_TBill	-0.5384	(-3.09)	-0.4604	(-2.37)	-0.2609	(-1.19)	-0.1781	(-0.81)		
L8_TBill	-0.8963	(-4.03)	-0.8045	(-3.47)	-0.1542	(-0.64)	-0.2090	(-0.85)		
Count_1					0.3923	(3.40)	0.3161	(2.66)	0.0161	(0.16)
Count_2					0.4272	(5.35)	0.3618	(4.49)	0.1027	(1.43)
Count_3					0.3234	(5.08)	0.2644	(4.09)	0.0396	(0.69)
Count_4					0.2745	(4.94)	0.2244	(4.00)	0.0400	(0.81)
Count_5					0.1910	(4.10)	0.1565	(3.36)	0.0301	(0.73)
Count_6					0.0938	(2.33)	0.0712	(1.78)	0.0062	(0.17)
Middle Rank Lag 1							1.2310	(11.97)	1.3953	(13.55)
Top 30%							-1.6005	(-6.43)	-1.6186	(-6.46)
Bottom 30%							-1.3992	(-5.55)	-1.3919	(-5.60)
Middle Rank Lag 2							0.1385	(1.36)	-0.0023	(-0.02)
Top 30%							-0.0234	(-0.10)	-0.0232	(-0.10)
Bottom 30%							-0.2540	(-1.07)	-0.2355	(-1.00)
Rank 24m alpha					0.1338	(2.69)	0.1118	(2.25)	0.1284	(2.57)
Rank 24m Sharpe Ratio					1.0384	(12.91)	0.7140	(8.10)	0.6918	(8.02)
Underwater dummy					-0.0338	(-0.87)	-0.0005	(-0.01)	0.0010	(0.02)
Downside-upside pot. ratio					0.0919	(4.44)	0.0849	(4.14)	0.0837	(4.09)
St.deviation of returns					-0.1249	(-0.27)	-0.9567	(-1.88)	-0.9643	(-1.91)
Share restrictions			0.1245	(3.21)	0.1291	(3.34)	0.1281	(3.37)	0.1273	(3.33)
Lockup periods			-0.0005	(-0.31)	-0.0018	(-0.98)	-0.0018	(-0.99)	-0.0018	(-0.96)
High-water mark			0.0370	(1.16)	0.0476	(1.48)	0.0447	(1.41)	0.0464	(1.46)
Return smoothing			-0.0316	(-0.59)	-0.0705	(-1.32)	-0.0670	(-1.27)	-0.0618	(-1.18)
Ln(AUM)			-0.0114	(-1.47)	-0.0295	(-3.66)	-0.0308	(-3.86)	-0.0324	(-4.09)
Ln(Age)			-0.0930	(-3.23)	-0.0701	(-2.44)	-0.0636	(-2.24)	-0.0577	(-2.04)
Offshore			-0.0127	(-0.42)	-0.0080	(-0.27)	-0.0055	(-0.19)	-0.0048	(-0.16)
Incentive fee			-0.0009	(-0.32)	-0.0012	(-0.41)	0.0001	(0.05)	0.0001	(0.04)
Management fee			0.0207	(0.92)	0.0247	(1.10)	0.0138	(0.61)	0.0121	(0.53)
Personal capital			-0.0011	(-0.04)	-0.0139	(-0.50)	-0.0143	(-0.52)	-0.0129	(-0.47)
Leveraged			0.0159	(0.52)	0.0083	(0.27)	0.0059	(0.19)	0.0080	(0.27)
Flows lag 1			0.4848	(7.15)	0.4180	(6.77)	0.3953	(6.80)	0.3980	(6.89)
Flows lag 2			0.3135	(6.80)	0.2544	(6.07)	0.2406	(5.94)	0.2267	(5.84)
Flows lag 3			0.2349	(5.60)	0.1799	(4.65)	0.1750	(4.61)	0.1549	(4.20)
Flows lag 4			0.1676	(5.14)	0.1175	(3.69)	0.1329	(4.09)	0.1257	(3.87)
Flows lags 5 to 8	No		Yes		Yes		Yes		Yes	
Style and Time dummies	No		Yes		Yes		Yes		Yes	
N	23212		20505		20420		20420		20420	
McFadden pseudo R^2	0.038		0.076		0.095		0.103		0.097	

Table 7. Net Inflows, Net Outflows and Performance Streaks. Crisis vs Pre-Crisis

The table reports estimates of a probit model explaining the sign of net flows. The sample includes 1856 open-end hedge funds between 1995Q1 and 2010Q3. We measure flows as a quarterly growth rate corrected for reinvestments. The dependent variable takes value 1 if net flows>0, and zero otherwise. The independent variables are defined in Table E2 in the appendix. Style and time dummies are included (estimates not reported). We pool all fund-quarter observations. Panel-robust z-statistics are in parentheses.

	Full Period		Pre-Crisis1995Q1-2007Q3		Crisis 2007Q4-2010Q3		1995Q1-2003Q4		2004Q1-2007Q3	
Intercept	-0.2007	(-0.60)	-0.1951	(-0.54)	-0.4880	(-1.24)	-0.2007	(-0.60)	-0.4437	(-1.31)
W2_TBill	0.1557	(4.65)	0.1689	(4.19)	0.1082	(1.68)	0.1557	(4.65)	0.2001	(3.65)
W3_TBill	0.1943	(4.88)	0.1929	(4.01)	0.1848	(2.42)	0.1943	(4.88)	0.2120	(3.54)
W4_TBill	0.2273	(4.83)	0.2317	(4.12)	0.2151	(2.48)	0.2273	(4.83)	0.2093	(2.88)
W5_TBill	0.2613	(4.62)	0.2815	(3.97)	0.2548	(2.60)	0.2613	(4.62)	0.3502	(3.92)
W6_TBill	0.3491	(5.01)	0.3027	(3.72)	0.4809	(3.42)	0.3491	(5.01)	0.4489	(4.46)
W7_TBill	0.2212	(2.59)	0.2476	(2.55)	0.0071	(0.03)	0.2212	(2.59)	0.2768	(2.32)
W8_TBill	0.1066	(1.64)	0.1559	(2.19)	-0.1746	(-1.17)	0.1066	(1.64)	0.2343	(2.66)
L1_TBill	-0.0886	(-3.10)	-0.0555	(-1.62)	-0.1508	(-2.87)	-0.0886	(-3.10)	-0.0490	(-1.01)
L2_TBill	-0.1893	(-4.84)	-0.2179	(-4.59)	-0.1619	(-2.43)	-0.1893	(-4.84)	-0.1232	(-1.89)
L3_TBill	-0.2780	(-5.09)	-0.3269	(-4.72)	-0.2838	(-3.15)	-0.2780	(-5.09)	-0.3383	(-2.87)
L4_TBill	-0.1885	(-2.46)	-0.3446	(-3.61)	-0.0594	(-0.48)	-0.1885	(-2.46)	-0.2149	(-1.34)
L5_TBill	-0.3507	(-3.29)	-0.5809	(-4.09)	-0.2415	(-1.55)	-0.3507	(-3.29)	-0.8001	(-3.01)
L6_TBill	-0.0750	(-0.52)	-0.3954	(-2.01)	0.1969	(1.00)	-0.0750	(-0.52)	-0.2464	(-0.57)
L7_TBill	-0.1781	(-0.81)	-0.4730	(-1.53)	0.0317	(0.10)	-0.1781	(-0.81)	-0.7471	(-1.27)
L8_TBill	-0.2090	(-0.85)	-0.2427	(-0.82)	-0.0783	(-0.19)	-0.2090	(-0.85)	-0.1365	(-0.20)
Count_1	0.3161	(2.66)	0.4148	(2.86)	0.2545	(1.18)	0.3161	(2.66)	0.3740	(1.32)
Count_2	0.3618	(4.49)	0.4510	(4.55)	0.3038	(2.20)	0.3618	(4.49)	0.5108	(3.13)
Count_3	0.2644	(4.09)	0.2613	(3.26)	0.3250	(2.84)	0.2644	(4.09)	0.1949	(1.74)
Count_4	0.2244	(4.00)	0.2110	(3.22)	0.2862	(2.82)	0.2244	(4.00)	0.2003	(2.34)
Count_5	0.1565	(3.36)	0.1679	(3.12)	0.1811	(2.02)	0.1565	(3.36)	0.2082	(3.11)
Count_6	0.0712	(1.78)	0.1103	(2.48)	-0.0055	(-0.06)	0.0712	(1.78)	0.1915	(3.49)
Middle Rank Lag 1	1.2310	(11.97)	1.4155	(11.30)	0.8322	(4.45)	1.2310	(11.97)	1.5151	(9.26)
Top 30%	-1.6005	(-6.43)	-1.5128	(-4.89)	-1.5870	(-3.82)	-1.6005	(-6.43)	-1.1143	(-2.56)
Bottom 30%	-1.3992	(-5.55)	-1.6223	(-5.39)	-1.4017	(-3.21)	-1.3992	(-5.55)	-1.3061	(-3.08)
Middle Rank Lag 2	0.1385	(1.36)	0.0313	(0.25)	0.2060	(1.12)	0.1385	(1.36)	0.1108	(0.65)
Top 30%	-0.0234	(-0.10)	0.0996	(0.36)	-0.2589	(-0.67)	-0.0234	(-0.10)	0.1230	(0.33)
Bottom 30%	-0.2540	(-1.07)	-0.0495	(-0.17)	-0.6375	(-1.47)	-0.2540	(-1.07)	0.1562	(0.39)
Rank 24m alpha	0.1118	(2.25)	0.0951	(1.59)	0.1499	(1.63)	0.1118	(2.25)	-0.0059	(-0.08)
Rank 24m Sharpe Ratio	0.7140	(8.10)	0.7126	(6.72)	0.7940	(4.71)	0.7140	(8.10)	0.6294	(4.50)
Underwater dummy	-0.0005	(-0.01)	-0.0036	(-0.07)	-0.0896	(-1.37)	-0.0005	(-0.01)	0.0905	(1.03)
Down/upside pot. ratio	0.0849	(4.14)	0.0835	(3.62)	0.0932	(2.22)	0.0849	(4.14)	0.1143	(3.11)
St.deviation of returns	-0.9567	(-1.88)	-1.3561	(-2.24)	0.0542	(0.07)	-0.9567	(-1.88)	-1.9576	(-2.12)
Share restrictions	0.1281	(3.37)	0.1025	(2.20)	0.1682	(2.79)	0.1281	(3.37)	0.0917	(1.61)
Lockup periods	-0.0018	(-0.99)	-0.0010	(-0.47)	-0.0042	(-1.64)	-0.0018	(-0.99)	0.0014	(0.49)
High-water mark	0.0447	(1.41)	0.0519	(1.42)	0.0068	(0.12)	0.0447	(1.41)	0.0414	(0.82)
Return smoothing	-0.0670	(-1.27)	-0.1016	(-1.63)	-0.0366	(-0.42)	-0.0670	(-1.27)	-0.2791	(-3.21)
Ln(AUM)	-0.0308	(-3.86)	-0.0230	(-2.32)	-0.0429	(-3.40)	-0.0308	(-3.86)	-0.0036	(-0.28)
Ln(Age)	-0.0636	(-2.24)	-0.0978	(-2.68)	-0.0254	(-0.55)	-0.0636	(-2.24)	-0.0915	(-1.97)
Offshore	-0.0055	(-0.19)	-0.0262	(-0.74)	0.0197	(0.42)	-0.0055	(-0.19)	-0.0659	(-1.49)
Incentive fee	0.0001	(0.05)	0.0003	(0.08)	0.0003	(0.06)	0.0001	(0.05)	0.0056	(1.29)
Management fee	0.0138	(0.61)	0.0319	(1.10)	-0.0191	(-0.45)	0.0138	(0.61)	0.0370	(1.12)
Personal capital	-0.0143	(-0.52)	-0.0154	(-0.46)	0.0043	(0.10)	-0.0143	(-0.52)	-0.0013	(-0.03)
Leveraged	0.0059	(0.19)	0.0087	(0.23)	0.0040	(0.09)	0.0059	(0.19)	-0.0161	(-0.35)
Flows lag 1	0.3953	(6.80)	0.3825	(5.34)	0.3819	(4.01)	0.3953	(6.80)	0.3393	(3.64)
Flows lag 2	0.2406	(5.94)	0.2443	(4.90)	0.2136	(3.15)	0.2406	(5.94)	0.2017	(3.42)
Flows lag 3	0.1750	(4.61)	0.2132	(4.11)	0.0740	(1.44)	0.1750	(4.61)	0.2584	(3.49)
Flows lag 4	0.1329	(4.09)	0.1249	(3.18)	0.1342	(2.50)	0.1329	(4.09)	0.1217	(2.48)
Flows lags 5 to 8	Yes		Yes		Yes		Yes		Yes	
Style and Time dummies	Yes		Yes		Yes		Yes		Yes	
N	20420		14103		6317		20420		7798	
McFadden pseudo R^2	0.103		0.112		0.088		0.103		0.120	

Table 8. Partition of Explained Variance: Relative Importance of Predictors

The Table presents estimates of relative weights (Johnson, 2000), from the model estimated in Table 6, column D, expressed as percentages of the McKelvey and Zavoina pseudo R^2. Standard errors and confidence intervals are estimated using a bootstrap approach (Johnson, 2004).

	Relative weights (% of pseudo R^2)	Standard error	99% Confidence Interval	
Combined effect of all streaks dummies	17.178	1.282	13.875	20.482
Combined effect of winning streaks	*9.017*	*0.867*	*6.784*	*11.251*
W2_TBill	1.201	0.342	0.319	2.083
W3_TBill	1.584	0.400	0.554	2.614
W4_TBill	1.610	0.391	0.602	2.618
W5_TBill	1.315	0.354	0.403	2.228
W6_TBill	1.553	0.416	0.482	2.623
W7_TBill	0.551	0.228	0.147	1.253
W8_TBill	1.203	0.281	0.478	1.929
Combined effect of losing streaks	*8.161*	*1.015*	*5.547*	*10.775*
L1_TBill	1.076	0.315	0.266	1.887
L2_TBill	2.549	0.523	1.202	3.896
L3_TBill	2.197	0.512	0.879	3.516
L4_TBill	0.748	0.294	0.237	1.692
L5_TBill	1.068	0.407	0.019	2.117
L6_TBill	0.136	0.137	0.039	0.729
L7_TBill	0.105	0.125	0.020	0.649
L8_TBill	0.281	0.623	0.028	1.918
Combined effect of Count dummies	2.291	0.337	1.423	3.159
Count_1	0.156	0.089	0.094	0.567
Count_2	0.343	0.065	0.176	0.510
Count_3	0.793	0.194	0.293	1.294
Count_4	0.484	0.138	0.129	0.839
Count_5	0.091	0.044	0.073	0.338
Count_6	0.424	0.155	0.024	0.824
Combined effect of lagged annual ranks	23.882	1.334	20.447	27.318
Combined effect of three-piece-wise linear specification – Rank lag 1	*21.083*	*1.282*	*17.779*	*24.386*
Middle ranks	12.234	0.785	10.212	14.256
Top 30%	3.977	0.336	3.111	4.842
Bottom 30%	4.871	0.389	3.870	5.873
Combined effect of three-piece-wise linear specification – Rank lag 2	*2.800*	*0.346*	*1.907*	*3.692*
Middle ranks	1.429	0.188	0.945	1.913
Top 30%	0.658	0.154	0.263	1.054
Bottom 30%	0.713	0.078	0.511	0.915
Combined effect other performance metrics	16.634	1.021	14.005	19.263
Rank 24m alpha	4.665	0.540	3.274	6.055
Rank 24m Sharpe Ratio	8.908	0.650	7.233	10.583
Underwater dummy	3.061	0.405	2.018	4.104

Continuation

	Relative weights (% of pseudo R^2)	Standard error	99% Confidence Interval	
Combined effect of lagged flows	18.661	2.096	13.261	24.060
Flows lag 1	9.632	1.783	5.040	14.225
Flows lag 2	4.255	0.922	1.880	6.629
Flows lag 3	2.368	0.617	0.780	3.956
Flows lag 4	1.414	0.445	0.267	2.560
Flows lag 5	0.204	0.151	0.041	0.885
Flows lag 6	0.351	0.201	0.036	1.002
Flows lag 7	0.186	0.149	0.021	0.762
Flows lag 8	0.251	0.192	0.022	1.129
Combined effect of fund characteristics	3.752	0.561	2.307	5.196
Share restrictions	0.793	0.298	0.026	1.561
Lockup periods	0.040	0.047	0.027	0.280
High-water mark	0.183	0.132	0.030	0.678
Return smoothing	0.125	0.105	0.031	0.560
Ln(AUM)	0.433	0.145	0.059	0.807
Ln(Age)	1.082	0.332	0.228	1.937
Offshore	0.052	0.062	0.020	0.355
Incentive fee	0.033	0.065	0.010	0.345
Management fee	0.095	0.106	0.015	0.582
Personal capital	0.016	0.046	0.011	0.278
Leveraged	0.046	0.089	0.006	0.459
Downside-upside potential ratio	0.535	0.055	0.395	0.676
Standard deviation of returns	0.318	0.099	0.064	0.572
Combined effect of style dummies	2.332	0.523	0.985	3.678
Dedicated Short Bias	0.793	0.315	0.173	1.812
Emerging Mrkets	0.605	0.241	0.131	1.397
Equity Market Neutral	0.040	0.057	0.021	0.333
Event Driven	0.083	0.061	0.049	0.361
Fixed Income Arbitrage	0.138	0.104	0.042	0.599
Global Markets	0.379	0.215	0.042	1.133
Long Short Equity	0.090	0.047	0.062	0.338
Managed Futures	0.204	0.126	0.054	0.646
Combined effect of time dummies	15.128	1.357	11.632	18.624
Total sum of relative weights	100.000			
McKelvey and Zavoina pseudo-R^2	0.207409			

Table 9

Forecast Models Predicting Four-Quarter-Ahead Performance Ranks

The table reports estimates of a model explaining relative performance as measured by a fractional rank, which 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 four criteria: raw returns (Model 1), style-adjusted return (Model 2), alphas (Model 3), and Sharpe ratios (Model 4). The sample includes 1856 open-end hedge funds for the period 1995 Q1 till 2010 Q3. The independent variables are defined in Table E2 in the appendix. We estimate our model by pooling all fund-period observations. T-statistics based on clustered robust standard errors are provided in parentheses.

	Model1		Model2		Model3		Model4	
Intercept	0.2907	(5.76)	0.4204	(8.44)	0.3865	(8.53)	0.2780	(5.46)
W2_TBill	0.0085	(1.27)	0.0082	(1.24)	0.0144	(2.01)	0.0184	(2.87)
W3_TBill	0.0401	(4.52)	0.0240	(2.71)	0.0266	(2.89)	0.0394	(4.37)
W4_TBill	0.0213	(1.92)	0.0025	(0.23)	0.0038	(0.34)	0.0329	(2.90)
W5_TBill	0.0201	(1.51)	-0.0017	(-0.13)	0.0037	(0.28)	0.0381	(2.77)
W6_TBill	0.0185	(1.25)	-0.0118	(-0.82)	-0.0003	(-0.02)	0.0259	(1.65)
W7_TBill	0.0160	(0.87)	-0.0116	(-0.65)	-0.0214	(-1.22)	0.0295	(1.48)
W8_TBill	0.0254	(1.93)	0.0101	(0.76)	0.0156	(1.27)	0.1341	(7.92)
L1_TBill	-0.0202	(-3.69)	-0.0128	(-2.35)	-0.0024	(-0.39)	-0.0282	(-5.36)
L2_TBill	-0.0322	(-3.80)	-0.0179	(-2.11)	-0.0134	(-1.51)	-0.0433	(-5.32)
L3_TBill	-0.0361	(-2.85)	-0.0113	(-0.89)	-0.0165	(-1.30)	-0.0526	(-4.52)
L4_TBill	-0.0512	(-2.94)	-0.0350	(-1.97)	-0.0182	(-1.01)	-0.0497	(-3.20)
L5_TBill	0.0012	(0.05)	0.0024	(0.10)	-0.0091	(-0.39)	-0.0153	(-0.70)
L6_TBill	-0.0499	(-1.58)	-0.0462	(-1.44)	-0.0464	(-1.46)	-0.0414	(-1.42)
L7_TBill	-0.0229	(-0.48)	0.0224	(0.50)	0.0433	(0.90)	-0.0047	(-0.10)
L8_TBill	0.0593	(0.84)	0.0648	(0.83)	0.0100	(0.12)	0.0092	(0.13)
Count_1	0.0763	(2.23)	0.0202	(0.62)	-0.0453	(-1.41)	0.0394	(1.26)
Count_2	0.0641	(3.05)	0.0230	(1.08)	-0.0215	(-1.10)	0.0390	(1.93)
Count_3	0.0333	(2.05)	0.0033	(0.20)	0.0240	(1.58)	0.0219	(1.35)
Count_4	0.0296	(2.20)	0.0066	(0.49)	0.0211	(1.66)	0.0209	(1.52)
Count_5	0.0284	(2.51)	0.0122	(1.08)	0.0158	(1.47)	0.0216	(1.81)
Count_6	-0.0112	(-1.19)	-0.0140	(-1.50)	-0.0083	(-0.93)	-0.0087	(-0.84)
Middle Rank Lag 1	0.0908	(3.58)	0.0601	(2.37)	0.0291	(1.23)	0.0504	(1.89)
Top 30%	0.0525	(0.82)	0.0927	(1.46)	0.1139	(1.89)	-0.0647	(-1.08)
Bottom 30%	-0.1859	(-2.91)	-0.1958	(-3.07)	-0.0842	(-1.40)	-0.1252	(-2.03)
Middle Rank Lag 2	0.0040	(0.16)	0.0022	(0.09)	0.0176	(0.72)	-0.0448	(-1.68)
Top 30%	0.0587	(0.94)	0.0965	(1.54)	-0.0618	(-1.03)	0.0059	(0.10)
Bottom 30%	-0.0028	(-0.04)	-0.1615	(-2.58)	-0.0661	(-1.09)	0.0591	(0.95)
Rank 24m alpha	-0.0139	(-0.93)	-0.0086	(-0.58)	-0.0074	(-0.53)	-0.0058	(-0.45)
Rank 24m Sharpe Ratio	0.0593	(2.63)	0.0853	(3.80)	0.0762	(3.66)	0.1321	(5.70)
Underwater dummy	0.0342	(3.40)	0.0451	(4.52)	0.0237	(2.51)	0.0404	(4.26)
Downside-ups. pot. ratio	0.0191	(3.46)	0.0059	(1.04)	0.0070	(1.54)	0.0154	(2.39)
St.deviation of returns	1.0293	(3.02)	1.1571	(3.31)	0.1740	(0.49)	-1.0352	(-3.28)
Squared St. Dev.	-3.6439	(-1.89)	-3.8674	(-1.91)	0.5552	(0.26)	3.8227	(2.35)
Share restrictions	0.0183	(2.19)	0.0102	(1.22)	0.0101	(1.34)	0.0303	(3.46)
Lockup periods	0.0013	(3.22)	0.0015	(3.61)	0.0011	(3.22)	0.0018	(4.26)
High-water mark	0.0318	(4.83)	0.0184	(2.79)	0.0042	(0.71)	0.0206	(3.17)
Return smoothing	0.0443	(3.42)	0.0303	(2.29)	0.0019	(0.16)	0.0721	(5.27)
Ln(AUM)	-0.0005	(-0.24)	-0.0002	(-0.08)	0.0014	(0.74)	0.0029	(1.45)
Ln(Age)	0.0063	(0.96)	0.0031	(0.48)	0.0049	(0.83)	0.0122	(1.89)
Offshore	0.0013	(0.18)	-0.0016	(-0.22)	-0.0052	(-0.81)	0.0027	(0.38)
Incentive fee	-0.0019	(-2.73)	-0.0014	(-2.07)	0.0000	(0.06)	-0.0011	(-1.70)
Management fee	0.0161	(2.73)	0.0166	(2.85)	0.0044	(0.80)	0.0032	(0.61)
Personal capital	0.0212	(3.35)	0.0193	(3.06)	0.0093	(1.64)	0.0194	(3.02)
Leveraged	0.0042	(0.60)	0.0073	(1.03)	-0.0042	(-0.66)	0.0090	(1.26)
Eight lags quarterly flows	YES		YES		YES		YES	
N	16498		16498		16498		16498	
Adj. R^2	0.056		0.043		0.018		0.090	

Table 10

Comparison of Forecast Models, One-Year Horizon

The Table compares four forecasts models explaining four-quarter-ahead cross-sectional ranks based on raw returns (Model 1), style-adjusted returns (Model 2), alphas (Model 3) and Sharpe ratios (Model 4). Panel A provides a comparison of the goodness-of-fit of all four models, in terms of R^2, adjusted R^2, AIC, BIC, and loglikelihood ratio. Panel B reports F-tests for the inclusion of streak dummies in all forecast models. Panel C provides a comparison of the accuracy of the forecasts using four measures. If we denote the ex post realizations by y_h and the series of predictions by $\widehat{y_h}$, h=1,2,…,H, where H is the number of forecasting periods, then the overall RMSE (root mean squared error), MAD (mean absolute deviation) and the out-of-sample R^2 are defined as follows: $Overall\ RMSE = \sqrt{\frac{1}{H}\sum_{h=1}^{H}(\widehat{y_h} - y_h)^2}$, $Overall\ MAD = \frac{1}{H}\sum_{h=1}^{H}|(\widehat{y_h} - y_h)|$, $R_{OS}^2 = corr^2(\widehat{y_h}, y_h)$. Finally, we report a hit rate defined as the proportion of times a model correctly predicts whether Expected rank≥0.5 or Expected rank<0.5.

	Model 1 Raw returns Ranks	Model 2 St.adj. Returns Ranks	Model 3 Alpha Ranks	Model 4 Sharpe ratio Ranks
Panel A: Comparison of goodness-of-fit				
N	16498	16498	16498	16498
R^2	0.0592	0.0470	0.0214	0.0936
Adj R2	0.0557	0.0435	0.0179	0.0903
AIC	4957.87	4801.34	5151.35	4634.02
BIC	5428.24	5271.71	5621.72	5104.39
Loglikelihood ratio	-2417.93	-2339.67	-2514.68	-2256.01
Panel B: F-tests for inclusion of winning and losing streaks				
F-test Winning streaks	4.914	2.236	2.542	8.129
p-value	(0.000)	(0.029)	(0.013)	(0.000)
F-test Losing streaks	5.831	2.798	0.864	8.353
p-value	(0.000)	(0.004)	(0.547)	(0.000)
F-test All streaks	6.116	2.650	1.834	9.537
p-value	(0.000)	(0.001)	(0.026)	(0.000)
Panel C: Comparison of forecast performance				
Overall RMSE	0.2901	0.2869	0.2889	0.2856
Overall MAD	0.2451	0.2428	0.2450	0.2411
R_{OS}^2	0.0295	0.0218	0.0067	0.0690
Hit rate	0.5695	0.5655	0.5371	0.5878

Table 11

Flows and Performance Forecasts

The table reports estimates of a probit model explaining positive and negative flows, similar to Table 6, but controlling for Predicted Ranks obtained from four different forecast models (Panels A to D) as reported in Table 9. We estimate each model by pooling all fund-period observations. Clustered-robust z-statistics are provided in parentheses.

	PANEL A: Expected Perf. from Raw-returns model						PANEL B: Expected Perf. from St.adj. returns model					
	(1)		(2)		(3)		(1)		(2)		(3)	
Intercept	-0.7175	(-9.70)	0.2555	(1.01)	-0.3533	(-1.33)	-0.6121	(-7.30)	0.2600	(0.99)	-0.3948	(-1.39)
Expected Perf.	1.4040	(9.36)	0.9777	(5.61)	-0.2382	(-1.27)	1.1345	(6.30)	0.8763	(4.38)	-0.0829	(-0.37)
RMSE	-0.2220	(-1.70)	0.0646	(0.51)	-0.0365	(-0.28)	-0.1595	(-1.14)	0.0685	(0.53)	0.0070	(0.05)
W2_TBill			0.2232	(6.26)	0.1820	(4.96)			0.2184	(6.10)	0.1816	(4.93)
W3_TBill			0.1969	(4.49)	0.1763	(3.93)			0.2197	(5.06)	0.1656	(3.70)
W4_TBill			0.3409	(6.63)	0.2853	(5.25)			0.3665	(7.11)	0.2744	(5.06)
W5_TBill			0.4168	(6.28)	0.3862	(5.65)			0.4575	(6.94)	0.3751	(5.53)
W6_TBill			0.4536	(5.79)	0.3956	(4.95)			0.4887	(6.22)	0.3904	(4.85)
W7_TBill			0.3304	(3.61)	0.2859	(3.05)			0.3849	(4.21)	0.2771	(2.94)
W8_TBill			0.2775	(3.82)	0.1448	(2.04)			0.3090	(4.25)	0.1388	(1.94)
L1_TBill			-0.0591	(-1.83)	-0.0668	(-2.02)			-0.0641	(-2.01)	-0.0646	(-1.97)
L2_TBill			-0.2303	(-5.27)	-0.1955	(-4.38)			-0.2568	(-5.95)	-0.1878	(-4.24)
L3_TBill			-0.3897	(-6.42)	-0.3105	(-4.95)			-0.4396	(-7.30)	-0.2987	(-4.81)
L4_TBill			-0.2882	(-3.54)	-0.2070	(-2.44)			-0.3142	(-3.88)	-0.1934	(-2.29)
L5_TBill			-0.4484	(-3.88)	-0.3854	(-3.23)			-0.4584	(-3.99)	-0.3728	(-3.14)
L6_TBill			-0.1104	(-0.73)	-0.0952	(-0.61)			-0.1012	(-0.67)	-0.0817	(-0.52)
L7_TBill			-0.4344	(-1.68)	-0.3772	(-1.43)			-0.4558	(-1.77)	-0.3731	(-1.41)
L8_TBill			-1.1141	(-3.80)	-0.1705	(-0.56)			-1.1628	(-3.93)	-0.1926	(-0.63)
Count_1			-0.3017	(-2.33)	0.3712	(2.61)			-0.2918	(-2.24)	0.3627	(2.51)
Count_2			-0.3278	(-4.31)	0.4108	(4.41)			-0.3139	(-4.11)	0.3924	(4.27)
Count_3			-0.3070	(-5.44)	0.3060	(4.22)			-0.2991	(-5.23)	0.2946	(4.05)
Count_4			-0.2084	(-4.21)	0.2543	(4.05)			-0.1991	(-3.95)	0.2463	(3.92)
Count_5			-0.1166	(-2.62)	0.1978	(3.80)			-0.1036	(-2.30)	0.1920	(3.68)
Count_6			-0.0371	(-0.87)	0.0875	(1.97)			-0.0366	(-0.86)	0.0878	(1.97)
Middle Rank Lag 1					1.3602	(11.40)					1.3301	(11.26)
Top 30%					-1.6908	(-6.06)					-1.7171	(-6.17)
Bottom 30%					-1.3406	(-4.64)					-1.2808	(-4.31)
Middle Rank Lag 2					0.1750	(1.56)					0.1556	(1.38)
Top 30%					0.1107	(0.44)					0.1342	(0.53)
Bottom 30%					-0.3206	(-1.19)					-0.3199	(-1.17)
Rank 24m alpha					0.0574	(1.02)					0.0726	(1.30)
Rank 24m Sharpe Ratio					0.7475	(7.45)					0.7304	(7.26)
Underwater dummy					0.0240	(0.53)					0.0217	(0.48)
Downside-ups. pot. ratio					0.1122	(5.07)					0.1078	(4.95)
St.deviation of returns					-1.1827	(-1.98)					-1.2428	(-2.09)
Share restrictions			0.0997	(2.33)	0.1560	(3.80)			0.1139	(2.67)	0.1492	(3.65)
Lockup periods			-0.0034	(-1.69)	-0.0014	(-0.68)			-0.0036	(-1.75)	-0.0018	(-0.81)
High-water mark			0.0150	(0.42)	0.0733	(2.06)			0.0409	(1.16)	0.0651	(1.86)
Return smoothing			-0.0396	(-0.67)	-0.0464	(-0.80)			-0.0388	(-0.66)	-0.0515	(-0.89)
Ln(AUM)			-0.0179	(-1.96)	-0.0294	(-3.23)			-0.0194	(-2.11)	-0.0289	(-3.17)
Ln(Age)			-0.1024	(-3.05)	-0.0622	(-1.90)			-0.0995	(-2.96)	-0.0637	(-1.95)
Offshore			-0.0123	(-0.37)	-0.0080	(-0.25)			-0.0047	(-0.14)	-0.0096	(-0.29)
Incentive fee			-0.0026	(-0.84)	-0.0004	(-0.13)			-0.0030	(-0.98)	-0.0004	(-0.12)
Management fee			0.0027	(0.11)	0.0151	(0.58)			0.0084	(0.33)	0.0124	(0.48)
Personal capital			-0.0334	(-1.08)	-0.0215	(-0.70)			-0.0225	(-0.73)	-0.0253	(-0.83)
Leveraged			0.0043	(0.12)	-0.0040	(-0.12)			-0.0020	(-0.06)	-0.0035	(-0.11)
Style and time dummies	NO		YES		YES		NO		YES		YES	
Eight lags quarterly flows	NO		YES		YES		NO		YES		YES	
N	16238		16238		16238		16238		16238		16238	
Pseudo R^2	0.009		0.087		0.112		0.004		0.086		0.112	

Table 11 (Continuation)
Flows and Performance Forecasts

	PANEL C: Expected Perf. from alpha ranks model						PANEL D: Expected Perf. from Sharpe Ratio rank model					
	(1)		(2)		(3)		(1)		(2)		(3)	
Intercept	-1.1451	(-11.03)	-0.1833	(-0.67)	-0.4629	(-1.64)	-0.6889	(-9.61)	0.4194	(1.66)	-0.2885	(-1.08)
Expected Perf.	2.3670	(11.58)	1.8241	(7.65)	0.2155	(0.82)	1.2962	(10.00)	0.6316	(3.33)	-0.5344	(-2.65)
RMSE	-0.4157	(-3.24)	-0.1356	(-1.02)	-0.1455	(-1.02)	-0.1743	(-1.24)	-0.0228	(-0.18)	-0.0379	(-0.29)
W2_TBill			0.1926	(5.35)	0.1770	(4.79)			0.2228	(6.25)	0.1884	(5.12)
W3_TBill			0.1885	(4.35)	0.1549	(3.46)			0.2298	(5.26)	0.1899	(4.25)
W4_TBill			0.3426	(6.73)	0.2665	(4.95)			0.3762	(7.33)	0.3022	(5.57)
W5_TBill			0.4191	(6.35)	0.3702	(5.44)			0.4356	(6.50)	0.4112	(5.99)
W6_TBill			0.4585	(5.86)	0.3924	(4.91)			0.4585	(5.84)	0.4108	(5.14)
W7_TBill			0.3927	(4.24)	0.2848	(3.04)			0.3398	(3.68)	0.3066	(3.27)
W8_TBill			0.2411	(3.24)	0.1362	(1.90)			0.2144	(2.74)	0.2033	(2.70)
L1_TBill			-0.0711	(-2.22)	-0.0639	(-1.95)			-0.0595	(-1.83)	-0.0742	(-2.22)
L2_TBill			-0.2389	(-5.52)	-0.1851	(-4.18)			-0.2393	(-5.43)	-0.2106	(-4.67)
L3_TBill			-0.3971	(-6.59)	-0.2972	(-4.81)			-0.4036	(-6.60)	-0.3230	(-5.13)
L4_TBill			-0.2177	(-2.66)	-0.1819	(-2.15)			-0.3006	(-3.70)	-0.2192	(-2.59)
L5_TBill			-0.3497	(-3.01)	-0.3549	(-2.96)			-0.4630	(-4.02)	-0.4039	(-3.37)
L6_TBill			-0.1954	(-1.30)	-0.0785	(-0.50)			-0.1445	(-0.97)	-0.1152	(-0.74)
L7_TBill			-0.5243	(-2.01)	-0.3861	(-1.46)			-0.4454	(-1.73)	-0.3743	(-1.42)
L8_TBill			-1.1727	(-3.74)	-0.2224	(-0.73)			-1.0261	(-3.50)	-0.1600	(-0.53)
Count_1			-0.1239	(-0.95)	0.3857	(2.69)			-0.2835	(-2.17)	0.3467	(2.43)
Count_2			-0.2377	(-3.12)	0.3909	(4.26)			-0.2860	(-3.74)	0.4063	(4.42)
Count_3			-0.3038	(-5.35)	0.2873	(3.96)			-0.2853	(-5.00)	0.3017	(4.18)
Count_4			-0.2241	(-4.53)	0.2400	(3.80)			-0.1924	(-3.83)	0.2494	(3.99)
Count_5			-0.1242	(-2.79)	0.1877	(3.59)			-0.1046	(-2.32)	0.1959	(3.78)
Count_6			-0.0195	(-0.46)	0.0913	(2.05)			-0.0423	(-0.99)	0.0862	(1.95)
Middle Rank Lag 1					1.3257	(11.32)					1.3667	(11.72)
Top 30%					-1.7395	(-6.28)					-1.7854	(-6.39)
Bottom 30%					-1.2598	(-4.43)					-1.3812	(-4.83)
Middle Rank Lag 2					0.1437	(1.28)					0.1520	(1.35)
Top 30%					0.2050	(0.80)					0.0457	(0.18)
Bottom 30%					-0.2694	(-1.00)					-0.2941	(-1.09)
Rank 24m alpha					0.0813	(1.46)					0.0526	(0.95)
Rank 24m Sharpe Ratio					0.6838	(6.61)					0.8305	(7.90)
Underwater dummy					0.0210	(0.47)					0.0363	(0.80)
Downside-ups. pot. ratio					0.1048	(4.80)					0.1175	(5.32)
St.deviation of returns					-1.1532	(-1.89)					-1.4850	(-2.50)
Share restrictions			0.0988	(2.31)	0.1419	(3.47)			0.1046	(2.41)	0.1757	(4.17)
Lockup periods			-0.0046	(-2.22)	-0.0024	(-1.15)			-0.0026	(-1.32)	-0.0004	(-0.17)
High-water mark			0.0445	(1.26)	0.0639	(1.83)			0.0302	(0.85)	0.0813	(2.30)
Return smoothing			-0.0310	(-0.52)	-0.0550	(-0.95)			-0.0572	(-0.96)	-0.0213	(-0.37)
Ln(AUM)			-0.0230	(-2.47)	-0.0295	(-3.23)			-0.0236	(-2.61)	-0.0276	(-3.04)
Ln(Age)			-0.0865	(-2.54)	-0.0657	(-2.00)			-0.0955	(-2.82)	-0.0603	(-1.84)
Offshore			-0.0032	(-0.10)	-0.0099	(-0.30)			-0.0129	(-0.39)	-0.0052	(-0.16)
Incentive fee			-0.0031	(-1.02)	-0.0005	(-0.16)			-0.0030	(-0.96)	0.0001	(0.04)
Management fee			0.0235	(0.92)	0.0133	(0.52)			0.0160	(0.63)	0.0143	(0.55)
Personal capital			-0.0258	(-0.83)	-0.0279	(-0.91)			-0.0234	(-0.76)	-0.0160	(-0.52)
Leveraged			-0.0141	(-0.41)	-0.0048	(-0.14)			0.0064	(0.19)	-0.0030	(-0.09)
Style and time dummies	NO		YES		YES		NO		YES		YES	
Eight lags quarterly flows	NO		YES		YES		NO		YES		YES	
N	16238		16238		16238		16238		16238		16238	
Pseudo R^2	0.014		0.089		0.112		0.012		0.086		0.112	

Table 12. Panels A and B

Partition of Explained Variance: Relative Importance of Predictors of Forecast Models

	PANEL A: Dependent var. Raw Returns Ranks				PANEL B: Dependent var.: **Style-adj. Ret. Rnks**			
	Relative weights % of R^2	Standard error	99% Confidence Interval		Relative weights % of R^2	Standard error	99% Confidence Interval	
Combined effect of all streaks dummies	9.994	1.767	5.442	14.545	6.936	1.597	2.821	11.050
Combined effect of winning streaks	*4.620*	*1.160*	*1.633*	*7.607*	*3.399*	*1.021*	*0.769*	*6.028*
W2_TBill	0.394	0.331	0.068	1.667	0.396	0.397	0.041	2.008
W3_TBill	2.823	0.945	0.388	5.258	1.535	0.768	0.154	4.451
W4_TBill	0.549	0.387	0.114	2.008	0.186	0.212	0.091	1.260
W5_TBill	0.255	0.254	0.067	1.329	0.082	0.130	0.061	0.820
W6_TBill	0.148	0.185	0.048	1.033	0.123	0.202	0.048	1.148
W7_TBill	0.086	0.163	0.036	0.874	0.065	0.147	0.041	0.841
W8_TBill	0.366	0.192	0.168	1.185	1.013	0.455	0.274	2.587
Combined effect of losing streaks	*5.373*	*1.298*	*2.030*	*8.717*	*3.537*	*1.272*	*0.259*	*6.814*
L1_TBill	2.111	0.836	0.449	4.619	1.225	0.700	0.095	3.342
L2_TBill	1.657	0.711	0.243	3.940	0.926	0.625	0.086	3.338
L3_TBill	0.659	0.462	0.098	2.287	0.178	0.273	0.074	1.403
L4_TBill	0.530	0.429	0.075	2.168	0.524	0.506	0.075	2.576
L5_TBill	0.233	0.335	0.043	1.863	0.097	0.233	0.046	1.308
L6_TBill	0.061	0.151	0.027	0.873	0.235	0.402	0.027	2.179
L7_TBill	0.056	0.155	0.014	0.833	0.106	0.244	0.014	1.422
L8_TBill	0.067	0.213	0.008	1.108	0.245	0.403	0.012	1.845
Combined effect of Count dummies	4.169	1.079	1.390	6.947	3.287	0.980	0.763	5.812
Count_1	0.433	0.388	0.055	1.885	0.189	0.242	0.076	1.276
Count_2	1.042	0.577	0.187	3.445	0.622	0.414	0.210	2.275
Count_3	0.298	0.174	0.202	1.310	0.363	0.189	0.253	1.400
Count_4	0.225	0.163	0.129	1.081	0.242	0.198	0.145	1.263
Count_5	0.577	0.361	0.106	1.884	0.282	0.259	0.109	1.478
Count_6	1.593	0.672	0.324	3.615	1.590	0.729	0.295	4.244
Combined effect of lagged annual ranks	17.870	2.121	12.406	23.335	24.430	2.556	17.846	31.015
Combined effect of three-piece-wise linear specification – Rank lag 1	*14.635*	*2.018*	*9.436*	*19.834*	*15.212*	*2.158*	*9.654*	*20.771*
Middle ranks	5.834	0.918	3.470	8.197	4.813	0.816	2.712	6.915
Top 30%	7.088	1.274	3.807	10.369	7.939	1.559	3.923	11.954
Bottom 30%	1.713	0.324	0.877	2.549	2.460	0.645	0.799	4.122
Combined effect of three-piece-wise linear specification – Rank lag 2	*3.235*	*0.926*	*0.849*	*5.622*	*9.218*	*1.739*	*4.738*	*13.698*
Middle ranks	0.751	0.256	0.093	1.409	1.731	0.331	0.878	2.583
Top 30%	1.833	0.662	0.128	3.537	3.528	1.091	0.717	6.340
Bottom 30%	0.652	0.319	0.300	1.866	3.959	1.088	1.156	6.763
Combined effect other performance metrics	20.265	2.144	14.741	25.789	24.728	2.581	18.080	31.376
Rank 24m alpha	0.731	0.280	0.010	1.452	1.295	0.469	0.086	2.504
Rank 24m Sharpe Ratio	1.772	0.394	0.757	2.787	3.279	0.641	1.627	4.930
Underwater dummy	3.386	0.896	1.077	5.694	4.972	1.245	1.764	8.180
Downside-upside potential ratio	3.299	0.936	0.887	5.710	1.765	0.740	0.519	4.103
Standard deviation of returns	6.854	1.078	4.077	9.630	8.085	1.254	4.854	11.316
Squared standard deviation of returns	4.224	0.824	2.101	6.348	5.333	1.059	2.606	8.061

Continuation of Panels A and B

	PANEL A: Dependent var. Raw Returns Ranks				PANEL B: Dependent var.: **Style-adj. Ret. Rnks**			
	Relative weights % of pseudo R^2	Standard error	99% Confidence Interval		Relative weights % of pseudo R^2	Standard error	99% Confidence Interval	
Combined effect of lagged flows	0.513	0.517	0.413	3.174	0.535	0.618	0.438	3.589
Flows lag 1	0.052	0.162	0.034	0.964	0.054	0.198	0.036	1.090
Flows lag 2	0.155	0.248	0.025	1.350	0.082	0.226	0.028	1.260
Flows lag 3	0.048	0.152	0.019	0.791	0.046	0.192	0.026	1.041
Flows lag 4	0.081	0.199	0.015	1.110	0.061	0.210	0.025	1.088
Flows lag 5	0.019	0.138	0.014	0.749	0.042	0.190	0.023	1.102
Flows lag 6	0.076	0.194	0.011	1.003	0.139	0.275	0.017	1.400
Flows lag 7	0.067	0.195	0.011	1.055	0.087	0.244	0.012	1.247
Flows lag 8	0.016	0.143	0.008	0.818	0.024	0.180	0.007	1.067
Combined effect of fund characteristics	18.107	2.155	12.557	23.658	16.915	2.470	10.551	23.278
Share restrictions	1.850	0.742	0.318	4.230	0.591	0.432	0.125	2.167
Lockup periods	3.479	0.977	0.963	5.995	3.097	1.053	0.385	5.810
High-water mark	4.122	1.144	1.176	7.068	1.816	0.842	0.345	4.473
Return smoothing	2.327	0.862	0.106	4.548	2.104	0.882	0.346	4.403
Ln(AUM)	0.307	0.157	0.227	1.182	0.382	0.186	0.283	1.349
Ln(Age)	0.292	0.301	0.044	1.544	0.260	0.321	0.049	1.590
Offshore	0.243	0.158	0.170	0.996	0.181	0.263	0.079	1.582
Incentive fee	1.020	0.549	0.120	2.885	0.518	0.445	0.058	2.161
Management fee	2.118	0.877	0.395	4.976	4.725	1.401	1.116	8.334
Personal capital	2.222	0.856	0.017	4.428	2.167	0.950	0.271	5.378
Leveraged	0.127	0.181	0.057	0.962	1.074	0.661	0.086	3.526
Combined effect of style dummies	29.082	2.811	21.839	36.324	23.164	2.564	16.559	29.769
Dedicated Short Bias	7.854	1.845	3.102	12.606	0.568	0.556	0.053	2.627
Emerging Mrkets	13.773	2.011	8.593	18.954	1.674	0.724	0.577	4.320
Equity Market Neutral	2.176	0.685	0.410	3.941	0.426	0.286	0.176	1.619
Event Driven	1.231	0.463	0.039	2.424	6.696	1.259	3.453	9.939
Fixed Income Arbitrage	1.402	0.563	0.354	3.220	5.793	1.285	2.483	9.103
Global Markets	0.853	0.520	0.132	2.710	1.839	0.856	0.332	4.336
Long Short Equity	0.924	0.146	0.547	1.300	3.702	0.961	1.226	6.178
Managed Futures	0.869	0.437	0.335	2.490	2.466	0.921	0.095	4.838
Total sum of relative weights	100.000				100.000			
R^2	0.059				0.047			

Table 12. Panels C and D

Partition of Explained Variance: Relative Importance of Predictors of Forecast Models

	Panel C: Dependent variable: **Alpha Ranks**				Panel D: Dependent variable: **Sharpe ratio Rnks**			
	Relative weights % of R^2	Standard error	99% Confidence Interval		Relative weights % of R^2	Standard error	99% Confidence Interval	
Combined effect of all streaks dummies	12.930	3.061	5.044	20.816	28.978	2.183	23.355	34.602
Combined effect of winning streaks	*7.550*	*2.239*	*1.784*	*13.317*	*20.490*	*1.834*	*15.766*	*25.214*
W2_TBill	1.421	1.072	0.058	4.869	0.482	0.273	0.154	1.418
W3_TBill	3.252	1.520	0.294	8.197	1.441	0.519	0.104	2.778
W4_TBill	0.226	0.370	0.103	2.476	0.658	0.329	0.118	1.878
W5_TBill	0.148	0.288	0.071	1.649	0.591	0.330	0.097	1.697
W6_TBill	0.087	0.250	0.064	1.431	0.225	0.194	0.077	0.983
W7_TBill	0.303	0.449	0.058	2.319	0.260	0.218	0.069	1.156
W8_TBill	2.113	0.858	0.463	5.041	16.833	1.747	12.331	21.334
Combined effect of losing streaks	*5.380*	*2.225*	*2.304*	*13.734*	*8.489*	*1.264*	*5.233*	*11.744*
L1_TBill	0.531	0.713	0.084	3.841	3.727	0.815	1.627	5.827
L2_TBill	1.435	1.177	0.114	5.984	2.561	0.727	0.689	4.434
L3_TBill	0.901	0.911	0.095	4.757	1.441	0.500	0.154	2.729
L4_TBill	0.596	0.766	0.068	3.943	0.627	0.332	0.096	1.718
L5_TBill	0.164	0.445	0.050	2.591	0.045	0.077	0.036	0.436
L6_TBill	1.577	1.201	0.059	6.852	0.050	0.096	0.023	0.516
L7_TBill	0.162	0.314	0.025	1.912	0.023	0.087	0.011	0.505
L8_TBill	0.013	0.446	0.010	2.525	0.012	0.081	0.008	0.486
Combined effect of Count dummies	9.163	2.514	2.688	15.638	3.071	0.648	1.401	4.741
Count_1	1.741	1.154	0.082	5.987	0.061	0.078	0.043	0.509
Count_2	3.692	1.644	0.522	8.942	0.202	0.073	0.014	0.389
Count_3	0.814	0.572	0.311	3.157	0.592	0.226	0.010	1.174
Count_4	0.787	0.602	0.268	3.381	0.840	0.294	0.084	1.597
Count_5	0.609	0.606	0.117	3.605	0.343	0.136	0.228	0.883
Count_6	1.519	1.005	0.150	5.253	1.034	0.406	0.326	2.310
Combined effect of lagged annual ranks	19.381	3.398	10.628	28.135	6.886	0.881	4.617	9.154
Combined effect of three-piece-wise linear specification – Rank lag 1	*17.072*	*3.352*	*8.439*	*25.706*	*4.296*	*0.701*	*2.490*	*6.101*
Middle ranks	6.336	1.329	2.912	9.761	2.238	0.410	1.182	3.293
Top 30%	9.022	2.353	2.962	15.083	0.729	0.151	0.340	1.118
Bottom 30%	1.714	0.442	0.576	2.852	1.329	0.265	0.648	2.011
Combined effect of three-piece-wise linear specification – Rank lag 2	*2.309*	*0.864*	*0.084*	*4.534*	*2.590*	*0.474*	*1.369*	*3.811*
Middle ranks	1.080	0.431	0.459	2.836	1.063	0.186	0.585	1.541
Top 30%	0.430	0.345	0.271	2.545	0.766	0.258	0.100	1.432
Bottom 30%	0.799	0.399	0.440	2.627	0.762	0.193	0.263	1.260
Combined effect other performance metrics	16.659	2.994	8.946	24.372	16.064	1.325	12.651	19.477
Rank 24m alpha	2.128	0.949	0.827	5.657	1.400	0.278	0.683	2.116
Rank 24m Sharpe Ratio	7.433	1.538	3.470	11.396	8.075	0.884	5.798	10.351
Underwater dummy	1.371	0.632	0.576	3.837	1.010	0.239	0.396	1.625
Downside-upside potential ratio	0.638	0.431	0.276	2.595	0.617	0.187	0.135	1.098
Standard deviation of returns	2.489	0.986	0.509	5.638	3.261	0.552	1.837	4.684
Squared standard deviation of returns	2.600	1.457	0.246	7.517	1.703	0.312	0.898	2.507

Continuation of Panels C and D

	Panel C: Dependent variable: **Alpha Ranks**				Panel D: Dependent variable: **Sharpe ratio Rnks**			
	Relative weights % of pseudo R^2	Standard error	99% Confidence Interval		Relative weights % of pseudo R^2	Standard error	99% Confidence Interval	
Combined effect of lagged flows	2.548	1.639	0.988	9.690	1.074	0.495	0.490	2.984
Flows lag 1	0.070	0.353	0.047	2.122	0.076	0.104	0.038	0.620
Flows lag 2	0.636	0.782	0.041	3.943	0.261	0.232	0.036	1.188
Flows lag 3	0.095	0.374	0.036	2.064	0.151	0.167	0.034	0.891
Flows lag 4	0.098	0.394	0.029	2.181	0.141	0.178	0.029	0.914
Flows lag 5	0.218	0.505	0.028	2.638	0.031	0.086	0.024	0.484
Flows lag 6	0.687	0.783	0.023	3.844	0.216	0.214	0.018	1.138
Flows lag 7	0.286	0.554	0.017	2.786	0.151	0.183	0.015	0.930
Flows lag 8	0.458	0.640	0.013	3.065	0.049	0.128	0.008	0.731
Combined effect of fund characteristics	14.614	3.052	6.751	22.477	21.015	1.957	15.974	26.056
Share restrictions	2.252	1.184	0.166	6.045	4.221	0.935	1.812	6.629
Lockup periods	5.371	1.869	0.558	10.185	3.402	0.834	1.253	5.551
High-water mark	0.629	0.712	0.071	3.638	2.205	0.663	0.497	3.912
Return smoothing	0.831	0.824	0.076	3.996	6.265	1.220	3.123	9.408
Ln(AUM)	0.855	0.725	0.218	3.615	2.785	0.719	0.932	4.639
Ln(Age)	0.708	0.761	0.056	4.118	0.282	0.214	0.058	1.134
Offshore	0.691	0.743	0.071	3.742	0.281	0.204	0.097	1.198
Incentive fee	0.097	0.350	0.027	1.940	0.180	0.188	0.050	1.056
Management fee	1.605	1.270	0.139	6.674	0.197	0.084	0.116	0.624
Personal capital	1.450	1.108	0.027	5.489	1.114	0.506	0.212	2.669
Leveraged	0.126	0.406	0.037	2.235	0.083	0.106	0.050	0.637
Combined effect of style dummies	24.455	3.580	15.232	33.677	22.908	1.916	17.972	27.843
Dedicated Short Bias	3.776	1.540	0.330	7.962	3.656	0.878	1.394	5.918
Emerging Mrkets	0.645	0.404	0.361	3.103	2.261	0.567	0.800	3.722
Equity Market Neutral	1.783	0.898	0.229	4.909	0.323	0.182	0.190	1.134
Event Driven	6.093	1.626	1.904	10.281	4.793	0.999	2.221	7.366
Fixed Income Arbitrage	0.469	0.413	0.163	2.426	4.312	1.037	1.641	6.983
Global Markets	1.927	1.250	0.178	6.910	0.341	0.202	0.147	1.260
Long Short Equity	7.172	1.905	2.265	12.079	5.214	0.883	2.941	7.488
Managed Futures	2.590	1.348	0.404	6.787	2.008	0.595	0.475	3.541
Total sum of relative weights	100.000				100.000			
R^2	0.022				0.094			

Table 13. Investment strategies based on four-quarter-ahead out-of-sample forecasts

The Table shows the ex-post performance evaluation of trading strategies based on four-quarter-ahead out-of-sample forecasts. We obtain forecasts from four models explaining cross-sectional ranks based on raw returns (Col. 2), style-adjusted returns (Col. 4), alphas (Col. 6) and Sharpe ratios (Col. 8). Each trading strategy prescribes to invest if Expected rank≥0.5, and divest otherwise. We report the performance (annualized) of investments (Panel A), divestments (Panel B) and their difference (Panel C) using four evaluation criteria, and compare to the performance of actual net inflows and net outflows (i.e. investors' performance) reported in Col. 1. Performance differences are reported in Columns 3, 5, 7 and 9. T-statistics (in parenthesis) are based on clustered robust standard errors.

Evaluation criteria		Raw return ranks model		Style-adj. ret. ranks model		Alpha ranks model		Sharpe ratio ranks model	
Four-quarter-ahead Performance	Investors Performance	Model Performance.	Difference (2) - (1)	Model Performance	Difference (4) - (1)	Model Performance	Difference (6) - (1)	Model Performance	Difference (8) - (1)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Panel A: Investments					
	N=7552 Obs.	N=6181		N=6025		N=6111		N=6433	
Raw Return	0.0912	0.1261	*0.0349*	0.1265	*0.0353*	0.1137	*0.0225*	0.0996	*0.0084*
			(4.34)		*(3.98)*		*(2.73)*		*(1.20)*
Style-adj. Return	0.0135	0.0295	*0.0160*	0.0408	*0.0273*	0.0240	*0.0105*	0.0109	*-0.0026*
			(2.14)		*(3.33)*		*(1.36)*		*(-0.40)*
Alpha	0.0300	0.0420	*0.0120*	0.0492	*0.0182*	0.0480	*0.0172*	0.0444	*0.0136*
			(1.55)		*(2.18)*		*(2.24)*		*(2.03)*
Sharpe Ratio	0.2861	0.2803	*-0.0058*	0.3195	*0.0334*	0.3221	*0.0360*	0.4342	*0.1481*
			(-0.16)		*(0.72)*		*(0.87)*		*(2.29)*
				Panel B: Divestments					
	N=8750 Obs	N=10121		N=10277		N=10191		N=9869	
Raw Return	0.0895	0.0684	*-0.0211*	0.0691	*-0.0204*	0.0762	*-0.0133*	0.0842	*-0.0053*
			(-3.63)		*(-3.59)*		*(-2.24)*		*(-0.81)*
Style-adj. Return	0.0097	0.0005	*-0.0092*	-0.0057	*-0.0154*	0.0040	*-0.0057*	0.0118	*0.0022*
			(-1.71)		*(-2.95)*		*(-1.05)*		*(0.36)*
Alpha	0.0324	0.0252	*-0.0076*	0.0216	*-0.0110*	0.0216	*-0.0107*	0.0240	*-0.0091*
			(-1.30)		*(-1.98)*		*(-1.87)*		*(-1.39)*
Sharpe Ratio	0.2229	0.2350	*0.0121*	0.2127	*-0.0102*	0.2103	*-0.0126*	0.1336	*-0.0894*
			(0.30)		*(-0.33)*		*(-0.37)*		*(-4.39)*
				Panel C: Investments minus Divestments					
Raw Return	0.0017	0.0577	*0.0560*	0.0574	*0.0557*	0.0375	*0.0358*	0.0154	*0.0137*
	(0.26)	(7.70)	*(5.61)*	(6.93)	*(5.26)*	(4.81)	*(3.51)*	(2.17)	*(1.41)*
Style-adj. Return	0.0038	0.0290	*0.0252*	0.0466	*0.0428*	0.0200	*0.0162*	-0.0009	*-0.0047*
	(0.64)	(4.15)	*(2.75)*	(6.07)	*(4.41)*	(2.75)	*(1.73)*	(-0.14)	*(-0.54)*
Alpha	-0.0024	0.0180	*0.0204*	0.0264	*0.0288*	0.0252	*0.0276*	0.0204	*0.0228*
	(-0.35)	(2.37)	*(1.99)*	(3.47)	*(2.81)*	(3.57)	*(2.81)*	(2.99)	*(2.36)*
Sharpe Ratio	0.0631	0.0453	*-0.0178*	0.1067	*0.0436*	0.1118	*0.0487*	0.3007	*0.2376*
	(1.63)	(1.19)	*(-0.33)*	(2.66)	*(0.78)*	(2.99)	*(0.90)*	(5.42)	*(3.51)*

Table 14. Investors' performance when they deviate from the model forecast

The Table shows the four-quarter-ahead performance evaluation of investments and divestments by investors when they deviate from a Models' prescription. Panel A shows the performance of net inflows while the Model prescribes to divest (i.e. Expected rank<0.5). Panel B shows the performance of net outflows while the Model prescribes to invest (i.e Expected rank≥0.5). We consider four benchmark models explaining cross-sectional ranks based on raw returns (Col. 2), style-adjusted returns (Col. 4), alphas (Col. 6) and Sharpe ratios (Col. 8). Panel C reports the performance spread (investments minus divestments). We use four evaluation criteria, and compare to the performance of all net inflows and net outflows (i.e. investors' overall performance) reported in Col. 1. Performance differences are reported in Columns 3, 5, 7 and 9. T-statistics based on clustered robust standard errors are reported in parenthesis.

Evaluation criteria Four-quarter-ahead Performance	Investors Performance	Raw return ranks model		Style-adj. ret. ranks model		Alpha ranks model		Sharpe ratio ranks model	
		Performance of Deviations	Difference (2) - (1)	Performance of Deviations	Difference (4) - (1)	Performance of Deviations	Difference (6) - (1)	Performance of Deviations	Difference (8) - (1)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Investments									
	N=7552 Obs.	N=4233		N=4426		N=4185		N=4084	
Raw Return	0.0912	0.0660	*-0.0252*	0.0694	*-0.0218*	0.0761	*-0.0151*	0.0845	*-0.0067*
			(-3.75)		*(-3.22)*		*(-2.12)*		*(-0.85)*
Style-adj. Return	0.0135	0.0007	*-0.0128*	-0.0028	*-0.0164*	0.0064	*-0.0071*	0.0129	*-0.0007*
			(-2.04)		*(-2.64)*		*(-1.07)*		*(-0.09)*
Alpha	0.0300	0.0252	*-0.0058*	0.0204	*-0.0098*	0.0204	*-0.0101*	0.0204	*-0.0105*
			(-0.83)		*(-1.42)*		*(-1.41)*		*(-1.28)*
Sharpe Ratio	0.2861	0.2812	*-0.0049*	0.2464	*-0.0397*	0.2475	*-0.0386*	0.1429	*-0.1432*
			(-0.07)		*(-0.77)*		*(-0.61)*		*(-4.04)*
Panel B: Divestments									
	N=8750 Obs	N=2862		N=2899		N=2744		N=2965	
Raw Return	0.0895	0.1293	*0.0398*	0.1312	*0.0417*	0.1183	*0.0288*	0.1003	*0.0108*
			(4.08)		*(3.94)*		*(2.77)*		*(1.31)*
Style-adj. Return	0.0097	0.0290	*0.0193*	0.0452	*0.0356*	0.0260	*0.0163*	0.0069	*-0.0028*
			(2.21)		*(3.84)*		*(1.70)*		*(-0.37)*
Alpha	0.0324	0.0480	*0.0151*	0.0528	*0.0205*	0.0540	*0.0208*	0.0456	*0.0128*
			(1.65)		*(2.00)*		*(2.21)*		*(1.67)*
Sharpe Ratio	0.2229	0.2663	*0.0434*	0.2949	*0.0719*	0.3074	*0.0844*	0.4102	*0.1873*
			(1.71)		*(1.87)*		*(2.50)*		*(3.59)*
Panel C: Investments minus Divestments									
Raw Return	0.0017	-0.0633	*-0.0650*	-0.0618	*-0.0635*	-0.0423	*-0.0440*	-0.0158	*-0.0175*
	(0.26)	(-6.41)	*(-5.47)*	(-5.76)	*(-5.04)*	(-3.91)	*(-3.47)*	(-1.68)	*(-1.53)*
Style-adj. Return	0.0038	-0.0283	*-0.0321*	-0.0481	*-0.0519*	-0.0195	*-0.0233*	0.0060	*0.0022*
	(0.64)	(-3.17)	*(-3.00)*	(-5.12)	*(-4.67)*	(-1.95)	*(-2.00)*	(0.70)	*(0.21)*
Alpha	-0.0024	-0.0228	*-0.0204*	-0.0324	*-0.0300*	-0.0336	*-0.0312*	-0.0252	*-0.0228*
	(-0.35)	(-2.41)	*(-1.75)*	(-3.06)	*(-2.38)*	(-3.32)	*(-2.55)*	(-2.76)	*(-2.00)*
Sharpe Ratio	0.0631	0.0149	*-0.0482*	-0.0485	*-0.1116*	-0.0599	*-0.1230*	-0.2673	*-0.3304*
	(1.63)	(0.24)	*(-0.67)*	(-0.95)	*(-1.74)*	(-1.00)	*(-1.72)*	(-5.38)	*(-5.24)*

Table 15

Investors' choice when model's forecast is negative

The table reports estimates of a probit model explaining the sign of net flows conditional to Expected rank<0.5 (i.e. the Model prescribes to divest). The sample includes 1856 open-end hedge funds between 1995Q1 and 2010Q3. The dependent variable takes value 1 if net flows>0, and zero otherwise. Expected rank is obtained from four models explaining cross-sectional ranks based on raw returns (Model 1), style-adjusted returns (Model 2), alphas (Model 3) and Sharpe ratios (Model 4). The independent variables are defined in Table E2 in the appendix. Style and time dummies are included (estimates not reported). We pool all fund-quarter observations. Panel-robust z-statistics are in parentheses.

	Model1		Model2		Model3		Model4	
Intercept	-0.2415	(-0.73)	-0.0835	(-0.24)	-0.1017	(-0.28)	-0.5411	(-1.51)
W2_TBill	0.1965	(4.35)	0.1793	(3.93)	0.1993	(4.28)	0.1359	(2.99)
W3_TBill	0.1416	(1.95)	0.1951	(2.95)	0.1585	(2.36)	0.1562	(2.36)
W4_TBill	0.1942	(2.21)	0.3082	(3.73)	0.2984	(3.63)	0.2351	(2.46)
W5_TBill	0.3999	(3.72)	0.4804	(4.98)	0.4587	(4.59)	0.4656	(3.46)
W6_TBill	0.4838	(4.70)	0.4354	(4.32)	0.3656	(3.48)	0.4261	(3.21)
W7_TBill	0.2560	(1.90)	0.2842	(2.35)	0.3271	(2.69)	0.6019	(3.01)
W8_TBill	0.2010	(2.23)	0.1693	(1.86)	0.1827	(1.83)	0.5275	(2.57)
L1_TBill	-0.0900	(-2.32)	-0.0350	(-0.90)	-0.0725	(-1.88)	-0.0997	(-2.66)
L2_TBill	-0.2389	(-4.90)	-0.1957	(-3.79)	-0.2044	(-3.93)	-0.2344	(-4.79)
L3_TBill	-0.3174	(-4.56)	-0.2511	(-3.39)	-0.2479	(-3.58)	-0.3376	(-4.95)
L4_TBill	-0.2129	(-2.24)	-0.2054	(-2.09)	-0.2041	(-2.31)	-0.2853	(-3.16)
L5_TBill	-0.3821	(-2.79)	-0.2929	(-2.33)	-0.3013	(-2.57)	-0.3882	(-3.11)
L6_TBill	-0.2602	(-1.43)	-0.2324	(-1.37)	-0.1365	(-0.83)	-0.2348	(-1.45)
L7_TBill	-0.3529	(-1.22)	-0.1601	(-0.54)	-0.0686	(-0.26)	-0.0971	(-0.34)
L8_TBill	-0.4166	(-0.77)			0.2524	(0.45)	-0.4378	(-0.83)
Count_1	0.2500	(1.47)	0.1948	(1.21)	0.1773	(1.14)	0.3220	(1.87)
Count_2	0.3776	(3.26)	0.3433	(2.98)	0.3051	(2.85)	0.5339	(4.64)
Count_3	0.2136	(2.42)	0.2401	(2.82)	0.2558	(2.84)	0.3234	(3.50)
Count_4	0.2070	(2.72)	0.1866	(2.59)	0.1940	(2.48)	0.3213	(3.87)
Count_5	0.1134	(1.73)	0.1198	(1.90)	0.1103	(1.64)	0.2471	(3.39)
Count_6	0.0750	(1.30)	0.0860	(1.48)	0.0964	(1.69)	0.1613	(2.39)
Middle Rank Lag 1	1.2743	(8.52)	1.3432	(9.19)	1.2661	(8.65)	1.1353	(7.30)
Top 30%	-1.8101	(-4.13)	-1.5211	(-3.50)	-1.6219	(-3.49)	-1.2592	(-3.14)
Bottom 30%	-0.5317	(-1.63)	-0.9134	(-2.69)	-0.8151	(-2.49)	-0.8091	(-2.33)
Middle Rank Lag 2	0.1204	(0.82)	0.1526	(1.07)	0.0081	(0.06)	0.0873	(0.58)
Top 30%	0.2831	(0.79)	0.1506	(0.44)	0.3498	(1.06)	0.0211	(0.07)
Bottom 30%	-0.0259	(-0.08)	-0.0428	(-0.12)	-0.0516	(-0.15)	-0.0095	(-0.03)
Rank 24m alpha	0.1007	(1.41)	0.0786	(1.08)	0.0122	(0.18)	0.0430	(0.66)
Rank 24m Sharpe Ratio	0.5767	(4.59)	0.5952	(4.85)	0.6935	(5.33)	0.8485	(5.86)
Underwater dummy	0.1258	(2.28)	0.1002	(1.77)	0.0756	(1.36)	0.0845	(1.57)
Downside-ups. pot. ratio	0.1170	(3.70)	0.0980	(2.69)	0.1585	(4.63)	0.1581	(3.76)
St.deviation of returns	-0.3825	(-0.47)	-0.9113	(-1.02)	-0.4614	(-0.58)	-0.7369	(-1.07)
Share restrictions	0.1515	(2.64)	0.1233	(2.12)	0.1751	(3.10)	0.1968	(2.89)
Lockup periods	-0.0045	(-1.25)	-0.0066	(-1.94)	-0.0046	(-1.35)	-0.0044	(-1.14)
High-water mark	0.0526	(1.31)	0.0707	(1.68)	0.0651	(1.59)	0.0289	(0.69)
Return smoothing	-0.0494	(-0.68)	0.0493	(0.70)	-0.0374	(-0.54)	-0.0282	(-0.36)
Ln(AUM)	-0.0577	(-5.42)	-0.0519	(-4.54)	-0.0438	(-3.70)	-0.0344	(-2.93)
Ln(Age)	-0.0238	(-0.64)	-0.0210	(-0.56)	-0.0434	(-1.15)	-0.0477	(-1.25)
Offshore	-0.0120	(-0.30)	-0.0203	(-0.49)	-0.0262	(-0.64)	-0.0579	(-1.43)
Incentive fee	-0.0010	(-0.27)	-0.0015	(-0.39)	-0.0010	(-0.27)	0.0025	(0.60)
Management fee	0.0220	(0.71)	-0.0059	(-0.16)	0.0105	(0.31)	0.0204	(0.73)
Personal capital	-0.0132	(-0.36)	-0.0143	(-0.37)	-0.0304	(-0.81)	-0.0240	(-0.61)
Leveraged	-0.0212	(-0.51)	-0.0160	(-0.39)	-0.0304	(-0.73)	-0.0075	(-0.17)
Eight lags quarterly flows	YES		YES		YES		YES	
Style and time dummies	YES		YES		YES		YES	
N	10121		10275		10191		9869	
Pseudo R^2	0.113		0.113		0.108		0.108	

Table 16

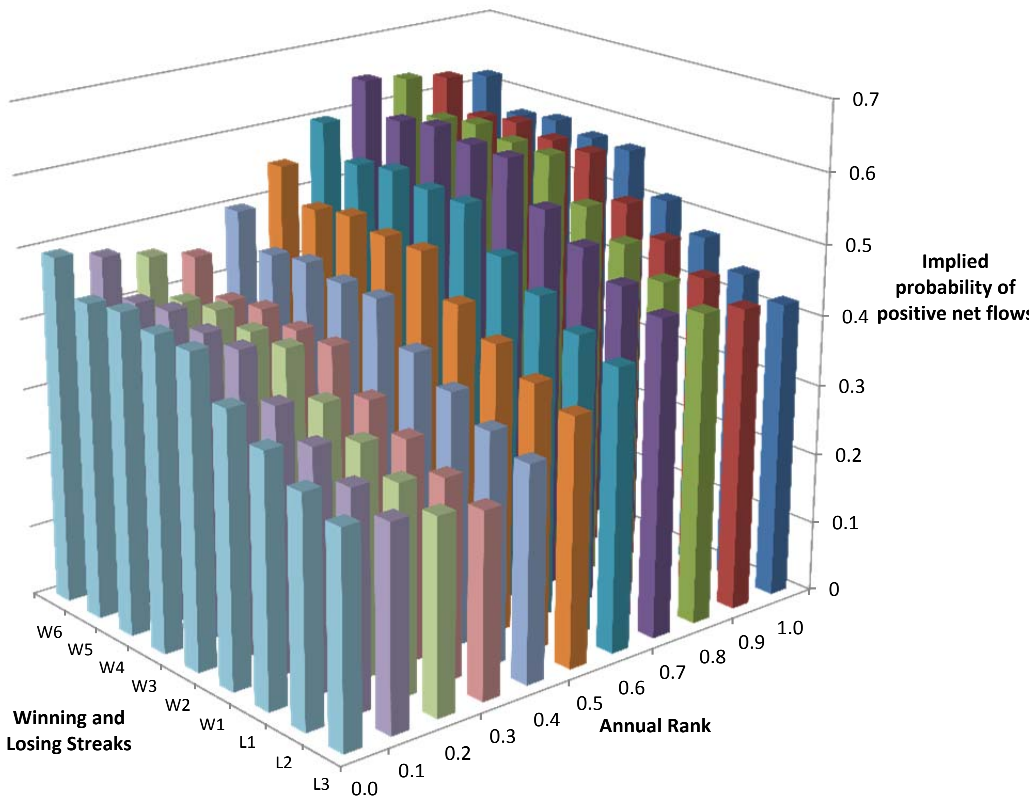
Investors' choice when model's forecast is positive

The table reports estimates of a probit model explaining the sign of net flows conditional to Expected rank≥0.5 (i.e. the Model prescribes to invest). The sample includes 1856 open-end hedge funds between 1995Q1 and 2010Q3. The dependent variable takes value 1 if net flows<0, and zero otherwise. Expected rank is obtained from four models explaining cross-sectional ranks based on raw returns (Model 1), style-adjusted returns (Model 2), alphas (Model 3) and Sharpe ratios (Model 4). The independent variables are defined in Table E2 in the appendix. Style and time dummies are included (estimates not reported). We pool all fund-quarter observations. Panel-robust z-statistics are in parentheses.

	Model1		Model2		Model3		Model4	
Intercept	0.3747	(0.92)	0.2618	(0.67)	0.4793	(1.19)	-0.0380	(-0.09)
W2_TBill	-0.1245	(-1.93)	-0.1365	(-2.12)	-0.0938	(-1.45)	-0.2165	(-3.53)
W3_TBill	-0.1765	(-2.57)	-0.1051	(-1.55)	-0.1261	(-1.77)	-0.1580	(-2.29)
W4_TBill	-0.3320	(-3.99)	-0.1904	(-2.33)	-0.2419	(-2.80)	-0.2401	(-2.92)
W5_TBill	-0.3389	(-3.61)	-0.1807	(-1.82)	-0.2500	(-2.47)	-0.2436	(-2.71)
W6_TBill	-0.2639	(-2.25)	-0.2171	(-1.72)	-0.3410	(-2.76)	-0.3214	(-3.09)
W7_TBill	-0.3296	(-2.45)	-0.3028	(-2.04)	-0.2429	(-1.69)	-0.1349	(-1.15)
W8_TBill	-0.0725	(-0.70)	-0.0897	(-0.93)	-0.0876	(-0.92)	-0.0965	(-1.12)
L1_TBill	0.0131	(0.20)	0.1174	(1.86)	0.0586	(0.93)	0.0479	(0.71)
L2_TBill	0.0791	(0.75)	0.1274	(1.43)	0.2180	(2.40)	0.3590	(3.27)
L3_TBill	0.2038	(1.40)	0.3279	(2.93)	0.4907	(3.48)	0.3700	(2.11)
L4_TBill	0.3290	(1.55)	0.1267	(0.66)	0.2329	(0.50)	-0.0426	(-0.16)
L5_TBill	0.1189	(0.52)	0.2897	(0.93)			-0.0007	(-0.00)
L6_TBill	0.1601	(0.47)	-0.4250	(-0.89)	0.5132	(0.94)	1.0558	(1.50)
L7_TBill	0.0916	(0.18)	0.2386	(0.45)				
L8_TBill	0.1375	(0.28)	0.1654	(0.41)	0.8008	(1.57)	0.0186	(0.04)
Count_1	-0.4734	(-1.81)	-0.4789	(-1.50)	-0.5546	(-0.64)	-0.5598	(-1.92)
Count_2	-0.5209	(-3.41)	-0.4636	(-3.12)	-0.7360	(-3.03)	-0.2659	(-1.67)
Count_3	-0.3780	(-2.99)	-0.3092	(-2.48)	-0.3367	(-2.60)	-0.3620	(-2.91)
Count_4	-0.3023	(-2.93)	-0.3488	(-3.39)	-0.3340	(-3.34)	-0.2003	(-2.07)
Count_5	-0.3220	(-3.95)	-0.3305	(-3.99)	-0.3390	(-4.31)	-0.1900	(-2.59)
Count_6	-0.1761	(-2.69)	-0.1445	(-2.23)	-0.1554	(-2.46)	-0.0910	(-1.63)
Middle Rank Lag 1	-1.7602	(-8.44)	-1.4653	(-6.66)	-1.6311	(-7.90)	-1.8686	(-10.13)
Top 30%	1.9738	(5.02)	1.9249	(4.44)	1.9912	(4.96)	2.2120	(5.47)
Bottom 30%	3.3290	(5.90)	1.9515	(3.57)	2.7268	(4.45)	2.7275	(5.30)
Middle Rank Lag 2	0.0437	(0.24)	0.0632	(0.33)	-0.2006	(-1.08)	-0.0497	(-0.29)
Top 30%	-0.1132	(-0.30)	-0.2557	(-0.63)	0.0615	(0.16)	-0.3822	(-0.99)
Bottom 30%	0.3263	(0.73)	0.3310	(0.75)	0.5915	(1.28)	0.3988	(0.86)
Rank 24m alpha	-0.0002	(-0.00)	-0.0383	(-0.47)	-0.0910	(-1.10)	-0.0600	(-0.61)
Rank 24m Sharpe Ratio	-0.9042	(-5.27)	-0.8865	(-5.51)	-0.7650	(-4.43)	-0.5544	(-3.68)
Underwater dummy	0.0844	(0.99)	0.0316	(0.40)	0.0064	(0.08)	0.0316	(0.34)
Downside-ups. pot. ratio	-0.0913	(-2.68)	-0.1099	(-4.34)	-0.0607	(-1.84)	-0.0938	(-3.70)
St.deviation of returns	2.4600	(3.29)	1.9187	(2.77)	2.1233	(2.95)	3.1878	(3.41)
Share restrictions	-0.1223	(-2.27)	-0.1362	(-2.34)	-0.0869	(-1.55)	-0.1091	(-2.18)
Lockup periods	0.0019	(1.05)	0.0026	(1.22)	0.0017	(0.86)	0.0013	(0.72)
High-water mark	-0.0675	(-1.25)	-0.0249	(-0.45)	-0.0417	(-0.80)	-0.1058	(-2.06)
Return smoothing	0.0170	(0.19)	0.1874	(2.04)	0.0128	(0.14)	0.0173	(0.22)
Ln(AUM)	-0.0161	(-1.09)	-0.0003	(-0.02)	0.0004	(0.03)	0.0167	(1.14)
Ln(Age)	0.2104	(4.12)	0.2028	(4.10)	0.1396	(2.72)	0.1248	(2.51)
Offshore	0.0105	(0.22)	-0.0123	(-0.25)	0.0025	(0.05)	-0.0616	(-1.32)
Incentive fee	-0.0015	(-0.32)	0.0008	(0.15)	-0.0007	(-0.16)	0.0046	(1.02)
Management fee	0.0297	(0.79)	-0.0253	(-0.74)	0.0107	(0.29)	0.0627	(1.34)
Personal capital	0.0120	(0.27)	0.0165	(0.38)	-0.0168	(-0.38)	-0.0139	(-0.33)
Leveraged	-0.0200	(-0.41)	-0.0406	(-0.77)	-0.0437	(-0.82)	0.0024	(0.05)
Eight lags quarterly flows	YES		YES		YES		YES	
N	6180		6025		6103		6427	
Pseudo R^2	0.119		0.124		0.112		0.121	

Figure 1
Implied probabilities of inflows

The figure presents the estimated probabilities of a positive net flow, based on the estimated probit model of investor flows (Table 6, Column D), as a function of past performance rank (1=highest, 0 = lowest), and winning and losing performance streaks. All other variables are fixed at their sample average.



Appendix A. Relative importance of predictors

This appendix describes the technique of *relative weights analysis* used in Sections 3 and 4. The purpose of this method is to estimate the relative contribution of each predictor to the explained variance of a regression model. When all predictor variables are uncorrelated, the relative contribution of each predictor is simply the squared correlation between the predictor and the dependent variable. This zero order correlation equals the standardized regression coefficient for the given predictor. The sum of the squared standardized coefficients is exactly equal to the R^2 of the model. This is no longer the case, however, when predictors are correlated. In this situation, there are two commonly accepted approaches to estimate relative importance: *dominance analysis* (see Lindeman et al., 1980, and Budescu, 1993) and *relative weights analysis* (see e.g. Johnson, 2000, and Tonidandel and LeBreton, 2011). It has been shown that both produce very similar solutions. In *dominance analysis*, the relative weight of each predictor is measured by the average contribution to the R^2 when the predictor is included with each possible combination of predictors. The sum of these relative weights is exactly equal to the R^2 of the model. Given p predictors, this method requires the estimation or (2^p-1) submodels. Thus, with a large number of regressors, this method becomes computationally highly demanding.

An alternative and more computationally efficient method is offered by *relative weights analysis*. Let $\boldsymbol{Y}$ be the dependent variable, and let $\boldsymbol{X}$ be the matrix of p standardized predictors. The correlation matrix of p predictors is given by $\boldsymbol{X'X}$. Let $\boldsymbol{Q}$ be the matrix of eigenvectors of $\boldsymbol{X'X}$ and let $\boldsymbol{\Delta}$ be the diagonal matrix containing the eigenvalues. The underlying idea of *relative weights analysis* is to obtain a set $\boldsymbol{Z}$ of orthogonal predictors via a linear transformation of $\boldsymbol{X}$, as follows:

$$\boldsymbol{Z} = \boldsymbol{X\Lambda^{-1}}, \text{ where } \boldsymbol{\Lambda} = \boldsymbol{\Delta^{1/2}} = \boldsymbol{Q\Delta Q'}.$$

This linear transformation was shown by Johnson (1966) to be the best-fitting orthogonal approximation of $\boldsymbol{X}$. Further, the elements of $\boldsymbol{\Lambda^2}$ represent correlations and account for the proportion of predictable variance in $\mathbf{Z}$ accounted for by $\mathbf{X}$.[37] In turn, the proportion of predictable variance in $\boldsymbol{Y}$ accounted for by $\boldsymbol{Z}$ is given by the elements of $\boldsymbol{\beta_s}^{\mathbf{2}}$, where $\boldsymbol{\beta_s}$ are coefficients from a regression of $\boldsymbol{Y}$ on

[37] It can be shown that $\boldsymbol{\Lambda} = \boldsymbol{\Delta^{1/2}} = \boldsymbol{Q\Delta Q'} = (\boldsymbol{ZZ'})^{-\mathbf{1}}\boldsymbol{Z'X}$. Thus the elements of $\boldsymbol{\Lambda}$ are in fact regression coefficients of a regression of $\mathbf{X}$ on $\boldsymbol{Z}$.

$\boldsymbol{Z}$. ($\boldsymbol{\beta_s} = (\boldsymbol{Z'Z})^{-1}\boldsymbol{Z'Y}$). Thus, the combined term $\boldsymbol{\varepsilon} = \boldsymbol{\Lambda}^2\boldsymbol{\beta}_s^2$ describes the proportion of predictable variance in $\boldsymbol{Y}$ accounted for by $\boldsymbol{X}$ (see Johnson, 2004, and Tonidandel, LeBreton and Johnson, 2009). The sum of these $\boldsymbol{\varepsilon}$ contributions equals the R^2 of the model and thus contributions are usually expressed as proportions of the R^2.

Tonidandel and LeBreton (2010) present an extension of relative weights analysis to logistic regression models. They suggest to fully standardize the $\boldsymbol{\beta}$ coefficients as in Menard, 2004. In this case, the sum of the $\boldsymbol{\varepsilon}$ contributions is equal to the pseudo R^2 described in Azen and Traxel (2009). [38] Alternatively, the $\boldsymbol{\beta}$ coefficients in probit and logit models can be fully standardized as follows: $\beta_{s,k} = (\sigma_k\beta_k)/\widehat{\sigma_{y^*}}$, where $\widehat{\sigma_{y^*}}$ is the estimated standard deviation of the latent variable y^*, and σ_k is the standard deviation of predictor k (see Long and Freese, 2001). In this case, the sum of the $\boldsymbol{\varepsilon}$ contributions equals the McKelvey and Zavoina's pseudo R^2, which is defined in terms of the variance of the latent variable y^*. Either way of standardizing coefficients leads to the same relative weights when converted to proportions of the corresponding pseudo R^2.

Johnson, 2004, and Tonidandel, LeBreton and Johnson, 2009, propose a bootstrap approach to estimate standard errors and confidence intervals of relative weights. Standard errors are computed as the standard deviation of the relative weights obtained across bootstrap samples. Confidence intervals are constructed assuming normality of the large sample distribution of relative weights. This is in general a reasonable assumption, according to Johnson (2004) except when relative weights are near zero. In this case, the sample distribution tends to be positively skewed because relative weights are proportions and cannot be negative. When relative weights are near zero Johnson (2004) proposes to use the observed confidence interval based on the bootstrapped percentiles (Efron and Tibshirani, 1993). In this case, the 100(1-α)% confidence interval is constructed by taking the upper and lower α/2 percentiles of the sample distribution.

[38] Menard (2004) proposed the following fully standardized logistic regression coefficient: $\beta_m = (b)(s_x)(R_0)/(s_{logit(\hat{y})})$, where b is the unstandardized logistic regression coefficient, s_x is the standard deviation of the predictor X, and R_0 is the square root of the pseudo R^2 described by Azen and Traxel (2009): $R_0^2 = 1 - \frac{\sum(y-\hat{y})^2}{\sum(y-\bar{y})^2}$, where y is the observed value of the dependent variable, $\bar{y}$ is its mean value and $\hat{y}$ is the predicted value from the model.

Appendix B. Welfare implications: robustness tests

In this Appendix we present a series of robustness tests for the allocation schemes based on forecast models presented in Section 5, that take into account potential restrictions to inflows and outflows, potential capacity constraints, and the potential effect of a survivorship bias. We also analyze the effect of thresholds other than the median to define the switching rule that underlies the benchmark allocations, and the effect of investment horizons longer than one year.

B.1. Restrictions to inflows and outflows and potential capacity constraints

A number of flow restrictions potentially in place in the hedge fund industry could affect the performance of the trading strategies prescribed by the forecast models in Section 5. First, because hedge fund investment strategies are typically not scalable, a manager may decide to close a fund to new investments due to capacity limits. A fund may also not be accessible to new investors due to regulatory constraints that limit the total number of investors. Outflows are often restricted by redemption frequencies and notice and lock-up periods.

We use two approaches to analyze the effect of potential flow restrictions. First, we infer the presence of flow restrictions from the shape of the expected flow-performance relation, estimated for every fund-period observation using the methodology from Baquero and Verbeek (2009, 2014). Previous studies of the flow-performance relation for hedge funds have documented a slow response of flows to past performance in the top and bottom 30% of the lagged return distribution (see, for example, Ding et al., 2009). This is typically captured by a concave kink around the 70th percentile and convex kink around the 30th percentile in a piece-wise linear estimation of the flow-performance relation. Usual interpretations of the concave kink at the 70th percentile is that top-performing funds are more likely to reach capacity constraints and thus impose restrictions on new money (see Naik, Ramadorai and Stromqvist, 2007), and of the convex kink at the 30th percentile, that poor-performing funds are likely to impose restrictions on outflows.

A regime-switching model with a piece-wise linear specification implemented by Baquero and Verbeek (2009, 2014) to capture time variation and cross-sectional variation in the shape of the flow-performance relation enables them to generate an implied flow-performance curve for each fund-period observation. The regime depends on the likelihood of observing net inflows or outflows.[39] We implement this approach in our hedge fund sample to capture the cross-sectional variation in the kinks at the 30th and 70th percentiles. We identify, and designate as flow-restricted, those among the top- and bottom-performing funds in quarter $t-1$ with the most extreme expected kinks (the top quintile) in quarter t. We identified 329 observations with inflow, and 848 observations with outflow, restrictions. Note that inflow restrictions are also indicative of a fund with potential capacity limits in quarter t.

Table B1, Panel C (Appendix) reports the performance spreads between investments and divestments when flow-restricted observations are removed. All spreads reduce to some extent with respect to Table 13, but generally remain statistically significant. Return differences range from 1.26% to 5.71%, alpha differences from 1.56% to 2.28%, and Sharpe ratio differences from 0.0431 to 0.298 (see columns (2), (4), (6), and (8)). Despite this reduced performance, all four forecast models still outperform investor performance spreads by a statistically significant margin on nearly all evaluation criteria (see columns (3), (5), (7), and (9)).

We use an alternative approach to remove, to some extent, the effect of potential flow restrictions. Specifically, we allow the trading strategies prescribed by the forecast models to invest only in funds that actually experienced net inflows in quarter t, that is, funds that are, in principle, open to new investments, and to divest only from the subset of funds that experienced net outflows, and for which our dummy for share restrictions equals zero, indicating that share restrictions do not prevent outflows in quarter t in response to information in quarter $t-1$.

Our results are shown in Table B1, Panel D. As before, we report only the performance spreads between investments and divestments. All forecast models prescribe investment in roughly 45% of the 7,552 funds with actual net inflows, and divestment from roughly 60% of the 8,750 funds with actual net

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[39] In their model (see e.g. Baquero and Verbeek, 2014), the probability of a positive flow into a particular fund is given by $p(x,z)$, where x denotes past performance and z denotes a set of fund characteristics and time dummies. Conditional upon having a positive flow, the expected relative flow amount is given by $f_1(x)$. Conditional upon having a negative flow, the expected flow amount is given by $f_2(x)$. The net flow to the fund is denoted by y. Thus, the expected inflow y depends upon x as follows:

$$E[y|x] = f_1(x)p(x,z) + f_2(x)(1-p(x,z)) = [f_1(x) - f_2(x)]p(x,z)$$

That is, for every fund-period observation, the expected flow-performance relation is a combination of $f_1(x)$ and $f_2(x)$ depending on $p(x,z)$, which is specific to each fund-period observation through the value z. Therefore, the equation, estimated as a regime-switching model, captures variation in the shape of the flow-performance relation across funds and time.

outflows. Performance differentials between investments and divestments for the four trading strategies, although reduced to some extent with respect to Table 13, in which flow restrictions are not taken into account, remain by and large significant. Return differences range from 1.32% to 5.24%, alpha differences from 1.32% to 2.40%, and Sharpe ratio differences, which actually increase, from 0.0902 and 0.303 (see columns (2), (4), (6), and (8)). Most important, as in Table 13, we find the four forecast models to outperform the investor zero-investment strategy on nearly all evaluation criteria, generally by a statistically significant margin (see columns (3), (5), (7), and (9)). Results from these two approaches suggest that removing funds likely to be subject to flow restrictions and funds likely to hit capacity constraints has only a marginal impact on the performance of the trading strategies prescribed by the forecast models.

Conditioning the analysis to the sign of current flows mitigates at the same time the concern that differences between our hypothetical investment strategies and the investor strategies reported in Table 13 are driven by flows negatively affecting subsequent performance. For instance, Berk and Green's (2004) equilibrium model predicts that flows, by chasing past performance, will compete away performance predictability in the presence of capacity constraints. The results in Table B1, Panel D, show that even among funds that experience net inflows in quarter t, subsequent performance is better predicted by the forecast models than by investors. Further tests that condition the analysis to funds that experience various levels of flows in quarter t produce similar results.

B.2. Survivorship biases

The analysis in Section 5 evaluates the performance of different trading strategies over a four-quarter horizon, conditional on past performance. Our empirical forecasting approach requires eight lagged quarters, over which we identify past performance streaks and other performance metrics. A sampling (look-ahead) bias arises because we implicitly condition upon survival during the evaluation and streak-formation periods (see, for example, Carpenter and Lynch, 1999). To correct for look-ahead bias and obtain the unconditional distribution of returns, we implement the procedure described by Baquero, Ter Horst and Verbeek (2005), which requires knowledge of the liquidation process modelled as a function of historical returns and fund characteristics (as detailed in Appendix C and D)[40]. The correction method implies multiplying the returns used in the analysis by a weight factor, specifically, a ratio, the numerator of which is an unconditional, and the denominator a conditional, non-liquidation probability.

Because the liquidation model estimates liquidation probabilities in the streak-formation period conditional on eight further lags, the number of observations in this exercise is considerably reduced, from 16,302 to 7,795. The performance of trading strategies for this reduced sample is reported in Table B1, in Panel E without look-ahead bias correction, and in Panel F after the correction.

As expected, nearly all performance metrics are moved downward, to some extent, by the correction for look-ahead bias. For example, pre correction return differences between investments and divestments for the first three trading strategies range from 2.36% to 4.79% (see columns (2), (4), and (6), Panel E) and are statistically significant; post correction, range from 2.26% to 4.4% and remain statistically significant. Similar patterns are observed for style-adjusted returns, alphas, and Sharpe ratios. As before, the forecasting models' exceed investors' performance spreads between investments and divestments on almost all criteria, generally by a statistically significant margin, even after the correction (see columns (3), (5), (7), and (9)).

In an additional robustness test (not reported), we correct the trading strategies for look-ahead bias after removing, as before, funds likely to be subject to flow restrictions. The number of observations is naturally significantly reduced, but our results remain robust, indicating that performance differences between investments and divestments based on out-of-sample forecasts are positive and statistically significant and outperform investor strategies.

B.3. Choice of switching rule

Thus far we have defined benchmark allocations based on a switching rule around an expected rank of τ =0.5. We now conduct a sensitivity analysis of our results by redefining the switching rule using thresholds ±5% around the expected rank used previously. Results are depicted in Figure B1, which compares the performance spreads from the four forecast models for raw returns (Panel A), style-adjusted returns (Panel B), alphas (Panel C), and Sharpe ratios (Panel D).

[40] Several studies have modelled hedge fund liquidation, for instance Brown, Goetzmann and Ibbotson (1999), Brown, Goetzmann and Park (2001), Liang (2000), Baquero, Ter Horst and Verbeek (2005), Grecu, Malkiel and Saha (2007), Liang and Park (2010), Aragon and Nanda (2011).

[Insert Figure B1]

We observe across the four panels as the threshold decreases diminished performance in all benchmark strategies. The strategies prescribed by Models 3 and 4 appear to be particularly sensitive to changes in τ. Yet, even when $\tau = 0.45$, the models' outperform investors' allocations on nearly all evaluation criteria. Note that, by construction, as the threshold moves from 0.55 to 0.45, the number of observations increases in the divestment, and decreases in the investment, allocations. The corresponding allocations for both thresholds represent opposite and relatively extreme departures compared to the average investor allocation, which invests in 7,552, and divests from 8,750, fund-period observations. For instance, Model 1, if $\tau = 0.55$, prescribes investment in only 3,358, and divestment from 12,944, observations, if $\tau = 0.45$, investment in 9,490, and divestment from 6,812, observations. That is, in the latter case the model prescribes investment disproportionately in funds below the expected median rank. Yet our sensitivity analysis shows that, even with such extreme allocations, the forecast models outperform investors.

B.4. Effect of longer time horizons

Our analysis thus far has been conducted based on four-quarter-ahead out-of-sample forecasts. We now analyze the possibility that investors have a longer investment horizon. Estimating four forecast models that explain eight-quarter-ahead cross-sectional ranks based on raw returns, style-adjusted returns, alphas, and Sharpe ratios reduces the number of observations to 12,303. Table B2 in the appendix summarizes the forecasting ability and goodness-of-fit of the four models. All models exhibit improved goodness-of-fit compared to the four-quarter horizon models reported in Table 10. Model 3 (which explains alpha ranks), in particular, exhibits an adjusted R^2 of 6.7%, compared to 1.8% in Table 10. Moreover, the hit rate reported in Panel C, based on out-of-sample forecasts, increases to 58% or more for the first three models. Note that only Model 4, which explains Sharpe ratios, performs slightly better at four-quarter horizons. The F-tests for including winning and losing streaks in each model, reported in Panel B, indicate that winning streaks play no role in predicting eight-quarter-ahead performance in Models 1 to 3. Neither does the F-test reject the null that all losing streaks have zero coefficients in Models 1 and 2 at the 1%, and in Model 3 at the 5%, significance level. The predictive ability of performance streaks remains confined to Model 4, for which the F-tests reject the null.

Consistent with improved hit rates and goodness-of-fit, the trading strategies based on eight-quarter forecasts (see Table B3) yield (annualized) performance spreads between investments and divestments that are generally larger than those based on four-quarter forecasts, whether in terms of raw returns, style-adjusted returns, or alphas (Panel C). Sharpe ratios are smaller compared to Table 10, but all models significantly outperform investor spreads in most accounts. Panel C, column (1) reveals that investors perform less well at eight- than at four-quarter horizons, their Sharpe ratio spread being 0.059, compared to 0.063 in Table 10.

Our results indicate that investors perform less well over a two-year than a one-year horizon, and that trading strategies based on out-of-sample forecasts deliver performance differences between investments and divestments that are positive and statistically significant and outperform investor strategies by a significant margin. These results are robust to a wide range of further tests, including tests for look-a head bias correction and removal of flow-restricted observations.[41]

[41] Look-ahead bias correction at eight-quarter horizons is, as expected, stronger than at four-quarter horizons. The raw return to investments for the strategy prescribed by Model 1, for example, is 12.2% without correction and 11.3% after correction (a 7.4% correction downwards). The corresponding figures at four-quarter horizons are 11.7% and 11.3% (a 3.4% correction downwards). For divestments, the returns after correction are 6.58% at eight-quarter horizons (a correction of 7.9%) and 7.36% at four-quarter horizons (a 3.9% correction). Overall, the spread between investments and divestments after correction is 4.7% at eight-quarter horizons and 3.9% at four-quarter horizons.

Table B1. Robustness tests of investment strategies based on out-of-sample forecasts

The table reports three robustness tests of four trading strategies based on out-of-sample forecasts. We report only the performance differential between investments and divestments. Panels A and B report performance in the pre-crisis period and crisis period. Panels C and D report performance results for two approaches that remove flow-restricted observations. Panels E and F report the results of look-ahead bias correction. Forecasts are obtained from four models explaining cross-sectional ranks based on raw returns (Col. 2), style-adjusted returns (Col. 4), alphas (Col. 6) and Sharpe ratios (Col. 8). Each trading strategy prescribes to invest if Expected rank≥0.5, and divest otherwise. We compare the four strategies to the performance of actual net inflows and net outflows (Col. 1). Performance differences are reported in Columns 3, 5, 7 and 9. T-statistics based on clustered robust standard errors are reported in parenthesis.

Evaluation criteria Four-quarter-ahead Performance		Raw return ranks model		Style-adj. ret. ranks model		Alpha ranks model		Sharpe ratio ranks model	
	Investors Performance	Model Performance.	Difference (2) - (1)	Model Performance	Difference (4) - (1)	Model Performance	Difference (6) - (1)	Model Performance	Difference (8) - (1)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Investments minus Divestments - Pre-Crisis Period (1995 Q1 – 2007 Q3)									
Investments	N=5325 funds	N=4018		N=4004		N=4169		N=4345	
Divestments	N=5588 funds	N=6895		N=6909		N=6744		N=6568	
Raw Return	0.0081	0.0763	0.0682	0.0668	0.0587	0.0536	0.0455	0.0264	0.0183
	(0.99)	(7.61)	(5.28)	(6.17)	(4.33)	(5.24)	(3.48)	(2.84)	(1.48)
Style-adj. Return	0.0110	0.0468	0.0358	0.0619	0.0509	0.0393	0.0283	0.0104	-0.0006
	(1.46)	(5.10)	(3.01)	(6.32)	(4.12)	(4.15)	(2.34)	(1.22)	(-0.05)
Alpha	0.0048	0.0264	0.0216	0.0336	0.0288	0.0384	0.0336	0.0348	0.0300
	(0.64)	(2.99)	(1.86)	(3.53)	(2.37)	(4.28)	(2.86)	(4.26)	(2.70)
Sharpe Ratio	0.0906	0.0795	-0.0111	0.1099	0.0193	0.1140	0.0234	0.3576	0.2670
	(1.82)	(1.72)	(-0.16)	(2.48)	(0.29)	(2.52)	(0.35)	(5.57)	(3.29)
Panel B: Investments minus Divestments - Crisis Period (2007 Q4 – 2010 Q3)									
Investments	N=1566 funds	N=1685		N=1571		N=1514		N=1513	
Divestments	N=2442 funds	N=2323		N=2437		N=2494		N=2495	
Raw Return	-0.0329	0.0425	0.0754	0.0425	0.0754	0.0170	0.0499	0.0118	0.0447
	(-2.72)	(3.38)	(4.32)	(3.22)	(4.21)	(1.33)	(2.84)	(0.98)	(2.62)
Style-adj. Return	-0.0055	-0.0045	0.0010	0.0080	0.0135	-0.0133	-0.0078	-0.0126	-0.0071
	(-0.50)	(-0.39)	(0.06)	(0.65)	(0.82)	(-1.13)	(-0.49)	(-1.11)	(-0.45)
Alpha	-0.0168	0.0000	0.0168	0.0132	0.0300	0.0084	0.0252	0.0036	0.0204
	(-1.38)	(0.03)	(1.38)	(0.92)	(1.59)	(0.61)	(1.37)	(0.26)	(1.10)
Sharpe Ratio	-0.0399	0.0400	0.0799	0.0968	0.1367	0.1407	0.1806	0.2048	0.2447
	(-0.95)	(1.08)	(1.43)	(2.34)	(2.32)	(2.73)	(2.72)	(3.85)	(3.61)

Table B1 (Continuation). Effect of flow restrictions

Panels C and D report results from two approaches that remove flow-restricted observations. The first test (Panel C) defines flow-restricted observations as those for which the implied flow-performance relation exhibits the most extreme kinks at the 30th percentile (outflow restrictions) and at the 70th percentile (inflow restrictions). The implied flow-performance relation for each fund-period observations is obtained from a regime switching model of flows (see Baquero and Verbeek 2009, 2014). In the second test (Panel D), all funds that experienced net outflows in quarter *t* are considered inflow-restricted, while those funds that experienced net inflows in quarter *t* are considered outflow-restricted.

Evaluation criteria Four-quarter-ahead Performance	Investors Performance	Raw return ranks model		Style-adj. ret. ranks model		Alpha ranks model		Sharpe ratio ranks model	
		Model Performance.	Difference (2) - (1)	Model Performance	Difference (4) - (1)	Model Performance	Difference (6) - (1)	Model Performance	Difference (8) - (1)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel C: Investments minus Divestments. Test with no flow restrictions (Test 1)									
Investments	N=7552 funds	N=5772		N=5610		N=5680		N=6101	
Divestments	N=8750 funds	N=9316		N=9579		N=9361		N=9021	
Raw Return	0.0017	0.0567	0.0550	0.0571	0.0554	0.0369	0.0352	0.0127	0.0110
	(0.26)	(7.40)	(5.44)	(6.74)	(5.16)	(4.62)	(3.40)	(1.76)	(1.13)
Style-adj. Return	0.0038	0.0276	0.0238	0.0456	0.0418	0.0191	0.0153	-0.0041	-0.0079
	(0.64)	(3.86)	(2.56)	(5.82)	(4.26)	(2.56)	(1.60)	(-0.61)	(-0.88)
Alpha	-0.0024	0.0156	0.0180	0.0228	0.0252	0.0228	0.0252	0.0168	0.0192
	(-0.35)	(2.20)	(1.83)	(2.99)	(2.46)	(3.21)	(2.55)	(2.51)	(2.01)
Sharpe Ratio	0.0631	0.0431	-0.0200	0.1022	0.0391	0.1084	0.0453	0.2986	0.2355
	(1.63)	(1.08)	(-0.36)	(2.49)	(0.69)	(2.82)	(0.83)	(5.21)	(3.40)
Panel D: Investments minus Divestments. Test with no flow restrictions (Test 2)									
Investments	N=7552 funds	N=3319		N=3126		N=3367		N=3468	
Divestments	N=8750 funds	N=5323		N=5199		N=5423		N=5358	
Raw Return	0.0017	0.0521	0.0504	0.0523	0.0506	0.0326	0.0309	0.0152	0.0135
	(0.26)	(6.17)	(4.70)	(5.80)	(4.53)	(4.06)	(2.97)	(1.96)	(1.33)
Style-adj. Return	0.0038	0.0290	0.0252	0.0439	0.0401	0.0189	0.0151	0.0034	-0.0004
	(0.64)	(3.72)	(2.57)	(5.17)	(3.87)	(2.59)	(1.61)	(0.47)	(-0.04)
Alpha	-0.0024	0.0120	0.0144	0.0228	0.0252	0.0180	0.0204	0.0156	0.0180
	(-0.35)	(1.29)	(1.25)	(2.52)	(2.22)	(2.17)	(1.90)	(1.95)	(1.71)
Sharpe Ratio	0.0631	0.1012	0.0381	0.1643	0.1012	0.1573	0.0942	0.3327	0.2696
	(1.63)	(3.38)	(0.78)	(4.11)	(1.82)	(4.71)	(1.84)	(4.91)	(3.45)

Table B1 (Continuation). Look-ahead bias correction

Panels E and F report results from a weighting procedure to eliminate look-ahead bias. The correction weights are obtained from a sample of 7795 fund-period observations and calculated as a ratio of an unconditional non-liquidation probability in the numerator and a conditional liquidation probability in the denominator. Panel E reports the performance of trading strategies without correction. Panel F reports performance after the correction.

Evaluation criteria Four-quarter-ahead Performance	Investors Performance	Raw return ranks model: Model Performance.	Raw return ranks model: Difference (2) - (1)	Style-adj. ret. ranks model: Model Performance	Style-adj. ret. ranks model: Difference (4) - (1)	Alpha ranks model: Model Performance	Alpha ranks model: Difference (6) - (1)	Sharpe ratio ranks model: Model Performance	Sharpe ratio ranks model: Difference (8) - (1)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel E: Investments minus Divestments. Sample without look-ahead bias correction.									
Investments	N=3426 funds	N=3020		N=2840		N=2846		N=3170	
Divestments	N=4369 funds	N=4775		N=4955		N=4949		N=4625	
Raw Return	-0.0044	0.0408	0.0452	0.0479	0.0523	0.0236	0.0280	0.0040	0.0084
	(-0.52)	(3.93)	(3.37)	(4.24)	(3.70)	(2.20)	(2.05)	(0.44)	(0.67)
Style-adj. Return	-0.0027	0.0212	0.0239	0.0409	0.0436	0.0141	0.0168	-0.0015	0.0012
	(-0.36)	(2.22)	(1.97)	(3.99)	(3.43)	(1.44)	(1.36)	(-0.18)	(0.11)
Alpha	-0.0168	0.0108	0.0276	0.0288	0.0456	0.0180	0.0348	0.0120	0.0288
	(-2.11)	(1.12)	(2.21)	(2.85)	(3.55)	(1.95)	(2.86)	(1.43)	(2.49)
Sharpe Ratio	0.0519	0.0327	-0.0192	0.0529	0.0010	0.0796	0.0277	0.3054	0.2535
	(0.95)	(0.61)	(-0.25)	(1.02)	(0.01)	(1.57)	(0.37)	(3.84)	(2.63)
Panel F: Investments minus Divestments. Sample with look-ahead bias correction.									
Investments	N=3426 funds	N=3020		N=2840		N=2846		N=3170	
Divestments	N=4369 funds	N=4775		N=4955		N=4949		N=4625	
Raw Return	-0.0049	0.0392	0.0441	0.0443	0.0492	0.0226	0.0275	0.0045	0.0094
	(-0.60)	(3.91)	(3.42)	(4.04)	(3.61)	(2.19)	(2.10)	(0.50)	(0.77)
Style-adj. Return	-0.0019	0.0212	0.0231	0.0398	0.0417	0.0146	0.0165	-0.0006	0.0013
	(-0.26)	(2.30)	(1.98)	(4.00)	(3.40)	(1.55)	(1.39)	(-0.08)	(0.12)
Alpha	-0.0144	0.0072	0.0216	0.0300	0.0444	0.0120	0.0264	-0.0072	0.0072
	(-1.74)	(0.79)	(1.75)	(2.78)	(3.26)	(1.29)	(2.12)	(-0.77)	(0.58)
Sharpe Ratio	0.0087	-0.0016	-0.0103	0.0371	0.0284	0.0624	0.0537	0.2735	0.2648
	(0.16)	(-0.03)	(-0.13)	(0.68)	(0.37)	(1.16)	(0.70)	(3.36)	(2.69)

Table B2

Comparison of Forecast Models, Two-Year Horizon

The Table compares four forecasts models explaining eight-quarter-ahead cross-sectional ranks based on raw returns (Model 1), style-adjusted returns (Model 2), alphas (Model 3) and Sharpe ratios (Model 4). Panel A provides a comparison of the goodness-of-fit of all four models, in terms of R^2, adjusted R^2, AIC, BIC, and loglikelihood ratio. Panel B reports F-tests for the inclusion of streak dummies in all forecast models. Panel C provides a comparison of the accuracy of the forecasts using four measures. If we denote the ex post realizations by $y_h$and the series of predictions by $\widehat{y_h}$, h=1,2,…,H, where H is the number of forecasting periods, then the overall RMSE (root mean squared error), MAD (mean absolute deviation) and the out-of-sample R^2 are defined as: $Overall\ RMSE = \sqrt{\frac{1}{H}\sum_{h=1}^{H}(\widehat{y_h} - y_h)^2}$, $Overall\ MAD = \frac{1}{H}\sum_{h=1}^{H}|(\widehat{y_h} - y_h)|$, $R_{OS}^2 = corr^2(\widehat{y_h}, y_h)$. Finally, we report a hit rate defined as the proportion of times a model correctly predicts whether Expected rank≥0.5 or Expected rank<0.5.

	Model1 Raw Returns Ranks	Model 2 St.adj. Returns Ranks	Model 3 Alpha Ranks	Model 4 Sharpe ratio Ranks
Panel A: Comparison of goodness-of-fit				
N	12303	12303	12303	12303
R^2	0.0795	0.0694	0.0671	0.0959
Adj R^2	0.0750	0.0648	0.0626	0.0914
AIC	3575.94	3469.38	3297.32	3697.33
BIC	4028.41	3921.85	3749.79	4149.80
Loglikelihood ratio	-1726.97	-1673.69	-1587.66	-1787.66
Panel B: F-tests for inclusion of winning and losing streaks				
F-test Winning streaks	0.875	1.372	1.699	5.098
p-value	(0.526)	(0.213)	(0.106)	(0.000)
F-test Losing streaks	2.447	2.279	1.402	2.602
p-value	(0.013)	(0.020)	(0.191)	(0.008)
F-test All streaks	1.814	1.786	1.665	4.116
p-value	(0.029)	(0.032)	(0.052)	(0.000)
Panel C: Comparison of out-of-sample forecast performance				
Overall RMSE	0.2875	0.2851	0.2830	0.2877
Overall MAD	0.2421	0.2405	0.2360	0.2410
R_{OS}^2	0.0536	0.0460	0.0495	0.0836
Hit rate	0.5802	0.5843	0.5852	0.5854

Table B3. Investment strategies based on eight-quarter-ahead out-of-sample forecasts

The Table shows the ex-post performance evaluation of trading strategies based on eight-quarter-ahead out-of-sample forecasts. We obtain forecasts from four models explaining cross-sectional ranks based on raw returns (Col. 2), style-adjusted returns (Col. 4), alphas (Col. 6) and Sharpe ratios (Col. 8). Each trading strategy prescribes to invest if Expected rank≥0.5, and divest otherwise. We report the performance (annualized) of investments (Panel A), divestments (Panel B) and their difference (Panel C) using four evaluation criteria, and compare to the performance of actual net inflows and outflows (i.e. investors' performance) reported in Col. 1. Performance differences are reported in Columns 3, 5, 7 and 9. T-statistics (in parenthesis) are based on clustered robust standard errors.

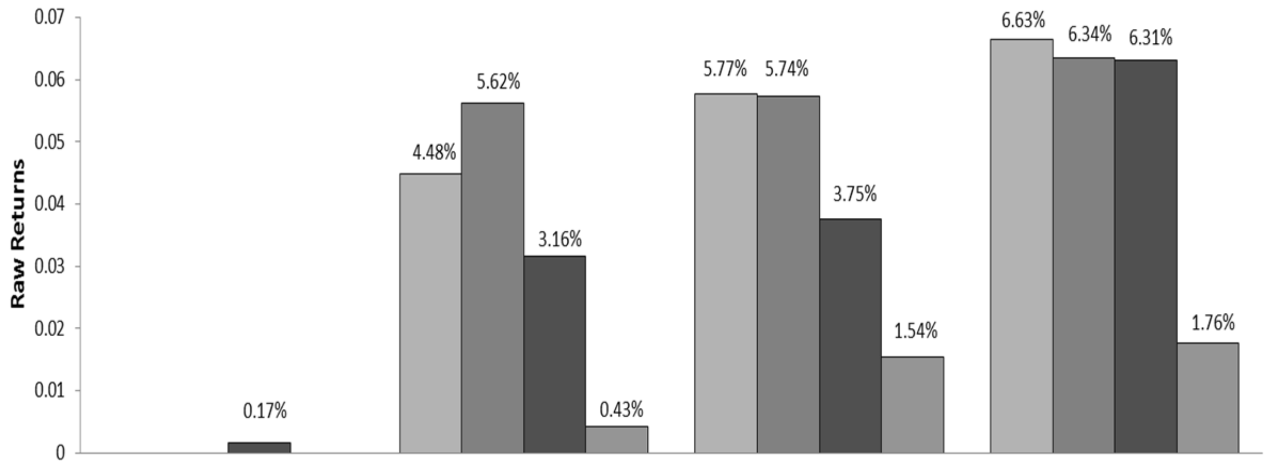
Evaluation criteria		Raw return ranks model		Style-adj. ret. ranks model		Alpha ranks model		Sharpe ratio ranks model	
Eight-quarter-ahead Performance	Investors Performance	Model Performance.	Difference (2) - (1)	Model Performance	Difference (4) - (1)	Model Performance	Difference (6) - (1)	Model Performance	Difference (8) - (1)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Investments									
	N=5928 funds	N=4285		N=4157		N=4136		N=4776	
Raw Return	0.0930	0.1335	*0.0405*	0.1407	*0.0477*	0.1339	*0.0409*	0.1009	*0.0080*
			(3.80)		*(4.25)*		*(3.60)*		*(0.89)*
Style-adj. Return	0.0150	0.0423	*0.0272*	0.0594	*0.0444*	0.0463	*0.0312*	0.0181	*0.0031*
			(2.72)		*(4.27)*		*(2.97)*		*(0.37)*
Alpha	0.0300	0.0504	*0.0201*	0.0576	*0.0275*	0.0576	*0.0269*	0.0396	*0.0087*
			(3.11)		*(3.93)*		*(4.01)*		*(1.68)*
Sharpe Ratio	0.2453	0.2325	*-0.0128*	0.2527	*0.0074*	0.2702	*0.0249*	0.3438	*0.0985*
			(-0.38)		*(0.21)*		*(0.69)*		*(1.97)*
Panel B: Divestments									
	N=6209 funds	N=7852		N=7980		N=8001		N=7361	
Raw Return	0.0916	0.0698	*-0.0218*	0.0671	*-0.0246*	0.0708	*-0.0209*	0.0867	*-0.0049*
			(-3.61)		*(-4.05)*		*(-3.43)*		*(-0.69)*
Style-adj. Return	0.0156	0.0006	*-0.0150*	-0.0077	*-0.0232*	-0.0007	*-0.0163*	0.0135	*-0.0021*
			(-2.60)		*(-4.08)*		*(-2.82)*		*(-0.32)*
Alpha	0.0336	0.0216	*-0.0115*	0.0180	*-0.0149*	0.0192	*-0.0145*	0.0276	*-0.0061*
			(-2.61)		*(-3.45)*		*(-3.29)*		*(-1.18)*
Sharpe Ratio	0.1864	0.2057	*0.0193*	0.1956	*0.0092*	0.1867	*0.0003*	0.1317	*-0.0547*
			(0.64)		*(0.31)*		*(0.01)*		*(-3.48)*
Panel C: Investments minus Divestments									
Raw Return	0.0014	0.0637	*0.0623*	0.0737	*0.0723*	0.0632	*0.0618*	0.0143	*0.0129*
	(0.19)	(6.41)	*(5.07)*	(6.98)	*(5.65)*	(5.90)	*(4.78)*	(1.60)	*(1.12)*
Style-adj. Return	-0.0006	0.0417	*0.0423*	0.0670	*0.0676*	0.0470	*0.0476*	0.0047	*0.0053*
	(-0.09)	(4.43)	*(3.63)*	(6.87)	*(5.66)*	(4.72)	*(3.93)*	(0.56)	*(0.48)*
Alpha	-0.0024	0.0288	*0.0312*	0.0396	*0.0420*	0.0384	*0.0408*	0.0120	*0.0144*
	(-0.56)	(4.70)	*(4.17)*	(5.97)	*(5.31)*	(6.06)	*(5.33)*	(2.20)	*(2.08)*
Sharpe Ratio	0.0589	0.0268	*-0.0321*	0.0571	*-0.0018*	0.0835	*0.0246*	0.2121	*0.1532*
	(1.75)	(0.88)	*(-0.71)*	(1.80)	*(-0.04)*	(2.65)	*(0.53)*	(5.29)	*(2.93)*

Figure B1

Trading Strategies: Sensitivity Analysis of the Underlying Trading Rule

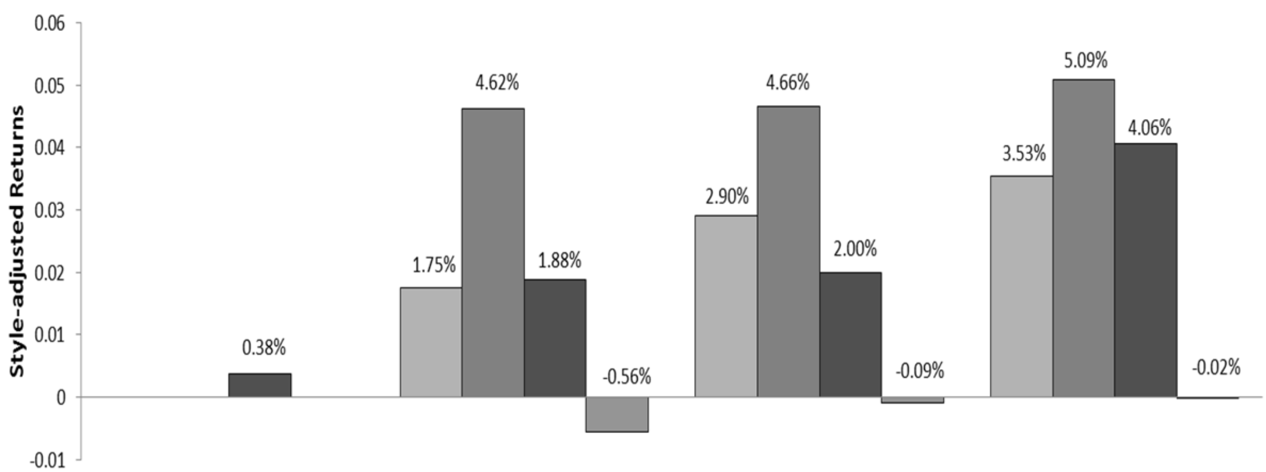
We obtain four-quarter ahead out-of-sample forecasts from four different forecast models of cross-sectional ranks. For each model we define a trading strategy that prescribes to invest if Expected rank≥ τ, and divest otherwise.The figure shows the performance differential, investments minus divestments, of all four strategies for different levels of the threshold τ. We evaluate performance using four criteria: raw returns (Panel A), style-adjusted returns (Panel B), alphas (Panel C) and Sharpe ratios (Panel D).

Panel A. Evaluation of Raw Returns



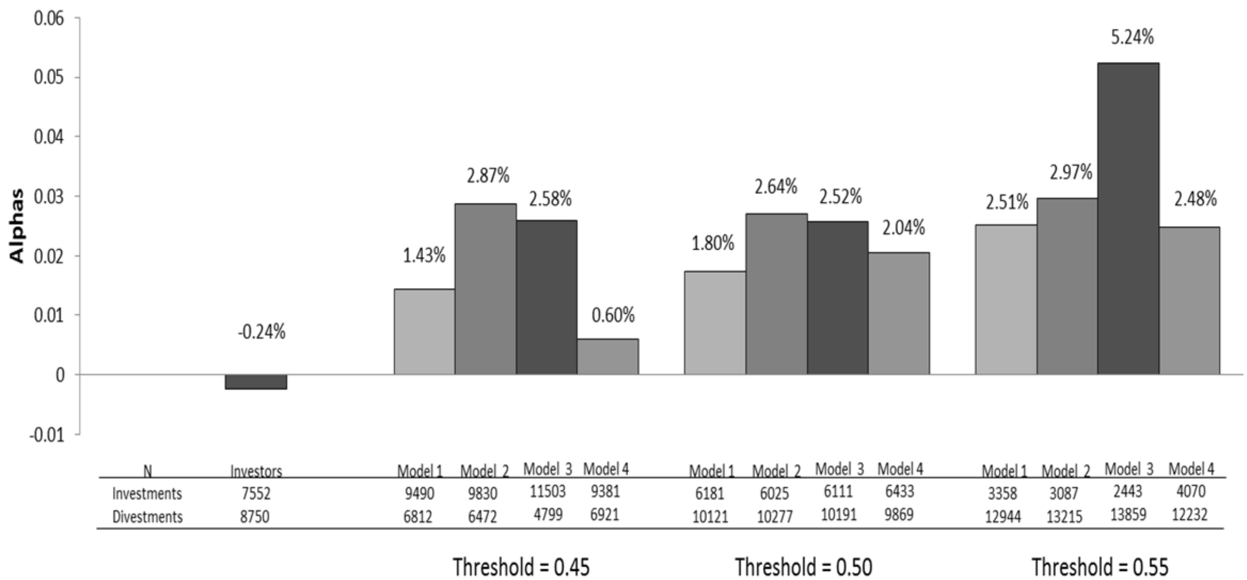
N	Investors	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Investments	7552	9490	9830	11503	9381	6181	6025	6111	6433	3358	3087	2443	4070
Divestments	8750	6812	6472	4799	6921	10121	10277	10191	9869	12944	13215	13859	12232
		Threshold = 0.45				Threshold = 0.50				Threshold = 0.55			

Panel B. Evaluation of Style-Adjusted Returns

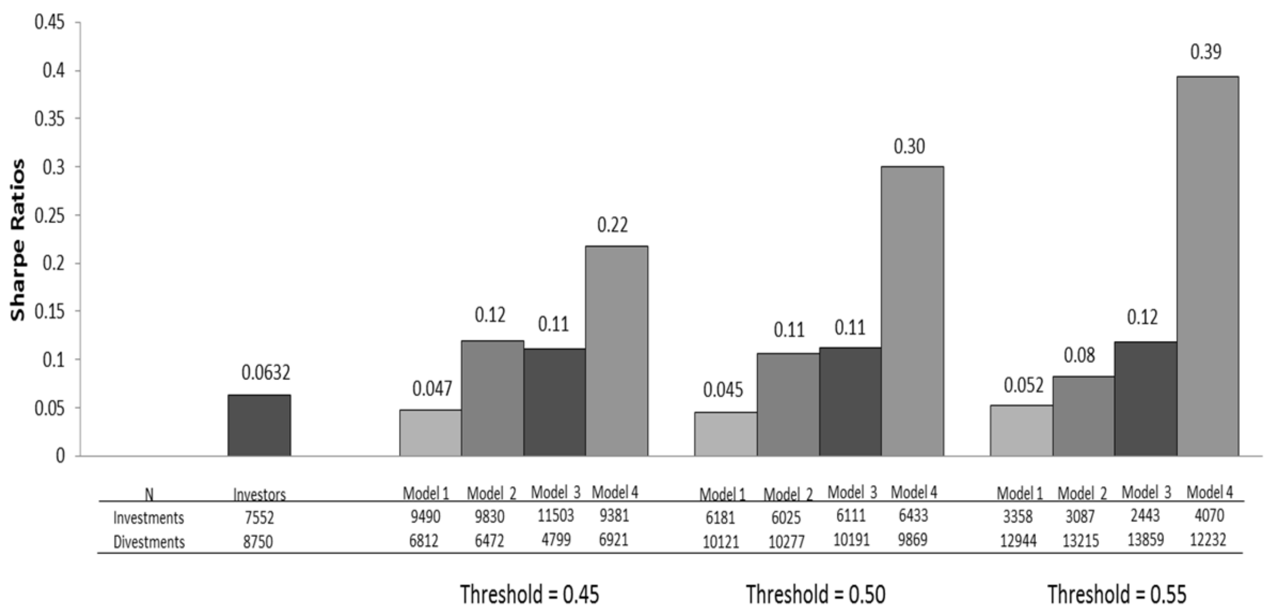


N	Investors	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Investments	7552	9490	9830	11503	9381	6181	6025	6111	6433	3358	3087	2443	4070
Divestments	8750	6812	6472	4799	6921	10121	10277	10191	9869	12944	13215	13859	12232
		Threshold = 0.45				Threshold = 0.50				Threshold = 0.55			

Panel C. Evaluation of Alphas



Panel D. Evaluation of Sharpe ratios



Appendix C. Liquidation model

Estimation of the survival process of hedge funds is key to implement the look-ahead bias correction in Appendix B. Let $y_{i,t}$ be an indicator variable that indicates whether fund i liquidates in quarter t. Our specification describes the probability of fund liquidation ($y_{i,t}$ =0) using a longitudinal probit model, such that a fund does not liquidate if an underlying latent variable, y^*_{it} is positive. That is:

$$y^*_{it} = \alpha + \sum_{j=1}^{8} \gamma_{ij} r_{i,t-j} + \beta' x_{i,t-1} + \lambda_t + \eta_{it} \quad \text{and}$$

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

where $r_{i,t-j}$ is the return of fund i in quarter $t-j$, $x_{i,t-1}$ is a vector of performance metrics and fund-specific characteristics, including a set of style dummies, and λ_t denotes fixed time effects describing economy-wide effects. The distribution of η_{it} is assumed to be i.i.d. standard normal, which results in a pooled probit model.

Table C1: Estimation Results of the Liquidation Model

Parameters	Estimate	Robust t-stat	Parameters	Estimate	Robust t-stat
Intercept	-3.8981	(-3.03)	Lockup period	0.0007	(0.24)
Raw return lag1	-0.5306	(-2.54)	Flows lag 1	-0.7022	(-5.39)
Raw return lag 2	-0.4127	(-1.58)	Flows lag 2	-0.6935	(-6.29)
Raw return lag 3	-0.3579	(-1.42)	Flows lag 3	-0.1670	(-1.27)
Raw return lag 4	-0.1738	(-0.74)	Flows lag 4	-0.2728	(-2.13)
Raw return lag 5	-0.1491	(-0.64)	Offshore	0.0383	(0.81)
Raw return lag 6	0.3637	(1.62)	Incentive fee	0.0030	(0.67)
Raw return lag 7	-0.0284	(-0.12)	Management fee	0.0348	(0.90)
Raw return lag 8	0.1821	(0.76)	Personal Capital	-0.0571	(-1.36)
Alfa 24m	-5.9218	(-2.60)	Leveraged	0.0307	(0.67)
Sharpe ratio 24m	-0.0558	(-0.56)	Ln (AUM)	-0.1276	(-10.56)
Underwater dummy	0.1656	(2.04)	St. Deviation of returns	-1.9222	(-2.57)
High-water mark	-0.1769	(-3.11)	DownUp. Potential ratio	0.0097	(0.34)
Underwater*High-water mark	0.1774	(2.12)	Ln(Age)	1.8075	(3.15)
Share restrictions	0.0198	(0.32)	$[\text{Ln(Age)}]^2$	-0.1965	(-3.00)
N	22510		Wald chi2(88) = 724.19		
pseudo R-sq	0.156		Prob > chi2 = 0.0000		
Log likelihood:	-2242.36				

Appendix D. Survivorship bias correction

Consider a fund in quarter t with eight lagged quarters of returns (i.e. the streak-formation period). For a given streak length ($Streak\_L_t$), we analyse average returns over the subsequent period of n quarters, from t to $t + (n - 1)$. Let $Y_{i,t}^{hist} = 1$ if fund i survived the streak-formation period of eight quarters ($Y_{i,t}^{hist} = 0$ otherwise). Let $Y_{i,t}^{eval} = 1$ if fund i survives the n-quarters evaluation period ($Y_{i,t}^{eval} = 0$ otherwise). The unconditional non-liquidation probability in the streak-formation period, $P\{Y_{i,t}^{hist} = 1\}$, can be estimated by the ratio of the funds not liquidated between the end of quarter $t - 9$ and the end of quarter $t - 1$ to the number of funds present in the sample at the end of quarter $t - 9$. The unconditional non-liquidation probability in the evaluation period, $P\{Y_{i,t}^{eval} = 1|Streak\_L_t\}$, is conditional to the streak length and can be estimated by the ratio of the funds not liquidated between the end of quarter $t - 1$ and the end of quarter $t + (n - 1)$ to the number of funds present in the sample at the end of quarter $t - 1$, for a given streak length.

The conditional non-liquidation probability can be obtained from the liquidation model, Appendix C. Let $y_{i,s}$ be an indicator variable that indicates whether fund i liquidates in quarter s ($y_{i,s}$ =0). The probability that a fund is observed during the entire streak-formation period given both its vector of fund returns R_i and characteristics $X_{i,t}$ (size, age, management fees, investment style), can be obtained as follows:[42]

$$P\{Y_{i,t}^{hist} = 1|R_i, X_{i,t}\} = \prod_{s=t-8}^{t-1} P\{y_{i,s} = 1|r_{i,s-1}, \dots, x_{i,s-1}\}$$

Estimates for the quarterly non-liquidation probabilities at the right-hand side are directly obtained from the liquidation model described in the appendix. Similarly, for the evaluation period:

$$P\{Y_{i,t}^{eval} = 1|R_i, X_{i,t}\} = \prod_{s=t}^{t+(n-1)} P\{y_{i,s} = 1|r_{i,s-1}, \dots, x_{i,s-1}\}$$

Now we can derive the weight factors needed to correct returns for look-ahead bias (see Baquero, Ter Horst, and Verbeek, 2005, for more background and details):

- in the streak-formation period, $w_{i,t}^{hist} = \frac{P\{Y_{i,t}^{hist}=1\}}{P\{Y_{i,t}^{hist}=1|R_i, X_{i,t}\}}$, and
- in the evaluation period, $w_{i,t}^{eval} = \frac{P\{Y_{i,t}^{eval}=1|Streak\_L_t\}}{P\{Y_{i,t}^{eval}=1|R_i, X_{i,t}\}}$.

[42] This definition assumes that liquidation is independent of current or future returns.

Appendix E: Variable definitions

E.1. Flow restrictions

Hedge fund flows are subject to restrictions on both withdrawals and subscriptions. Nearly 91% of funds in our database impose subscription frequencies of 30 days or less; 8.5% impose quarterly subscription periods. The remaining 0.5% allows subscriptions every six months or every year. Liquidity restrictions like redemption frequencies and redemption notice periods are relatively short-term constraints of less than one year. Lockup periods constitute instead long-term constraints (see, for example, Baquero and Verbeek, 2009, Ding et al., 2009, Aiken et al., 2013). Whereas lockup periods restrict only the most recent investors, the combination of redemption and notice periods might adversely affect investor liquidity generally at quarterly horizons. Table E1 shows the possible combinations of redemption frequencies and notice periods found in our sample. Most funds have monthly or quarterly redemption periods and minimum notice periods of 15 to 90 days. Twenty-four percent of funds combine a redemption frequency of 30 days with a notice period of 30 days, but 51% have redemption or notice periods of one quarter or more, which is likely to affect our model of quarterly flows. Our approach differs from previous studies in taking account of the combined effect of redemption frequencies and notice periods independently of lockup periods.[43] We assume an investor at the beginning of quarter t who decides to redeem in response to the performance of fund i reported in quarter $t-1$. For each fund i and quarter t we compute the maximum time for the redeeming decision to become effective. If the delay is longer than one quarter, we classify net flows for fund i in quarter t as *restricted* (dummy variable *ShareR* = 1). We find this to be the case in 15% of fund-quarter observations in our data.

Most funds - around 70% - do not impose long lockup periods, 87% of lockups being 12 months or less. Common lockup periods are 12 months (70%), six months (10%), three months (5%), 24 months (7%) and 36 months (3%). The average lockup is 12.9 months.

[43] In a similar vein, Ding et al. (2009) investigate the effect of share restrictions and illiquidity on the annual flow-performance relationship.

Table E1. Redemption and notice periods

The table shows the frequency (in %) of all combinations of redemption periods and redemption notice periods in our sample.

	Redemption notice periods							
Redemption Periods (days)	No notice period	1 to 7 days	8 to 15 days	16 to 30 days	31 to 90 days	91 to 180 days	180 to365 days	TOTAL
No redemption period	0.58	0.19	0.13	0.45	0.00	0.06	0.00	1.4
1	0.89	0.77	0.00	0.19	0.00	0.00	0.00	1.8
7	0.58	1.53	0.38	0.06	0.00	0.00	0.00	2.6
15	0.00	0.45	0.26	0.13	0.00	0.00	0.00	0.8
30	3.00	5.30	9.97	24.15	11.12	0.26	0.00	53.8
90	1.53	0.13	1.41	12.78	15.27	0.77	0.06	31.9
180	0.19	0.00	0.00	0.38	2.56	0.19	0.00	3.3
365	0.19	0.00	0.00	1.28	2.36	0.19	0.00	4.0
730	0.00	0.00	0.00	0.00	0.00	0.13	0.00	0.13
1095	0.00	0.00	0.00	0.13	0.00	0.00	0.00	0.13
TOTAL	6.96	8.37	12.14	39.55	31.31	1.60	0.06	100

E.2. Return smoothing

We account for the effects of potential return smoothing on streaks and flows by using Getmansky, Lo and Makarov's (2004) time-series model of smoothing. The authors argue that patterns of serial correlation found in hedge fund data are induced by return smoothing, and allege fund exposure to illiquid securities to be the most important source thereof (see also Cassar and Gerakos, 2011). To model return smoothing, Getmansky et al. (2004) assume the reported monthly return R_t^0 to be a weighted average of the contemporaneous true economic returns R_t and k lags:

$$R_t^0 = \theta_0 R_t + \theta_1 R_{t-1} + \cdots + \theta_k R_{t-k}$$

$$\text{where } \theta_j \in [0,1] \; for \; j = 0, \dots, k \text{ and}$$

$$1 = \theta_0 + \theta_1 + \cdots + \theta_k.$$

Getmansky et al. (2004) define the de-meaned return process $X_t = R_t^0 - \mu$, and assume the actual monthly performance innovations to be smoothed using a moving average model with two lags: $X_t = \theta_0 \eta_t + \theta_1 \eta_{t-1} + \theta_2 \eta_{t-2}$, where $\eta_k \sim N(0, \sigma_\eta^2)$. The MA(2) process is estimated using maximum likelihood. The estimated coefficients are normalized by dividing each $\hat{\theta}_i$ by $1 + \hat{\theta}_1 + \hat{\theta}_2$.

We employ three measures of smoothing. The monthly first-order serial correlation coefficient of observed returns, $Corr(R_t^0, R_{t-1}^0)$, is estimated over a rolling window of 24 months. The estimated coefficient $\hat{\theta}_0$ from the above MA(2) process, estimated over a rolling window of 24 months, indicates the proportion of the actual contemporaneous monthly performance innovation included in the reported return. Lower values thus represent greater smoothing. Lastly, we use the smoothing index $\xi = \sum_{j=0}^{2} \theta_j^2$, which measures the concentration of the θ_j coefficients among lags. Lower values of ξ indicate that coefficients are evenly distributed among lags, thus inducing higher serial correlation.

We remove the effects of outliers by winsorizing the three measures to the 5th and 95th percentiles. The average monthly serial correlation coefficient in our sample is 0.11 (with standard deviation 0.23), the average $\hat{\theta}_0$, 0.89, indicating that nearly 90% of the contemporaneous monthly observed return is an innovation to fund performance.

E.3. Performance metrics

Streak length potentially correlates as well with other performance variables and risk metrics. To tease out the effects of streaks in our econometric models, we consider both absolute and relative performance measures over the previous 24 months as controls. We use lagged raw returns and raw ranks on a quarterly, yearly, or two-year basis. We also consider style-adjusted returns (calculated as excess returns relative to the style benchmark) and style-adjusted ranks. We include Sharpe ratios obtained by dividing the mean of the previous 24 monthly returns in excess of the risk-free rate by their standard deviation. Alternatively, to account for autocorrelation in hedge fund monthly returns, we consider smoothing-adjusted Sharpe ratios.[44]

Alphas of individual funds are obtained using Fung and Hsieh's (2004) seven-factor model, commonly used in the literature to model hedge fund returns. The seven asset-based factors include an equity market factor, a bond market factor, a size-spread factor for stocks, a credit spread factor for bonds, and three Primitive Trend-Following risk factors constructed by Fung and Hsieh (2001) based on lookback straddles. More recently, an emerging markets factor has been added to the model. We assume that investors evaluate managers' alphas every quarter by considering the returns over the previous 24 months.[45] In alternative

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[44] Following Lo (2002) and Getmansky et al. (2004), who argue that autocorrelation in monthly returns will bias the Sharpe ratio, we obtain a smoothing-adjusted Sharpe ratio by multiplying the regular Sharpe ratio by $\sqrt{\theta_0^2+\theta_1^2+\theta_2^2}$.

[45] Considering, for instance, the second quarter in 2005 (from April to June), our hypothetical investor would estimate the alpha of a given fund i, α_i, as the intercept from the following regression estimated with eight risk factors over the 24-month period from April 2003 to March 2005,

$$r_{i,t} = \alpha_i + \beta_{1,i} S\&PMRF_t + \beta_{2,i} SCMLC_t + \beta_{3,i} BD10Y_t + \beta_{4,i} CREDSPR_t + \beta_{5,i} PTFSBD_t + \beta_{6,i} PTFSFX_t + \beta_{7,i} PTFSCOM_t + \beta_{8,i} MSCIEM_t + \varepsilon_{i,t} ,$$

specifications, we use alphas obtained from a one-factor CAPM model, also widely used among investors, and alphas from either model estimated over a longer horizon of 36, or shorter horizon of 12, months. We report in Table 4 summary statistics for these different alpha estimates. The average alpha from the eight-factor model estimated by rolling regressions over a 24-month horizon is 0.32% per month, and varies widely across funds, having a standard deviation of 1.29%.

Another potentially valuable performance indicator is whether or not a manager's option-like contract is deeply out of the money relative to the high-water mark provision (HWM). Several studies have shown an under-water indicator reflecting cumulative negative returns over a period of four to eight quarters to be a strong predictor of fund liquidation (see, for example, Brown, Goetzmann and Park, 2001, and Baquero, ter Horst and Verbeek, 2005). This is particularly relevant to our study, as a long losing streak could simply reflect a fund deeply under the high-water mark. We follow this literature in defining an under water dummy that is equal to one if a fund's cumulative return over the past eight quarters is negative.[46]

E.4. Risk metrics

We capture fund riskiness in terms of total risk (standard deviation of historical returns) and measures of downside risk. One popular measure that captures aversion to negative skewness is the downside-upside potential ratio, which combines downward variation as the numerator and upside potential as the denominator. We use the following definition of the downside-upside potential ratio,

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

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where $r_{i,t}$ is the excess monthly return of fund i in month t, $S\&PMRF_t$ is the excess return on the S&P500 index in month t, $SCMLC_t$ is a size spread factor constructed as the difference between the Russell 2000 index monthly total return and the S&P 500 monthly total return, $BD10Y_t$ is the yield spread of the U.S. 10-year Treasury bond over the three-month T-bill, $CREDSPR_t$ is the change in the credit spread of Moody's BAA bond over the 10-year Treasury constant maturity yield, $PTFSBD_t$, $PTFSFX_t$ and $PTFSCOM_t$ are the excess returns on portfolios of lookback straddle options on bonds, currencies, and commodities, respectively,[45] and $MSCIEM_t$ is the excess return on the MSCI Emerging Market index monthly total return in month t. Return data on primitive trend-following risk factors based on lookback straddles on bonds, currency, and commodities are obtained from David Hsieh's Data Library at http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls. This link also provides the sources of the other risk factors in the model.

[46] Using an under-water indicator based on negative cumulative returns over the past four quarters yields somewhat weaker results.

where $\iota^{-} = 1$ if $r_{i,t} \leq r_{mar}$, 0 otherwise, $\iota^{+} = 1$ if $r_{i,t} > r_{mar}$, 0 otherwise, $r_{i,t}$ is the return of fund *i* at time *t*, and r_{mar} refers to the minimal acceptable rate of return, or investor's target return. We measure downside deviations and upside potential with respect to the return of three-month Treasury bills over the prior 24 months or, alternatively, the entire past history of the fund.

The length of a performance streak might also correlate with a fund's exposure to operational risk arising from inadequate internal governance. The ω-score, a proxy for operational risk developed by Brown, Goetzmann, Liang and Schwarz (2008) that captures conflicts of interest and legal and regulatory problems in the Form ADV filings,[47] is obtained by correlating the variables from the Form ADV filings in February 2006 with fund characteristics from the TASS hedge fund database. Although their study finds no influence of operational risk on the flow-performance relation, we include the ω-score for the year 2005 as a control variable in several robustness tests.

E.5. Managerial incentives

The asymmetric incentive fee contract affords hedge fund managers options on investors' assets under management. We measure managerial dollar incentives using managers' option delta, calculated quarterly following a modified version of the algorithm proposed in the appendix of Agarwal, Daniel and Naik (2009). Our calculation assumes incentive fees to be paid quarterly (as opposed to yearly, in Agarwal et al., 2009), and the exercise price to be reset as of quarter-end. It further assumes investors to enter or quit funds sequentially, and managers to reinvest all after-tax incentive fees into their funds, at the end of each quarter (quarter-end flows are assumed to come from a single investor). We use the US Treasury bill as the hurdle rate. All other assumptions are as in Agarwal et al. (2009). We compute the option delta for each contract for each quarter using Black and Scholes (1973) formula, the market value of each investor's AUM net of fees at the end of the previous quarter as the spot price, and the exercise price after reset as of the previous-quarter-end. A fund's total delta is the sum of the manager's option delta and the delta from the manager's stake. The average total delta in our sample is USD 382,634, the average manager's option delta about USD 155,990 (see Table 4).

[47] The study exploits a short time window in 2006 when hedge fund managers were required to file Form ADV with the SEC. We are grateful to Bing Liang for facilitating the ω-score for the year 2005.

Table E2

Definition of variables

All variables are estimated at the same quarter-end (t-1) unless otherwise noted.

Variable name	Definition
Performance Streaks	
W2_TBill - W8_TBill	Mutually exclusive dummies indicating a past winning streak relative to the US Treasury bill of length *j* quarters ending in quarter *t-1* for fund *i*.
L1_TBill - L8_TBill	Mutually exclusive dummies indicating a past losing streak relative to the US Treasury bill of length *j* quarters ending in quarter *t-1* for fund *i*.
Performance variables	
Count_k	Dummy indicators corresponding each to a given number of winning quarters within the previous eight-quarter period. Count_8 is omitted as it coincides with W8_TBill, while Count_0 is omitted as it coincides with L8_TBill.
Annual Rank_lag1	Fractional rank based on four-quarter compounded raw returns between quarters t-1 and t-4.
Annual Rank_lag2	Fractional rank based on four-quarter compounded raw returns between quarters t-5 and t-8.
Rank12m alpha	Fractional rank based on alphas obtained from the estimation of Fung & Hsieh model over the previous 12 months
Rank 24m alpha	Fractional rank based on alphas obtained from the estimation of Fung & Hsieh model over the previous 24 months
Rank 36m alpha	Fractional rank based on alphas obtained from the estimation of Fung & Hsieh model over the previous 36 months
Rank 12m Sharpe Ratio	Fractional rank based on Sharpe ratios calculated using the previous 12 monthly returns
Rank 24m Sharpe Ratio	Fractional rank based on Sharpe ratios calculated using the previous 24 monthly returns
Rank 36m Sharpe Ratio	Fractional rank based on Sharpe ratios calculated using the previous 36 monthly returns
Rank 24m Information Ratio	Fractional rank based on information ratios calculated by dividing alpha by the standard deviation of residuals, using the previous 24 monthly returns
Rank alphaCAPM12	Alpha obtained from an estimation of a CAPM model over the previous 12 months
Rank alphaCAPM24	Alpha obtained from an estimation of a CAPM model over the previous 24 months
Rank alphaCAPM36	Alpha obtained from an estimation of a CAPM model over the previous 36 months
Underwater Dummy	Dummy indicating whether the fund has a negative cumulative return over the past eight quarters.
Downside-Upside Potential Ratio	Ratio combining downside potential as the numerator and upside potential as the denominator, relative to the US Treasury bill, calculated over the previous 24 months, or over the entire previous history of the fund.
Downside Potential	Root mean squared deviations of monthly returns below a given threshold referred to as the minimal acceptable rate of return (e.g. the US Treasury bill).
Upside Potential	Mean deviation of monthly returns above a given threshold referred to as the minimal acceptable rate of return (e.g. the US Treasury bill).
Standard Deviation	One-quarter lagged Standard Deviation of monthly returns, calculated over the previous 24 months, or over the entire previous history of the fund.
Expected Rank	Forecast from a model explaining fractional ranks.
RMSE	Root mean squared error of the eight lagged forecasts and a proxy for the accuracy of Expected Rank

Fund characteristics	
Share Restrictions	Dummy indicating whether short-term share restrictions (i.e. redemption frequency combined with redemption notice periods) prevent outflows in current quarter in response to performance observed in previous quarter.
Lockup periods	Long term constraint to redeem. The lockup period is time invariant and expressed in months.
High-water mark	Dummy indicating the presence of a high-water mark in the manager's contract (time invariant).
Omega score 2005	Proxy for operational risk developed by Brown, Goetzmann, Liang and Schwarz (2008) for the year 2005.
Ln(AUM)	Natural log of fund's size (Assets Under management, in USD) in the prior quarter
Ln(AGE)	Natural log of fund's age in the prior quarter (in months since inception).
Offshore	Dummy taking value 1 if the fund is offshore, as opposed to Onshore (time invariant).
Incentive Fees	% of profits paid as an incentive bonus to the fund's manager.
Total Delta	Sum of the manager's option delta and the delta from the manager's stake.
Manager's Option Delta	Sum of deltas of the portfolio of options on all investors' AUM. Calculated quarterly following the algorithm from Agarwal, Daniel and Naik (2009).
Management Fees	% of Assets under management paid as a fee to the manager.
Personal Capital	Dummy taking value one if the manager's personal capital is invested in the fund (time invariant).
Leverage	Dummy indicating whether the fund uses leverage (time invariant).
Omega score 2005	Proxy for operational risk developed by Brown, Goetzmann, Liang and Schwarz (2008) for the year 2005.
Smoothing variables	
Serial Correlation	The monthly first-order serial correlation coefficient of observed returns, estimated over a rolling window of 24 months.
Theta Coefficient	The estimated coefficient $\hat{\theta}_0$ from the MA(2) process from Getmansky et al [2004], estimated over a rolling window of 24months.
Smoothing Index	The smoothing index, $\xi = \sum_{j=0}^{2} \theta_j^2$, measures the concentration among lags of the θ_j coefficients from the MA(2) process from Getmansky et al [2004]
Cash flows	
Cash Flows	Net flows measured as a 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} for the quarter, had all dividends been reinvested
Dollar Flows	Net flows measured in dollar terms, computed as a net change in assets minus internal growth.
Flows lag k	Net flows k^{th} quarterly lag
Style dummies (defined on the basis of CSFB/Tremont indices)	
Convertible Arbitrage, Dedicated Short Bias, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro, Long/Short Equity, Managed Futures, Other Styles.	