Management Science

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Published in Management Science on August 12, 2021 as DOI: 10.1287/mnsc.2021.4067.
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MANAGEMENT SCIENCE
Vol. 68, No. 6, June 2022, pp. 4151–4172
ISSN 0025-1909 (print), ISSN 1526-5501 (online)

Hedge Fund Flows and Performance Streaks: How Investors Weigh Information

Guillermo Baquero,[a] Marno Verbeek[b]

[a] European School of Management and Technology, 10178 Berlin, Germany; [b] Department of Finance, Rotterdam School of Management, Erasmus University, 3000 DR Rotterdam, Netherlands

Contact: baquero@esmt.org, https://orcid.org/0000-0003-1929-7863 (GB); mverbeek@rsm.nl, https://orcid.org/0000-0002-4079-6774 (MV)

Received: April 13, 2018
Revised: November 16, 2019; February 19, 2021
Accepted: February 22, 2021
Published Online in Articles in Advance: August 12, 2021

https://doi.org/10.1287/mnsc.2021.4067

Abstract. Cash flows to hedge funds are highly sensitive to performance streaks, a streak being defined as subsequent quarters during which a fund performs above or below a benchmark, even after controlling for a wide range of common performance measures. At the same time, streaks have limited predictive power regarding future fund performance. This suggests investors weigh information suboptimally, and their decisions are driven too strongly by a belief in continuation of good performance, consistent with the "hot hand fallacy." The hedge funds that investors choose to invest in do not perform significantly better than those they divest from. These findings are consistent with overreaction to certain types of information and do not support the notion that sophisticated investors have superior information or superior information processing abilities.

History: Accepted by David Simchi-Levi, finance.
Supplemental Material: The online appendices are available at https://doi.org/10.1287/mnsc.2021.4067.

Keywords: hedge funds • cash flows • hot hand fallacy • performance streaks • relative weights • smart money

1. Introduction

The literature from psychology and economics documents 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 (Greenwood and Shleifer 2014). Investors may attach disproportionate importance to streak lengths because performance streaks are easily observable and may be perceived to be more informative than is justified empirically. This tendency may also drive investors' decisions on how to allocate their wealth. As a result, investors' money flows may be particularly directed toward professional asset managers that have consistently performed above average in a number of consecutive periods and moved away from managers with losing streaks in their performance. In this paper, we empirically investigate hedge fund investors' money flows and the extent to which their behavior is driven by the lengths of performance streaks.

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 that past performance, summarized in several different measures, plays a significant role in hedge fund investors' capital allocation (Li et al. 2011, Aragon et al. 2014, Agarwal et al. 2018, Liang et al. 2019). Our focus is on the role of performance streaks in hedge fund investors' allocation decisions from the broader perspective of how investors process information. Investigating a sample of hedge funds over the period 1995–2018, 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, even when a wide range of other performance metrics are controlled for. Yet, given that the information content of such streaks relative to future performance is limited, hedge fund investors, on average, appear to weigh information signals suboptimally and thus make inferior investment and divestment decisions.

People's biased tendency to respond to streak patterns has been widely documented in the psychological literature (Gilovich et al. 1985). Several 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. Rabin (2002) describes a model based on representativeness and the law of small numbers (Tversky and Kahneman 1971), which leads to two well-known biases in pattern recognition: the *gambler's fallacy*, a mistaken belief in mean reversion,[1] and the *hot-hand fallacy*, a belief that a series of signals is too long to be random.[2] We focus on the latter bias, implying that agents expect continuation of a series of

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signals after longer streaks of similar signals. In the context of hedge funds, investors who believe that, say, six consecutive quarters of performance above a given benchmark is likely to reflect managerial skill, expect the fund to outperform in the future, even when winning streaks are completely driven by randomness.[3] The model of Rabin and Vayanos (2010) hinges on a mistaken belief by economic agents that the true series of signals exhibits reversals and also predicts that individuals overreact to long streaks. Similarly, the model of Barberis et al. (1998) of investor sentiment generates under-reaction to signals that revert frequently and overreaction to signals that trend.

In line with these predictions, we document that investor flows are strongly sensitive to performance streaks. Our empirical analysis of hedge fund flows over the period 1995–2018 shows that the length of performance streaks matters to investors in an economically and statistically significant way, beyond the role of other performance measures, like past alpha, Sharpe ratio, and performance ranks. Hedge funds with long streaks of winning quarters are expected to experience significantly higher growth rates than those with losing streaks, conditional on other measures of past performance. The difference in expected flows is about 5%–6% (percentage points), which is in the same order of magnitude as the impact of past performance ranks. This finding is robust across investment styles and sample periods.

We continue our analysis to determine whether investors' sensitivity to performance streaks can be attributed to the ability of streaks to predict future performance. We do this in different ways. First, we compare the relative weights of the explanatory variables in the flow regressions with those in several alternative performance forecasting models, using a relative weights analysis (Johnson 2000). This shows that investors attach more weight to performance streaks than is justified by their importance in predicting hedge funds' relative performance. For example, when predicting style-adjusted return ranks, fund characteristics, annual ranks, other performance controls, and style dummies attribute 87% to the explanatory power, leaving only 10% or less for the performance streaks. In the flows model, annual ranks and other performance controls account for 46%, followed by the streaks. Second, we expand the flow regressions by including predicted performance, as well as a measure of its accuracy. If investors respond to performance streaks solely because of their ability to predict future performance, the streaks should become irrelevant once the performance forecasts are controlled for. However, the role of performance streaks (and most other variables) hardly changes, suggesting that investors attach differential importance to streaks and other performance measures than is justified by their ability to predict future fund performance.

These results could be partly explained if flows themselves affect future performance negatively, for instance, because of a temporary impact on valuations in a fund's underlying securities, capacity constraints, or decreasing returns to scale (as implied by the model of Berk and Green 2004). 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 flows on subsequent performance.

There are potentially omitted factors in both the flows model and the performance forecast model that are unobservable to the econometrician but known to investors. In the final part of the paper, we test the hypothesis that investors are better informed than the empirical forecast models by comparing how investors perform ex post relative to some simple strategies based on the models' predictions. The average return of funds that investors invest in exceeds that of funds investors divest from by a small and statistically insignificant 0.56%/yr on an equally weighted basis. On a cashflow-weighted basis, the difference is −1.48%/yr, suggesting little evidence of a smart money effect on the side of hedge fund investors. Despite the fact that their forecasting ability is limited, the average performance of funds the forecast models tell to invest in is significantly higher than that of funds the models divest from. This shows that, on average, money flows of hedge fund investors are not wealth enhancing, and a straightforward econometric model relatively easily beats their performance. These results are robust to tests that take into account potential restrictions to inflows and outflows, different trading rules underlying the benchmark allocations, and potential flow-induced performance as suggested by the model of Berk and Green (2004).

Our work makes a number of important contributions to the 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.[4] 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 significantly larger flows, and those with long negative streaks experience lower flows, even after controlling for a wide range of performance measures and other fund characteristics. Second, we complement the behavioral literature on individual investors and mutual fund investors (Bailey et al. 2011 and references therein) by focusing on a more sophisticated segment of financial markets and showing the behavior of hedge funds investors is consistent with the

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hot hand fallacy. 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 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 and fund alpha). Fourth, we contribute from a new angle to the small but growing literature that studies hedge fund investors' ability to anticipate future fund performance (Baquero and Verbeek 2009, Dichev and Yu 2011, Ramadorai 2013, Ozik and Sadka 2015, Liang et al. 2019). The relatively poor performance of hedge fund investors appears partly attributable to their overreaction to performance streak lengths.

Overall, 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 allocation decisions attach too much weight to performance streaks.

2. Data and Variables

We use survivorship-free data on individual hedge funds from the Lipper Hedge Fund Database (TASS). 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-hedge-funds and multistrategy funds. Our sample covers the period January 1995 to September 2018 and contains 7,252 funds. Effectively, most of our results are based on a smaller sample of 2,794 funds, for which all necessary fund characteristics, assets under management and lagged performance measures are observed. Of these, 2,342 do not provide information through the end of our sample period, for various reasons (e.g., liquidation (559 cases) or removal at the fund manager's request). We refer to the latter phenomenon as self-selection. 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 Online Appendix A for a description of flow restrictions in our sample.

We argue investors are sensitive to the precise pattern of performance signals they observe. In the hedge fund industry, information on individual funds' returns and assets under management is released to investors for monitoring purposes, typically through monthly or quarterly performance reports. However, self-reported monthly returns tend to suffer from return smoothing (Getmansky et al. 2004) and data revisions (Patton et al. 2015).[5] In addition, most redemption restrictions operate quarterly. Consequently, we prefer to study investor flows in response to performance signals over quarterly rather than monthly frequencies (similar to Lim et al. 2016 and Liang et al. 2019).

Our data set is corrected for backfilling, or instant history, bias, a type of selection bias owing to the self-reported nature of hedge fund information (Ackermann et al. 1999, Fung and Hsieh 2000). Backfilling bias arises if a manager chooses to commence reporting only after a period of good performance, in which case backfilled returns appear systematically higher than nonbackfilled returns and relatively long winning streaks are more likely to occur. We control for backfilling bias by considering only returns reported after the date a fund was added to the TASS database (Aggarwal and Jorion 2010). Following a standard definition, 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, that is,

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

We winsorize the distribution of cash flows at the 1% level to control for the extreme outliers typically observed in cash flow data. Across the entire sample, the average growth rate is −0.7% per quarter, whereas we observe positive growth in only 45% of the cases. We interpret net money flows as a measure of investors' average opinion of a fund.

We argue that performance streaks, defined as the numbers of successive signals above or below a relevant benchmark, have a major impact on hedge fund flows beyond the usual sensitivity to past performance documented in previous studies (Agarwal et al. 2009, Baquero and Verbeek 2009, Liang et al. 2019). Table 1 summarizes the series of successive quarterly return signals above and below the quarterly U.S. Treasury bill identified in our data set. We refer to these, respectively, as winning and losing streaks. A winning streak commences when a return reverses from below to above the benchmark. Its length is the number of consecutive quarters the fund performs above the benchmark. For example, for a fund that is a loser in 2007Q1 (first quarter of 2007) but a winner in 2007Q2, 2007Q3, and 2007Q4, we identify one-quarter (2007Q2), two-quarter (2007Q2, 2007Q3), and three-quarter (2007Q2, 2007Q3, 2007Q4) winning

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Table 1. Summary of Winner and Loser Streaks

(1) Streak length	(2) Number of observations	(3) Subsequent liquidation %	(4) Subsequent self-selection %	(5) Subsequent persistent winner % (panel A) and loser % (panel B)	(6) Unknown subsequent performance %	(7) Subsequent positive (panel A) and negative (panel B) money flows %	(8) Percent of missing money flows observations	(9) Average amount of dollar flows invested (panel A) and divested (panel B)	(10) Frequency of wrong forecasts up % (panel A) and down % (panel B)
Panel A: Winner Streaks									
1	20,829	1.17	0.86	63.44	0.00	42.64	10.65	−972,585	32.11
2	13,213	1.02	0.54	65.72	0.24	48.35	10.86	3,386,273	31.29
3	8,684	0.77	0.59	69.24	0.12	52.08	11.05	6,546,748	27.79
4	6,012	0.72	0.55	64.82	0.33	55.66	11.03	9,746,145	31.50
5	3,897	0.72	0.44	68.87	0.10	57.35	11.01	13,530,071	27.92
6	2,684	0.48	0.63	66.17	0.56	58.12	11.48	12,455,015	31.03
7	1,776	0.34	0.62	72.41	0.06	58.39	11.99	13,736,634	24.78
8	1,286	0.62	0.70	71.85	0.31	59.95	11.66	17,414,802	23.09
Panel B: Loser streaks									
1	20,859	1.54	0.92	40.07	0.00	46.59	10.34	−2,899,320	56.20
2	8,357	2.23	1.35	41.29	0.93	54.54	9.90	−9,285,323	55.20
3	3,451	3.10	1.68	44.48	0.43	60.50	9.53	−13,102,332	52.78
4	1,535	3.78	1.37	51.07	0.20	60.98	8.93	−15,031,057	46.05
5	784	4.21	1.15	52.93	0.51	62.37	9.18	−20,125,412	45.19
6	415	2.89	2.17	49.16	0.24	60.24	10.60	−12,772,699	54.00
7	204	4.90	2.94	37.75	0.49	59.31	12.75	−11,724,807	58.68
8	77	3.90	3.90	57.14	0.00	57.14	12.99	−19,815,204	36.36

Notes. In each quarter, we define the winners and the losers taking the 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.

streaks observed in 2007Q3, 2007Q4, and 2008Q1, respectively.

For a first impression of the distribution of winning and losing streaks, and subsequent money flows, we present a number of summary statistics in Table 1. Panel A shows the results for winning streaks. For instance, we identify 8,684 three-quarter winning streaks between 1995Q1 and 2018Q2. In the subsequent quarter, 0.77% of funds liquidate, 0.59% self-select out, 69.2% remain winners (i.e., persistent funds), and 52.1% receive positive net flows of money. Net money flows directed toward funds with a successful three-quarter streak average more than $US 6.5 million per fund (note that subsequent performance and money flows are missing for some observations; see columns 6 and 8).

Results reported in panel A suggest that remaining above the U.S. Treasury bill is difficult for a hedge fund, only 63.4% of the observations with a one-quarter winning streak persisting above the T-bill for a second quarter. The likelihood of remaining above the T-bill increases to some extent with streak length (see column 5). We observe a concomitant reaction on the part of investors, who appear to increase their investments significantly as streak lengths increase (see column 9). The average money flow experienced by a fund following a two-quarter winning streak is approximately $US 3.39 million and about $US 13.5 million following five successful quarters. For longer streaks, amounts tend to stabilize, possibly because money inflows become increasingly restricted as funds grow in size. The percentage of funds receiving positive net flows of money increases monotonically with streak length, as indicated in column 7. 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 column 10. For streaks two quarters in length, positive money flows were directed to subsequent loser funds in 31.3% of cases. This percentage diminishes to some extent for longer streaks.

Panel B of Table 1 shows the results for losing streaks. Interestingly, longer losing streaks are less likely to occur than winning streaks of the same length (column 2). For example, there are only 77 cases of a losing streaks of eight quarters or more versus 1,286 cases of such winning streaks. Second, liquidation rates after losing streaks are much higher and so is the likelihood of no longer reporting to TASS, often a first step toward final liquidation (Ter Horst and Verbeek 2007). For example, after a losing streak of four quarters, 3.8% percent of the funds subsequently liquidate. From column 5, 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 52.9% probability of persisting as a loser in the subsequent quarter, whereas only 41.3% of funds remain a loser after two consecutive quarters of poor performance.[6] 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 might be left to withdraw from a fund with a long losing streak. Several 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.

Two patterns emerge from the stylized evidence presented in Table 1. First, 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 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.

Obviously, performance streaks correlate with measures of fund performance and risk. Empirically, funds with longer winning streaks tend to have higher historical alphas and Sharpe ratios, a lower standard deviation, and a better downside-upside potential ratio. The opposite picture holds for funds with longer losing streaks. Thus, the lengths of performance streaks capture, to some extent, information about funds' past risk and performance. For example, a long winning streak is associated with lower risk and superior risk-adjusted performance over the previous two years. The key questions are whether is there any role for performance streaks in explaining investor flows, controlling for various performance and risk metrics,

Table 2. Descriptive Statistics

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
		Fund characteristics			
Ln(AUM)	52,771	17.8908	1.7953	0.0000	24.3281
Ln(Age)	52,771	4.5669	0.4515	3.8501	5.9243
Offshore	52,771	0.5137	0.4998	0.0000	1.0000
Incentive Fee	52,771	18.6295	4.8478	0.0000	50.0000
Management Fee	52,771	1.3636	0.4618	0.0000	4.0000
Personal Capital	52,771	0.4206	0.4937	0.0000	1.0000
Leveraged	52,771	0.6425	0.4793	0.0000	1.0000
High-Water Mark	52,771	0.7562	0.4294	0.0000	1.0000
Lockup Period	52,771	4.4371	7.0264	0.0000	84.0000
Convertible Arbitrage dummy	52,771	0.0434	0.2038	0.0000	1.0000
Dedicated Short Bias dummy	52,771	0.0070	0.0834	0.0000	1.0000
Emerging Markets dummy	52,771	0.1335	0.3402	0.0000	1.0000
Equity Market Neutral dummy	52,771	0.0528	0.2237	0.0000	1.0000
Event Driven dummy	52,771	0.1337	0.3403	0.0000	1.0000
Fixed income Arbitrage dummy	52,771	0.0475	0.2126	0.0000	1.0000
Global Macro dummy	52,771	0.0621	0.2413	0.0000	1.0000
Long Short Equity dummy	52,771	0.4591	0.4983	0.0000	1.0000
Managed Futures dummy	52,771	0.0022	0.0472	0.0000	1.0000
Other Styles	52,771	0.0586	0.2349	0.0000	1.0000
		Cash flows			
Cash Flows (growth rate)	52,771	−0.0070	0.1866	−0.6086	1.4119
Cash Flows>0	23,719	0.1006	0.1916	0.0000	1.4119
Cash Flows<0	29,040	−0.0949	0.1270	−0.6086	−0.0000
Dollar Flows	52,771	−919,368	68,683,768	−1,432,103,168	1,555,416,704
		Performance variables			
Quarterly Return	52,771	0.0183	0.1027	−1.0000	4.6725
alpha Fung&Hsieh_24 months	52,771	0.0031	0.0119	−0.1496	0.2462
Sharpe Ratio 24m	52,771	0.2525	0.5527	−1.6602	21.2664
Underwater dummy	52,771	0.2163	0.4117	0.0000	1.0000
Standard Deviation (monthly ret.)	52,771	0.0386	0.0402	0.0000	1.9456
Downside-Upside Pot. Ratio	52,771	1.7074	8.4010	0.0000	1249.2905
Autocorrelation Coefficient	52,771	0.0932	0.2392	−0.7745	0.9738

Notes. Averages of main variables, based on a sample of 2,794 open-end hedge funds between 1995Q1 and 2018Q2, as well as standard deviations and extremes. Variable definitions are provided in Online Appendix A.

and whether this improves investor allocations in terms of subsequent performance. We move to the first of these questions in the next section.

Table 2 presents descriptive statistics for several fund-specific characteristics, as well as a range of performance and risk metrics used in our regressions. We obtain eight-factor alphas from the seven-factor model of Fung and Hsieh (2004), augmented with an emerging markets factor, estimated over moving windows of 24 months. Similarly, the Sharpe ratio and return standard deviation are estimated using 24-month windows. The underwater dummy indicates whether cumulative returns over a period of eight quarters are negative (Brown et al. 2001). Return smoothing is proxied by the monthly first-order serial correlation coefficient. A brief description of each variable is provided in Table A2 in Online Appendix A. Average fund age in our final sample is about eight years and assets under management $US 58.9 million. The most common investment style is long-short equity (45.9% of our sample), followed by event driven (13.4%) and emerging markets (13.4%).

3. Explaining Hedge Fund Flows

The results in Table 1 suggest that hedge fund investors allocate more money to funds that perform successfully above the U.S. Treasury bill over multiple quarters, that is, to funds with longer winning streaks. Clearly, other factors are likely to affect investor decisions, like size, age, style, and other fund-specific features. Sophisticated investors, especially, attend to these characteristics and to other performance measures and variables that account for risk. Following most of the literature (Lim et al. 2016, Agarwal et al. 2018, Liang et al. 2019), we consider a linear model explaining the relative flows (growth rates) of hedge fund i in quarter t from a wide range of characteristics, including indicators for the lengths of winning and losing performance streaks:

$$
\begin{aligned}
&\mathit{Cash\ Flow}_{it}\\
&\quad = \alpha + \sum_{j=2}^{8}\beta_{1j}W_{jit-1} + \sum_{j=1}^{8}\beta_{2j}L_{jit-1} + \sum_{j=1}^{6}\beta_{3j}\mathit{Count}_{jit-1}\\
&\qquad + \left[\beta_4 \mathit{AnnualRnk}_{it-1} + \beta_4^B \mathit{Bottom30}_{it-1} + \beta_4^T \mathit{Top30}_{it-1}\right]\\
&\qquad + \left[\beta_5 \mathit{AnnualRnk}_{it-5} + \beta_5^B \mathit{Bottom30}_{it-5} + \beta_5^T \mathit{Top30}_{it-5}\right]\\
&\qquad + \beta_6 \mathit{Rnk\_alpha}_{it-1}^{2y} + \beta_7 \mathit{Rnk\_Sharpe}_{it-1}^{2y} + \beta_8 \mathit{Under}_{it-1}^{2y}\\
&\qquad + \beta_9 \sigma_{it-1} + \beta_{10}\mathit{DWUP}_{it-1} + \beta_{11}\mathit{Corr}_{it-1}^{2y} + \beta_{12}\mathit{ShareR}_{it}\\
&\qquad + \beta_{13}\mathit{ln}(\mathit{AUM}_{it-1}) + \beta_{14}\ln(\mathit{AGE}_{it-1})\\
&\qquad + \sum_{j=1}^{8}\beta_{15j}\mathit{Cash\ Flow}_{it-j} + \gamma'\mathbf{X}_{it} + \lambda_t + \varepsilon_{it}, \qquad (1)
\end{aligned}
$$

where W_{jit-1} and L_{jit-1} $(j = 1 \dots 8)$ are 16 dummies indicating a past winning or losing streak of length j quarters ending in quarter $t-1$ for fund i. These dummies are mutually exclusive and reflect the length of the longest winning or losing streak over the preceding quarters. That is, $W_{jit-1} = 1$ if fund i is a winner in the previous j quarters *only*, and 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 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 only the total number of winning periods over a two-year horizon matters to investors, independent of their sequence. We control for this by including 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. In a similar vein, Bollen and Pool (2009) include the number of above-benchmark returns in their flow regressions. We avoid multicollinearity by including only $Count_1$ to $Count_6$.

Annual performance ranks over each of the previous two years are included, where we allow for a nonlinear 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.[7] We also control for other performance measures commonly used by sophisticated investors, like eight-factor alphas (Fung and Hsieh 2004) and Sharpe ratios over the preceding 24-month period. Our main specification uses ranks based on Sharpe ratios and alphas.[8] A dummy indicating whether two-year cumulative returns are negative or positive is used as a proxy for a fund being deep under the high-water mark, and 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. $ShareR_{it}$ is a dummy representing fund share restrictions that apply as a result of redemption frequencies combined with redemption notice periods. Based on this information, we compute the maximum time for an investor's decision to become effective. If that delay is longer than one quarter, we classify net flows as restricted ($ShareR_{it} = 1$). The standard deviation of monthly returns, σ_{it-1}, and downside-upside potential ratio, $DWUP_{it-1}$, are computed over the previous 24 months. The model controls for log size (total assets under management), age of the fund, flows lagged one to eight quarters, and further includes a set of fund-specific, time-invariant characteristics like management and incentive fees, lockup periods, and managerial ownership and investment style.

Before presenting our estimation results, we briefly highlight three key choices underlying the model specification in (1). First, we define winning and losing in the streak variables relative to the T-bill return, which appears to beat alternative choices in terms of goodness-of-fit. Economically, the Treasury bill return provides a 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 risk-adjusted performance measures. Second, we include performance ranks based on annual returns. Experimenting with annual or quarterly returns rather than ranks, or ranks based on style-adjusted returns, shows that specifications using annual ranks provide better explanatory power. Finally, we performed a range of tests using one-, two-, and three-year horizons. The two-year horizon model performs substantially better than the alternative specifications, suggesting that hedge fund investors attend most closely to historical performance over a two-year horizon. None of our key findings regarding the role of performance streaks is sensitive to these choices.

We estimate Equation (1) using pooled Ordinary Least Squares (OLS) including time fixed effects, with robust standard errors clustered at the fund level.[9] The results are reported in Table 3. The full specification, which includes the full set of streak dummies, is presented in column C. As a comparison, we present some alternative specifications, with fewer controls, in columns A and B, and a model without the performance streak indicators, in column D. In column C, all winning streaks have a statistically significant impact on fund flows, whereas losing streaks up to four quarters have a statistically negative impact. For losing streaks of five quarters or more, the results are a bit mixed, which is probably attributable to the relatively low number of observations (Table 1). The magnitudes of the coefficients closely resemble a monotonic pattern as streak length increases. Ceteris paribus, the longer the winning streak, the larger the flows, and the longer the losing streak, the lower the flows. Clearly, these results show streaks to have an impact

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Table 3. Flows and Performance Streaks

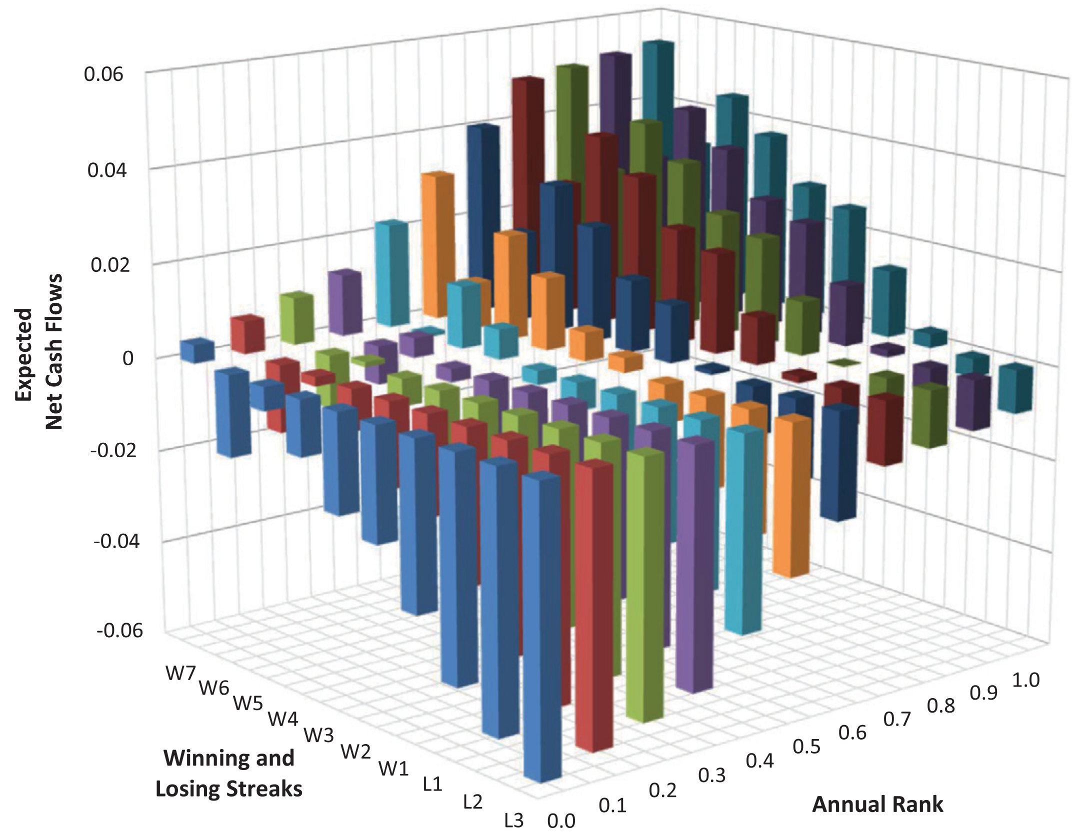
	A		B		C		D	
Variable	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
W2_TBill	0.0218	(8.94)	0.0163	(5.27)	0.0113	(3.65)		
W3_TBill	0.0366	(12.12)	0.0239	(6.72)	0.0143	(3.95)		
W4_TBill	0.0497	(13.61)	0.0385	(9.25)	0.0236	(5.53)		
W5_TBill	0.0596	(13.20)	0.0436	(8.78)	0.0305	(6.03)		
W6_TBill	0.0559	(11.11)	0.0294	(5.64)	0.0180	(3.42)		
W7_TBill	0.0605	(9.56)	0.0508	(6.57)	0.0394	(5.11)		
W8_TBill	0.0283	(6.91)	0.0196	(4.30)	0.0146	(3.20)		
L1_TBill	−0.0334	(−15.61)	−0.0116	(−4.14)	−0.0113	(−4.07)		
L2_TBill	−0.0786	(−28.45)	−0.0259	(−7.38)	−0.0182	(−5.15)		
L3_TBill	−0.1026	(−25.31)	−0.0353	(−7.17)	−0.0235	(−4.69)		
L4_TBill	−0.1188	(−21.59)	−0.0331	(−4.72)	−0.0182	(−2.56)		
L5_TBill	−0.1182	(−15.36)	−0.0085	(−0.85)	0.0050	(0.50)		
L6_TBill	−0.1201	(−10.08)	−0.0250	(−1.75)	−0.0128	(−0.89)		
L7_TBill	−0.0991	(−6.30)	0.0261	(1.35)	0.0371	(1.91)		
L8_TBill	−0.0839	(−5.11)	0.0428	(2.38)	0.0402	(2.23)		
Count_1			0.0251	(2.57)	0.0149	(1.49)	−0.0039	(−0.45)
Count_2			0.0250	(4.09)	0.0176	(2.79)	−0.0092	(−1.66)
Count_3			0.0236	(4.86)	0.0169	(3.48)	−0.0078	(−1.80)
Count_4			0.0179	(4.38)	0.0126	(3.06)	−0.0092	(−2.53)
Count_5			0.0152	(4.32)	0.0110	(3.17)	−0.0053	(−1.66)
Count_6			0.0104	(3.40)	0.0072	(2.38)	−0.0034	(−1.26)
Middle Rank Lag 1					0.0842	(11.08)	0.0965	(12.71)
Top 30%					−0.0817	(−4.34)	−0.0765	(−4.06)
Bottom 30%					−0.0296	(−1.53)	−0.0325	(−1.66)
Middle Rank Lag 2					0.0065	(0.79)	−0.0039	(−0.47)
Top 30%					0.0053	(0.29)	0.0009	(0.05)
Bottom 30%					−0.0303	(−1.52)	−0.0323	(−1.62)
Rank 24m alpha			0.0152	(4.23)	0.0101	(2.82)	0.0107	(2.97)
Rank 24m Sharpe Ratio			0.0952	(14.76)	0.0672	(9.26)	0.0651	(9.39)
Underwater dummy			0.0016	(0.53)	0.0057	(1.84)	0.0059	(1.90)
Downside-upside pot. ratio			0.0001	(1.96)	0.0001	(1.94)	0.0001	(3.39)
Standard deviation of returns			0.0386	(1.22)	−0.0106	(−0.44)	−0.0101	(−0.41)
Fund characteristics	No		Yes		Yes		Yes	
Cash flows lags 1 to 8	No		Yes		Yes		Yes	
Style and time dummies	No		Yes		Yes		Yes	
N	111,656		52,771		52,771		52,771	
R^2	0.034		0.105		0.110		0.107	

Notes. The table reports estimates of a model explaining net flows to hedge funds. The sample includes 2,794 open-end hedge funds between 1995Q1 and 2018Q2. We measure flows as a quarterly growth rate corrected for reinvestments. The independent variables are defined in Online Appendix A. Fund characteristics controls, style, and time dummies are included (estimates not reported). We use OLS pooling all fund-quarter observations; robust *t* statistics, based on clustering by fund, are in parentheses.

on flows beyond the effect of annual ranks documented in studies of the flow-performance relation, as well as other performance metrics like alphas and Sharpe ratios, which are all statistically significant. A joint test on the inclusion of the streak dummies strongly rejects the null, both for positive ($p = 0.000$) and negative streaks ($p < 0.001$), indicating that the full specification reported in column C performs significantly better than the one excluding the streak dummies (reported in column D).

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. The piece-wise linear specification captures a nonlinear relation between flows and ranks. The response of flows is positive and more prominent in the midrange of ranks and decreases for funds ranked above the 70th or below the 30th percentile, most likely attributable to restrictions operating on inflows and outflows. A joint test on the inclusion of annual ranks indicates that the full specification reported in column C performs significantly better than the one excluding annual ranks (reported in column B). Both performance streaks and annual ranks thus appear to be major determinants of hedge fund investors' decision to invest or divest. The effects of streaks are slightly smaller, but still highly significant, after inclusion 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 also have significant effects on flows. Below

Figure 1. (Color online) Expected Net Cash Flows



Notes. The figure shows expected net cash flows based on the estimated model of investor flows (Table 3, column C), 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.

we analyze the relative importance investors attribute to each of these performance metrics.

The economic significance is analyzed in Figure 1, which depicts predicted flows for the most important performance streaks and a range of annual ranks, using the model reported in column C of Table 3, with all other variables fixed at their sample average. A fund with an annual performance rank equal to 0.5 in each of the previous two years, on average, experiences subsequent quarterly inflows of 2.2% if the previous five-quarter returns are all above the T-bill (i.e., a five-quarter winning streak), compared with outflows of 0.8% if only the previous quarter return is above the T-bill (i.e., a one-quarter winning streak). The same fund will experience subsequent quarterly outflows of 2.0% if the previous quarter return is below the T-bill (i.e., a one-quarter losing streak), and 3.2% if the previous three quarters are below the T-Bill (i.e., a three-quarter losing streak). Economically, the impact of annual performance ranks and the impact of the performance streaks are in the same order of magnitude, corresponding to spreads of around 5%–6% in subsequent flows in either dimension (conditional upon the other), and a combined spread of 11%.

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 net cash flows to hedge funds. Apparently, investors respond strongly and positively to long winning streaks and negatively to 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 performance. A detailed investigation of the information value of performance streaks is reported in Section 4.

3.1. Robustness

Our results thus far are consistent with the notion that investor flows are influenced by specific sequences of performance signals, as captured by the streak indicators. In this section, we discuss a number of robustness checks. First, it is possible that investors give more weight to the most recent performance, for example because of the existence of short-run persistence. This would make the most recent quarter much more informative to investors than performance over the previous two years. To control for the possibility that the performance streaks capture investors simply giving more weight to the most recently available performance information, we include prior quarter performance rank in the model. Alternatively, it is possible that investors pay attention to performance over longer periods, beyond our evaluation window of two years. To capture this, we also include the performance rank of the fund over its entire available history. The results are presented in Online Appendix B, Table 3b. Both additional variables are statistically significant and have a positive impact on flows. Our main findings related to the positive streaks are hardly affected by these additional controls. However, the negative streaks seem to lose statistical significance in most cases. Partly, this can be expected. Conditional on having a previous quarter rank, now included as a control, below 0.5, a negative performance streak of one quarter actually implies that the performance in quarter $t-2$ was *above* the T-bill, so this becomes a positive signal. Consistent with this, the sign for the one-quarter losing streak becomes positive in columns C and D in Table 3b in Online Appendix B. The *F* tests on the joint significance of the performance streaks remain highly significant after the inclusion of these two additional control variables ($p = 0.000$ for positive streaks and $p < 0.001$ for negative streaks).

An alternative explanation why investors give so much attention to performance streaks is that streaks are informative about fund liquidation. This does not appear to be the case. In Online Appendix E, we report the estimation results of a probit model predicting fund liquidation based on essentially the same set of predictor variables as Equation (1). Conditional on other performance metrics and fund characteristics, neither winning nor losing streaks have a significant impact on the probability of fund liquidation (with *p* values on the joint hypotheses of 0.71 and 0.21, respectively). We also explore whether operational risk, proxied by the ω-score developed by Brown et al. (2008), explains part of the impact of streaks on flows. After including the ω-score, the impact of streaks on flows remains strongly robust. Accordingly, it does not appear the case that investors are attending to performance streaks as a proxy for operational risk.

Last, we test the robustness of our results to the choice of sample period. Inspired by Franzoni and Schmalz (2017), who document that the flow-performance relation for mutual funds is steeper when aggregate risk factors have moderate realizations than during more extreme upward or downward moves, we split our sample in two parts based on the magnitude of the return on the stock market index in each period. We define moderate periods as quarters where the market return is in deciles 4 to 7. The idea is that in periods with extreme risk realizations, noise pollutes the performance signals, and investors react less strongly to fund performance. The results of this analysis are reported in Table 3c in Online Appendix B and show that the role of performance streaks is present in both subperiods, and particularly strong in periods with more extreme risk realizations (at times when the information signal from past performance is noisier). However, we observe little variation in the roles of most performance measures across the two subsamples.

3.2. Role of Investment Style

It is possible that the degree of investor sensitivity to performance streaks varies across different hedge fund styles. If so, our main findings may be driven by a small subset of investment styles, the reported patterns being essentially absent from the others. To investigate this, we also estimate separate models for the five most important investment styles. The results, for the most complete specification of the flows model, are presented in Online Appendix B. Qualitatively, the patterns of coefficients for the performance streaks are reasonably similar across investment styles. Obviously, the precision of the estimates reduces substantially when the number of funds becomes smaller. The largest segment of funds follows a long/short equity strategy. For this group of 1,257 funds, the estimated role of the performance streaks is consistent with our main results: investors respond positively to winning streaks, and, in most cases, negatively to losing streaks. The majority of coefficients is significantly different from zero. For the 342 event-driven funds, the results are similar, albeit with lower levels of significance. For emerging market funds ($n = 360$) and global macro funds ($n = 188$), the magnitudes and signs of the streak coefficients are again similar. For equity-market neutral and fixed income arbitrage funds (not reported), the results are quite noisy and no clear patterns emerge, probably because of the small number of observations in combination with our rich specification in terms of performance-related variables. Long losing streaks are relatively uncommon, which may explain the somewhat erratic results for losing streaks of seven quarters or more. Overall, these results do not display striking differences across investment styles.

3.3. Relative Importance of Predictors

As described previously, several performance and risk metrics in our model have a significant impact on investor decisions of how much to invest in a hedge fund. However, model coefficients do not directly provide information on the relative importance of a regressor variable (or a combination of regressors) in predicting hedge fund flows, particularly when predictor variables are correlated. To complement our estimation results, we analyze the relative importance of predictors in terms of their contribution to the R^2 using a relative weights analysis that is developed for this purpose (Johnson 2000, Johnson and LeBreton 2004, Tonidandel and LeBreton 2011). Loosely formulated, this creates a set of new independent variables that are the maximally related to the original independent variables but are uncorrelated to each other and then investigates their contribution to the fit of the model. Technical details are discussed in Online Appendix C.

Table 4 presents our estimates of relative weights for the model reported in column C, Table 3, expressed as percentages of the R^2, and aggregated by groups of variables. The lagged annual ranks are the most important predictors 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 22.6% (second lagged annual rank less than 4%) of the predictable variance of fund flows. The combined contribution of streak dummies is the second largest among the performance variables, explaining 15.8% of the predictable variance (winning streaks explain 9.4%, losing streaks explain 6.4%). Other performance metrics explain a significantly lower proportion of the predictable variance, 24-month Sharpe ratios and alphas, for instance, 10.7% and 5.6%, respectively, the underwater dummy (3.1%) and the combined effect of the count dummies (3.9%).

All estimates of relative weights for the performance variables are statistically significant.[10] 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 8.6% of the explained variance (lagged quarterly flows in the second year explain less than 0.5%). The set of time dummies also makes a large contribution to the R^2, of about 18.9%, much 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 4.8%, and style dummies only 1.6%, of predictable variance.

This ranking of the relative importance of predictors offers a novel perspective on the behavior of hedge fund investors and enhances our understanding of their information processing strategies. It indicates that lagged annual ranks, performance streaks, and lagged flows are more important predictors for hedge fund flows than other performance metrics like alphas and Sharpe ratios. Remarkably, hedge fund investors appear to attribute significantly less importance to style and fund-specific characteristics. Most importantly for our purpose, however, it highlights the prominence of performance streaks relative to other variables, supporting the notion that sequences of performance signals influence investor flows.

4. Information Value of Performance Streaks

We now investigate whether fund characteristics and performance indicators like streaks are able to predict subsequent performance and, if so, which are the

Table 4. Partition of Explained Variance: Relative Importance of Predictors

	Relative weights (% of R^2)	Standard error	99% Confidence interval	
Combined effect of all streak dummies	15.791	0.912	13.442	18.140
Combined effect of winning streaks	*9.406*	*0.736*	*7.511*	*11.300*
Combined effect of losing streaks	*6.385*	*0.593*	*4.858*	*7.912*
Combined effect of Count dummies	3.932	0.401	2.898	4.965
Combined effect of lagged annual ranks	26.583	1.101	23.748	29.418
Combined effect of three-piece-wise linear specification – Rank lag 1	*22.615*	*1.061*	*19.883*	*25.347*
Combined effect of three-piece-wise linear specification – Rank lag 2	*3.968*	*0.354*	*3.057*	*4.879*
Combined effect other performance metrics	19.722	0.903	17.397	22.047
Rank 24m alpha	*5.559*	*0.453*	*4.392*	*6.726*
Rank 24m Sharpe Ratio	*10.708*	*0.594*	*9.177*	*12.239*
Underwater dummy	*3.090*	*0.285*	*2.356*	*3.824*
Combined effect of lagged flows	8.630	1.809	3.971	13.289
Combined effect of fund characteristics	4.831	0.610	3.260	6.401
Combined effect of style dummies	1.644	0.390	0.640	2.647
Combined effect of time dummies	18.867	1.229	15.701	22.032
Total sum of relative weights	100.000			
R^2	0.0859			

Notes. The table presents estimates of relative weights of groups of explanatory variables (Johnson 2000) for the flows regression reported in Table 3, column C, expressed as percentages of the R^2. Standard errors and confidence intervals are estimated using a bootstrap approach (Johnson 2004). Numbers in italics refer to subgroups of variables, already included in larger groups. Technical details are provided in Online Appendix C.

better predictors, and over what investment horizons. We then analyze the extent to which cash flows can be explained by these forecasts or their accuracy. In Section 5, we use the selected models to determine out-of-sample forecasts, on which we base simple investment strategies, and compare these with the allocation of the aggregate investor.

Given that performance ranks are typically included in models explaining investor flows, we investigate the ability of streaks and other variables to predict a fund's relative performance. We focus on the one-year investment horizon, given that 88% of funds impose lockup periods of 12 months or less or redemption and notice periods confined within a year. Consider the following predictive model:

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

where $Rank^i_{t,t+3}$ is the relative performance of fund i in quarters t to $t+3$, measured by the fund's cross-sectional rank based on the following three criteria: raw returns (model 1), style-adjusted returns (model 2), and eight-factor alphas (model 3).[11] The main explanatory variables are the 15 mutually exclusive streak dummies, 7 of which account for winning and 8 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.

We estimate (2) using OLS pooling all quarterly observations. Because the dependent variable is measured over four quarters, which is longer than the data frequency, we use Newey-West (HAC) standard errors to account for heteroskedasticity and autocorrelation in the error terms. Our estimation results are reported in Table 5. The explanatory power of the three models is relatively low, particularly for the model predicting ranks based on eight-factor alphas (model 3). This may be because the eight-factor alphas are relatively noisy, given the short window over which they are estimated. These R^2s measure within-sample predictability; we evaluate out-of-sample forecasting power later. Interestingly, the impact of winning and losing streaks appears limited, although some coefficients of the streak indicators are statistically significant.

The estimation results of the models explaining a fund's raw return rank or style-adjusted rank are reasonably similar (models 1 and 2). Of the variables that capture historical fund performance, two-year Sharpe ratios positively predict subsequent performance, whereas two-year alphas have some predictive ability for subsequent alphas. Fund-specific characteristics (not reported) like short-term share restrictions, lockup periods, high-water marks, management fees, the offshore dummy, and managers' personal capital have a positive and statistically significant effect on subsequent performance.[12] The coefficient of return smoothing is also positive and significant. A number of these covariates play a quite different role in the model of cash flows in Table 3. For instance, most fund-specific characteristics (except for the high-water mark indicator) have no impact, whereas the coefficients of two-year alphas, size, and especially lagged flows have a statistically significant effect, on flows. This suggests 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 later.

Table 6, panel A, reports the F tests for including winning and losing streaks in each model. The F tests yield the highest values in model 1 and reject 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 for one-year-ahead raw returns, we find limited evidence that losing streaks are able to predict one-year-ahead alphas. In model 2, the null that all losing streaks have zero coefficients is not rejected at the 1% significance level.

In a robustness test, we include 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 the equilibrium of Berk and Green (2004). 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.

4.1. Out-of-Sample Forecast Evaluation

The foregoing results indicate that streaks may have limited information value for the prediction of one-year-ahead raw returns, style-adjusted returns, or alphas. A number of predictors of performance have no

Published in Management Science on August 12, 2021 as DOI: 10.1287/mnsc.2021.4067.
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Table 5. Forecast Models Predicting Four-Quarter-Ahead Performance Ranks

	Model 1		Model 2		Model 3	
Variable	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
W2_TBill	0.0051	(1.46)	0.0092	(2.64)	−0.0006	(−0.14)
W3_TBill	0.0215	(4.37)	0.0223	(4.54)	0.0115	(2.18)
W4_TBill	0.0103	(1.66)	0.0106	(1.71)	−0.0006	(−0.09)
W5_TBill	0.0229	(3.05)	0.0162	(2.17)	0.0220	(2.91)
W6_TBill	0.0157	(1.80)	0.0046	(0.54)	0.0103	(1.19)
W7_TBill	0.0330	(3.08)	0.0164	(1.55)	0.0161	(1.53)
W8_TBill	0.0404	(4.70)	0.0388	(4.48)	0.0282	(3.66)
L1_TBill	−0.0074	(−2.60)	−0.0074	(−2.64)	−0.0007	(−0.19)
L2_TBill	−0.0120	(−2.42)	−0.0082	(−1.65)	0.0017	(0.31)
L3_TBill	−0.0204	(−2.50)	−0.0102	(−1.25)	0.0106	(1.29)
L4_TBill	−0.0496	(−4.19)	−0.0348	(−2.92)	−0.0150	(−1.19)
L5_TBill	0.0038	(0.23)	−0.0011	(−0.07)	−0.0078	(−0.46)
L6_TBill	0.0045	(0.21)	0.0080	(0.38)	0.0150	(0.68)
L7_TBill	0.0239	(0.70)	0.0247	(0.73)	0.0679	(1.92)
L8_TBill	0.0059	(0.10)	−0.0111	(−0.17)	−0.0452	(−0.91)
Count_1	0.0042	(0.17)	−0.0180	(−0.77)	−0.0767	(−3.53)
Count_2	−0.0063	(−0.43)	−0.0253	(−1.73)	−0.0412	(−3.13)
Count_3	−0.0123	(−1.09)	−0.0213	(−1.89)	−0.0128	(−1.30)
Count_4	0.0060	(0.66)	−0.0030	(−0.33)	−0.0010	(−0.12)
Count_5	0.0062	(0.82)	0.0011	(0.15)	−0.0046	(−0.69)
Count_6	−0.0039	(−0.65)	−0.0060	(−0.99)	0.0022	(0.40)
Middle Rank Lag 1	0.0695	(4.27)	0.0208	(1.27)	0.0084	(0.57)
Top 30%	0.1034	(2.47)	0.1759	(4.22)	0.1226	(3.23)
Bottom 30%	−0.0481	(−1.09)	−0.0154	(−0.35)	−0.0260	(−0.65)
Middle Rank Lag 2	−0.0370	(−2.24)	−0.0551	(−3.33)	−0.0131	(−0.87)
Top 30%	0.0610	(1.50)	0.0674	(1.66)	0.0118	(0.32)
Bottom 30%	0.0236	(0.54)	−0.0257	(−0.60)	−0.0495	(−1.23)
Rank 24m alpha	−0.0066	(−0.63)	0.0070	(0.67)	0.0320	(3.36)
Rank 24m Sharpe Ratio	0.0318	(1.98)	0.0533	(3.33)	0.0240	(1.73)
Underwater dummy	0.0543	(8.05)	0.0557	(8.24)	0.0221	(3.63)
Downside-ups. pot. ratio	−0.0014	(−2.10)	−0.0014	(−2.19)	−0.0007	(−2.59)
Standard deviation of returns	0.5450	(3.96)	0.7317	(5.15)	−0.0186	(−0.18)
Squared standard deviation	−0.5922	(−2.59)	−0.7105	(−2.87)	−0.0803	(−0.76)
Fund characteristics	Yes		Yes		Yes	
Eight lags quarterly flows	Yes		Yes		Yes	
Style dummies	Yes		Yes		Yes	
N	46,017		46,013		46,017	
Adjusted R^2	0.042		0.043		0.023	

Notes. The table reports estimates of a model explaining relative performance as measured by a fractional rank, which ranges from zero to one and is defined as the fund's percentile performance over the next four quarters relative to all the funds existing in the sample in the same period, based on three criteria: raw returns (model 1), style-adjusted return (model 2), and alphas (model 3). The sample includes 2,794 open-end hedge funds for the period 1995Q1 to 2018Q2. The independent variables are defined in Online Appendix A. Fund characteristics controls and style dummies are included (estimates not reported). We estimate our model by OLS pooling all fund-period observations. Robust t statistics, based on HAC standard errors, in parentheses.

apparent impact on flows, and some predictors of flows play no role in the performance models. A potential reason for the seemingly poor performance of these forecasting models is that these models are overspecified, with many interrelated predictors on the right-hand side. Moreover, it is possible that the true model coefficients are time varying, attributing differential importance to the predictors over time. To address these concerns, we evaluate the out-of-sample forecasting power of these models based on a recursive estimation of Equation (2). In each quarter, we compute out-of-sample forecasts of one-year-ahead performance ranks for quarter t to $t+3$ using the coefficients based on $t-1$ information. The first forecast corresponds to the four-quarter period 1997Q4–1998Q3, based on prior information available from 1995Q1–1997Q3.

The accuracy of the forecasts generated by these models is evaluated in Table 6, panel B, which compares the predictions with the ex post realizations in four ways. We report the root mean squared error (RMSE), which punishes larger forecast errors more heavily, and 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

Table 6. Comparison of Forecast Models

	Model 1 Raw returns ranks	Model 2 Style-adjusted returns ranks	Model 3 Alpha ranks
Panel A: F tests for inclusion of winning and losing streaks			
F-test Winning streaks	6.793	5.785	3.967
p-value	(0.000)	(0.000)	(0.000)
F-test Losing streaks	3.963	2.401	1.344
p-value	(0.000)	(0.014)	(0.217)
F-test All streaks	6.430	4.931	2.784
p-value	(0.000)	(0.000)	(0.000)
Panel B: Comparison of forecast performance			
Overall RMSE	0.2959	0.2936	0.2907
Overall MAD	0.2466	0.2454	0.2484
R^2_{OS}	0.0234	0.0230	0.0121
Hit rate	0.5624	0.5694	0.5444

Notes. The table compares three forecast models explaining four-quarter-ahead cross-sectional ranks based on raw returns (model 1), style-adjusted returns (model 2), and alphas (model 3), as presented in Table 5. Panel A reports F tests for the inclusion of streak dummies in all forecast models. Panel B 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 $\widehat{y}_h$, $h = 1,2,\ldots,H$, where H is the number of forecasting periods, and then the overall RMSE, MAD, and the out-of-sample R^2 are defined as follows: $Overall\ RMSE = \sqrt{\frac{1}{H}\sum_{h=1}^{H}(\widehat{y}_h - y_h)^2}$, $Overall\ MAD = \frac{1}{H}\sum_{h=1}^{H}|(\widehat{y}_h - y_h)|$, and $R^2_{OS} = corr^2(\widehat{y}_h, y_h)$, respectively. 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.

and ex post realizations (Pesaran and Timmermann 1995). Finally, we report a hit rate defined as the proportion of times a model correctly predicts whether a fund performs above the median. The latter measure implicitly assumes an investment allocation 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).

Consistent with our previous analysis, models 1 and 2 exhibit the highest out-of-sample R^2 of about 2.3%. The mean rank error across models, as measured by RMSE and MAD, is as large as 24–30 rank percentiles, the hit rate across models above 50%. 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, although predictability at the level of the individual fund is fairly limited (Avramov et al. 2013).

4.2. Relative Importance of Predictors

In our first approach to compare the importance of variables that drive investor decisions, as reflected in net flows, with their information content for forecasting hedge fund performance, we analyze the relative weights for the predictor variables in the forecast models. This enables us to evaluate the information processing strategy of investors against the model's benchmark.

Table 7 reports our estimates of the relative weights for the three models (panels A–C), expressed as percentages of R^2s and aggregated by groups of variables. The combined contribution of the streak dummies to the R^2 varies across models, explaining around 10.5% of the predictable variance in model 1 (raw return rank) and model 2 (style-adjusted rank) and 11% in model 3 (alpha rank). Across all models, the most important predictors are the set of performance and risk metrics (including the combined effect of lagged annual ranks), the set of fund-specific characteristics, and the style dummies, which together account for at least 80% of the explained variance. The least important predictors are the sets of count dummies, the performance streak indicators, and lagged flows.

There is the remarkable contrast with the relative weights analysis in the flows model in Table 6; the set of fund-specific characteristics and set of style dummies, although 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 important predictors relative to other variables in the flows model, have the lowest relative importance in the forecast models. That said, 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) that under decreasing returns to scale, flows chasing a certain past performance signal compete away in equilibrium the forecasting power of that signal.

These results indicate investors weigh past information very differently than the forecast models that predict raw or style-adjusted returns or alphas. Put differently, the relative importance investors attribute to

Published in Management Science on August 12, 2021 as DOI: 10.1287/mnsc.2021.4067.
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Table 7. Partition of Explained Variance: Relative Importance of Predictors of Performance Ranks

	Panel A: Dependent variable: *Raw Ret. Ranks*				Panel B: Dependent variable: *Style-adj. Ret. Ranks*				Panel C: Dependent variable: *Alpha Ranks*			
	Relative weights % of R^2	Standard error	99% Confidence interval		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	10.480	1.241	7.284	13.676	10.670	1.227	7.509	13.831	11.068	1.632	6.865	15.271
Combined effect of winning streaks	*5.929*	*0.904*	*3.601*	*8.258*	*6.875*	*0.993*	*4.316*	*9.434*	8.472	1.381	4.914	12.031
Combined effect of losing streaks	*4.551*	*0.863*	*2.327*	*6.775*	*3.795*	*0.810*	*1.709*	*5.880*	2.596	0.936	0.184	5.008
Combined effect of Count dummies	1.670	0.397	0.647	2.693	1.995	0.419	0.916	3.075	6.188	1.359	2.689	9.688
Combined effect of lagged annual ranks	25.186	1.956	20.146	30.225	23.597	1.801	18.957	28.238	15.122	1.925	10.163	20.082
Combined effect of three-piece-wise linear specification – Rank lag 1	*22.270*	*1.915*	*17.336*	*27.203*	*18.034*	*1.711*	*13.626*	*22.442*	13.331	1.903	8.430	18.233
Combined effect of three-piece-wise linear specification – Rank lag 2	*2.916*	*0.598*	*1.376*	*4.456*	*5.563*	*0.849*	*3.376*	*7.750*	1.791	0.421	0.707	2.875
Combined effect other performance metrics	21.892	2.778	14.735	29.048	24.746	2.539	18.206	31.287	15.552	1.993	10.418	20.685
Combined effect of lagged flows	0.427	0.326	0.209	1.782	0.300	0.290	0.157	1.663	1.092	0.660	0.495	3.583
Combined effect of fund characteristics	25.431	2.021	20.225	30.636	25.788	1.925	20.829	30.746	31.540	2.710	24.558	38.521
Combined effect of style dummies	14.816	1.689	10.465	19.167	12.897	1.361	9.392	16.402	19.238	2.084	13.871	24.606
Total sum of relative weights	100.000				100.000				100.000			
R^2	0.059				0.042				0.012			

Notes. The table presents estimates of relative weights (Johnson 2000) from the three models estimated in Table 5, expressed as percentages of the R^2. Standard errors and confidence intervals are estimated using a bootstrap approach (Johnson 2004). Numbers in italics refer to subgroups of variables, already included in larger groups.

predictors diverges from the relative importance of predictors in the forecast models.

4.3. Performance Forecasts and Flows

In our second analysis of investor decisions versus model forecasts, we interpret the out-of-sample forecasts generated by our econometric models as an appropriate summary of the forecasting ability of the variables in the investor's information set. In a strict interpretation, investors should base their decisions only on the ability of the predictor variables to say something about future hedge fund performance. That is, the predictor variables should no longer play a role in the investor decision process, once their influence on expected performance, or its accuracy, is controlled for. Table 8 reports our estimates of a number of alternative specifications that explains investor choices, including the expected performance obtained from the three forecast models (panels A–C). If investors respond to performance streaks solely because of their ability to predict future fund performance, this would be captured through the performance forecasts, and performance streaks themselves would become irrelevant once these forecasts are controlled for.[13]

In each panel, we first report the estimates of a simple specification model (column 1) that explains cash flows from the expected rank, defined as the out-of-sample forecasts for the performance rank in quarter t, obtained from each of the models reported in Table 6, estimated using available information until $t-1$. Because investors may not only take into account the rank but also the precision, of these forecasts, we control for a measure of forecast accuracy, calculated for each fund-period observation as the RMSE of the eight lagged forecasts. Across models, we find expected performance to have a positive and statistically significant impact on flows. The higher the predicted rank, the more likely a fund will experience positive money flows. That the RMSE has a negative impact on flows indicates that investors are less likely to invest as the mean forecasting error increases. The effect of RMSE is statistically significant only in panel C.[14]

Investors may perceive a tradeoff 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. The fairly low R^2s of the specifications in column 1 (between 0.4% and 0.7%) suggest out-of-sample forecasts of one-year-ahead performance have little explanatory power for flows.

In column 2 in each of the panels, we report an extended specification including the streak dummies, count dummies, lagged flows, style and time dummies, and controls (omitted from the table) for fund characteristics and fund performance (i.e., annual ranks, Sharpe ratios, alphas, underwater dummy, standard deviation of historical returns, and downside risk). The effects of expected performance and RMSE become insignificant in all models. Almost all estimated coefficients for winning and losing streaks are 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. The coefficients of all other variables are similar in magnitude and statistical significance to those in the flow regressions reported in Table 3 (column C), although all of these variables are included in the estimation of the performance forecasts. These results suggest that investors attend more to performance streaks in their fund selection process than what is justified by their ability to predict future fund performance. More generally, investor choices appear to be determined by a different combination of covariates than that estimated in any of the forecast models.

The results in Tables 7 and 8 do not imply 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 flows, 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 whether investors are better informed than our forecasting models by comparing their ex post performance with some simple strategies based on the models' predictions.

5. Welfare Implications

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 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 $t+3$

Published in Management Science on August 12, 2021 as DOI: 10.1287/mnsc.2021.4067.
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Table 8. Flows and Performance Forecasts

	Panel A: Expected performance from raw-returns model				Panel B: Expected performance from style-adjusted returns model				Panel C: Expected performance from alpha ranks model			
	(1)		(2)		(1)		(2)		(1)		(2)	
Expected Performance	0.1143	(3.87)	0.0076	(0.88)	0.1115	(3.99)	0.0076	(0.81)	0.2314	(6.21)	0.0049	(0.25)
RMSE	−0.0159	(−1.40)	0.0151	(1.41)	−0.0009	(−0.09)	0.0174	(1.64)	−0.0234	(−2.05)	0.0035	(0.31)
W2_TBill			0.0123	(3.70)			0.0122	(3.67)			0.0123	(3.70)
W3_TBill			0.0153	(4.00)			0.0152	(3.99)			0.0155	(4.04)
W4_TBill			0.0253	(5.63)			0.0253	(5.64)			0.0253	(5.64)
W5_TBill			0.0329	(5.96)			0.0331	(5.99)			0.0330	(5.96)
W6_TBill			0.0213	(3.77)			0.0215	(3.81)			0.0214	(3.80)
W7_TBill			0.0366	(4.64)			0.0369	(4.68)			0.0368	(4.66)
W8_TBill			0.0179	(3.74)			0.0180	(3.76)			0.0180	(3.76)
L1_TBill			−0.0112	(−3.72)			−0.0111	(−3.70)			−0.0112	(−3.73)
L2_TBill			−0.0169	(−4.52)			−0.0169	(−4.54)			−0.0170	(−4.57)
L3_TBill			−0.0208	(−3.88)			−0.0210	(−3.93)			−0.0212	(−3.96)
L4_TBill			−0.0112	(−1.48)			−0.0115	(−1.52)			−0.0118	(−1.56)
L5_TBill			−0.0041	(−0.43)			−0.0038	(−0.40)			−0.0040	(−0.42)
L6_TBill			−0.0208	(−1.42)			−0.0204	(−1.40)			−0.0211	(−1.45)
L7_TBill			0.0301	(1.36)			0.0307	(1.39)			0.0296	(1.34)
L8_TBill			0.0291	(1.94)			0.0294	(1.95)			0.0295	(1.95)
Count_1			0.0194	(1.82)			0.0196	(1.83)			0.0201	(1.85)
Count_2			0.0183	(2.77)			0.0185	(2.80)			0.0188	(2.84)
Count_3			0.0159	(3.16)			0.0160	(3.18)			0.0161	(3.20)
Count_4			0.0105	(2.49)			0.0107	(2.53)			0.0107	(2.52)
Count_5			0.0091	(2.49)			0.0091	(2.51)			0.0092	(2.51)
Count_6			0.0061	(1.93)			0.0061	(1.91)			0.0061	(1.92)
Performance control variables	No		Yes		No		Yes		No		Yes	
Fund characteristics	No		Yes		No		Yes		No		Yes	
Style and time dummies	No		Yes		No		Yes		No		Yes	
Eight lags quarterly flows	No		Yes		No		Yes		No		Yes	
N	45,451		45,451		45,447		45,447		45,451		45,451	
Pseudo-R^2	0.004		0.108		0.004		0.108		0.007		0.108	

Notes. The table reports estimates of a model explaining cash flows, similar to Table 5, but controlling for predicted ranks obtained from three different forecast models (panels A–C) as reported in Table 8. We estimate each model by pooling all fund-period observations. Robust *t* statistics, based on clustering by fund, are provided in parentheses.

Management Science, 2022, vol. 68, no. 6, pp. 4151–4172, © 2021 INFORMS

by obtaining equally weighted averages across all funds selected by each model of four-quarter-ahead raw returns, style-adjusted returns, and alphas. Because the fund-specific eight-factor alphas are estimated using only 12 monthly returns, they tend to be quite noisy. Accordingly, we interpret the corresponding results with caution, and mostly focus on raw and style-adjusted returns.

We investigate the average performance of funds that experience investments versus those that experience divestments, where we average across all decisions over the entire sample period. Performance metrics are averages across funds/periods rather than metrics for a time series of portfolio returns. Essentially, we address the question whether the average investment decision performs better than the average divestment decision over the subsequent year. We consider this to be an appropriate approach given that hedge fund investors typically will not invest in a large well-diversified portfolio of hedge funds. Rather, they select only one or a few funds and rebalance infrequently. In contrast, Ozik and Sadka (2015) evaluate the performance of monthly rebalanced equally weighted flow-sorted portfolios and conclude that the top quintile significantly outperforms the bottom quintile for share-restricted hedge funds.[15]

Table 9, panel A, reports our results for investments. All t statistics (in parentheses) are based on double-clustered robust standard errors to account for within-fund and within-period correlation (Thompson 2011). The performance of investors capital allocation across funds is shown in column 1. On average, funds that experience actual net money inflows (n = 20,644 observations) at the beginning of quarter t deliver a subsequent four-quarter return of 8.91%, a style-adjusted return of 1.81%, and an annualized alpha of 0.27%. We contrast the investor allocation with a simple investment rule based on our performance forecasts (obtained from recursively estimating Equation (2)). Investing in a fund if it has above-median predicted performance results in an average subsequent return of 10.4%, 10.5%, and 9.55% (based on the model predicting raw return ranks, style-adjusted return ranks, and alpha ranks, respectively). The first two of these beat the investor allocation by a statistically significant 1.5%–1.6%/yr. In terms of style-adjusted returns, the corresponding performance differential is 1.3%–2.0% in favor of the model-based allocations.[16] In a robustness check, reported in Online Appendix D, we changed the investment rule so as to select funds with predicted performance rank above 0.6 and observe much larger differences. This result is mostly driven by the fact that the model-based allocations now select far fewer funds, which, on average, outperform subsequently.

We observe a similar pessimistic picture for divestments of the average investor in column 1 of panel B. In this case, a good divestment decision should have low returns. On average, funds that experience net outflows at the beginning of quarter t (n = 23,974 observations) deliver a subsequent four-quarter return of 8.36%, a style-adjusted return of 1.12%, and an annualized alpha of 0.23%. This means that the performance difference between investments and divestments (as reported in panel C) is less than 0.7% per year on either dimension and statistically insignificant. That is, the average fund an investor invests in performs only slightly better than the average fund an investor divests from, suggesting little evidence of a "smart money" effect. Again, the actual divestments of investors are easily outperformed by simple divestment strategies based on the first two models. For example, divesting from any fund with a predicted raw return rank of less than 0.5, results in a negative return of 6.3% per year, significantly better than the 8.35% for the actual average fund investors divest from. For the models predicting ranks based on raw or style-adjusted returns, the investment portfolio outperforms the divestment portfolio by more than 4% per year in terms of raw returns, with a high level of statistical significance. In terms of style-adjusted returns the difference is between 2.9% and 4.2% per year, again highly significant. The investment allocation based on the model predicting the ranks of alphas (model 3) performs equally well by any measure. The difference between the investment and divestment portfolios amounts to almost 2.5% per year in terms of raw returns, 2.3% per year in terms of style-adjusted returns, and 0.2% in terms of alphas compared with 0.6%, 0.7%, and 0.04%, respectively, for the actual investor allocations, all differences being statistically significant.

The results in Table 9 show that, on average, funds in which investors invest do not perform significantly better than funds from which they divest. Moreover, simple model-based investment and divestment rules outperform the decisions of the average hedge fund investor by an economically significant margin. This indicates that our forecasting models, despite their overparameterization and low in-sample and out-of-sample R^2s, do much better than the average investors in separating subsequently well-performing funds from the poor-performing ones.[17]

One reason the model-based allocations outperform could be that the strategies prescribe to invest in funds that are actually closed to new investments or divest from funds that impose severe share restrictions or lockup periods. In one of the robustness checks (reported in Online Appendix D), we restrict the model-based investment and divestment portfolios to those funds that actually experience inflows or outflows,

Table 9. Performance of Model-Based Capital Allocations Across Hedge Funds Based on Four-Quarter-Ahead Out-of-Sample Forecasts

Evaluation criteria four-quarter-ahead performance	Investors performance (1)	1. Raw return ranks model: Model performance (2)	1. Raw return ranks model: Difference (2) − (1) (3)	2. Style-adjusted ret. ranks model: Model performance (4)	2. Style-adjusted ret. ranks model: Difference (4) − (1) (5)	3. Alpha ranks model: Model performance (6)	3. Alpha ranks model: Difference (6) − (1) (7)
Panel A: Investments							
	N = 20,644	N = 19,543		N = 18,792		N = 19,149	
Raw Return	0.0891	0.1040	0.0149	0.1050	0.0158	0.0955	0.0064
			(2.70)		(2.95)		(1.57)
Style-adj. Return	0.0181	0.0311	0.0131	0.0389	0.0208	0.0285	0.0104
			(3.80)		(5.79)		(3.44)
Alpha	0.0027	0.0030	0.0003	0.0032	0.0005	0.0035	0.0008
			(1.15)		(2.19)		(3.46)
Panel B: Divestments							
	N = 23,974	N = 22,913		N = 23,664		N = 23,307	
Raw Return	0.0836	0.0630	−0.0206	0.0635	−0.0200	0.0707	−0.0129
			(−4.17)		(−4.25)		(−3.17)
Style-adj. Return	0.0112	0.0026	−0.0087	−0.0027	−0.0139	0.0052	−0.0060
			(−2.70)		(−4.32)		(−2.16)
Alpha	0.0023	0.0017	−0.0006	0.0015	−0.0008	0.0013	−0.0010
			(−3.29)		(−4.07)		(−5.60)
Panel C: Investments minus divestments							
Raw Return	0.0056	0.0411	0.0355	0.0414	0.0359	0.0248	0.0192
	(0.97)	(4.85)	(3.99)	(5.39)	(4.35)	(3.07)	(2.24)
Style-adj. Return	0.0068	0.0286	0.0218	0.0416	0.0347	0.0233	0.0164
	(1.81)	(4.60)	(3.39)	(7.00)	(5.63)	(3.51)	(2.42)
Alpha	0.0004	0.0013	0.0009	0.0017	0.0013	0.0022	0.0018
	(1.64)	(3.55)	(2.37)	(4.74)	(3.49)	(6.37)	(4.94)

Notes. The table shows the ex post performance evaluation of trading rules based on four-quarter-ahead out-of-sample forecasts. We obtain forecasts from three models explaining cross-sectional ranks based on raw returns (column 2), style-adjusted returns (column 4), and alphas (column 6). Each trading rule prescribes to invest in a fund 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 three evaluation criteria and compare with the performance of actual net inflows and net outflows (i.e., investors' performance) reported in column 1. Performance differences are reported in columns 3, 5, and 7. Robust t statistics, based on double clustering by fund and time, are provided in parentheses.

respectively. We consider this a reasonable approximation for the existence of liquidity constraints on actual inflows and outflows, for example when a fund is not willing to accept new money (or does not allow redemptions). This results in smaller groups in both the investment and divestment portfolios, but the patterns are remarkably similar to those in Table 9. If anything, the performance of our model-based strategies improves.

It is possible, however, that investors are able to identify the better funds within the investment portfolio, 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 (reported in Online Appendix D) 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 7.13%, an average style-adjusted return of 1.22%, and average annualized alpha of 0.28%. Funds that experience actual net outflows at the beginning of quarter t deliver a subsequent four-quarter cash-flow weighted average return of 8.60%, an average style-adjusted return of 1.90%, and average annualized alpha of 0.34%. The spread on investors' allocations thus delivers a cash flow weighted performance significantly smaller than the equally weighted performance and negative in all cases.

We interpret the relatively poor performance of actual investor allocations as a sign of investors suboptimally weighing the information signals that are available to them, with a crucial role for the performance streaks. We also compared the investor allocations relative to allocations based on a performance forecasting model that does not incorporate information about past performance streaks. This means performance streaks are given zero weight in the forecasting models. The results (reported in Online Appendix D) are very similar to those in Table 9. This confirms that performance streaks have limited predictive value, despite investors giving weight to them in their allocation decisions.

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. Earlier evidence in Brown et al. (2008, 2012), however, already indicates hedge fund investors tend to ignore red flags from due diligence reports related to operational risk. Our analyses confirm that the average hedge fund investment and divestment are not particularly smart (Baquero and Verbeek 2009, Ramadorai 2013); simple investment strategies based on out-of-sample forecasts of linear performance models easily outperform the average investor by an economically and statistically significant margin.

We analyze net money flows of hedge fund investors in relation to a wide range of information variables available to them. We pay particular attention to the relevance of performance streak variables; a performance streak being defined as subsequent quarters during which a fund performs above or below a benchmark. We show that investor flows react positively to winning and negatively to losing streaks, the strength of the reaction typically increasing with the length of the streak. Performance streaks 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. Relative weights analyses of the explanatory factors in the econometric models that explain flows and performance reveal that investors are likely to overweigh the importance of performance streaks, and, more generally, fail to optimally weigh the information available to them. Furthermore, investor decisions underperform, ex post, simple model-based investment strategies. 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.

Acknowledgments

The authors benefited from extensive discussions with Francis de Vericourt, Ben Jacobsen, Yaakov Kareev, Anthony Lynch, Dimitri Vayanos, and Georg Weizsäcker. The authors thank Vikas Agarwal, Yong Chen, Frank de Jong, Alberta Di Giuli, Bart Keijsers, Simone Kohnz, Ignacio Palacios-Huerta, Tarun Ramadorai, David Stolin, Zheng Sun, Ashley Wang, Florian Weigert, two anonymous referees, and the associate editor for valuable and constructive comments and participants at the 2016 American Economic Association Annual Meetings, the 2015 China International Conference in Finance, the 2008 European Finance Association Annual Meetings, the 2007 American Finance Association Meetings, and the 2006 European Economic Association Annual Meetings. Dmitry Ilin and Zhou Ren provided excellent research assistance. Early versions of this manuscript were circulated under the title "Do Sophisticated Investors Believe in the Law of Small Numbers?".

Endnotes

[1] Evidence in Asparouhova et al. (2009) and Loh and Warachka (2012) of investor responses to streaks of earnings surprises is in line with this prediction.

[2] The hot-hand phenomenon was first documented by Gilovich et al. (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. Yet, Gilovich et al. (1985) show 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 (see also Durham et al. 2005).

[3] When a winning quarter occurs randomly with a probability of 50%, the chance of observing a six-period winning streak in any given window is more than 1.5%.

[4] Our findings complement both the recent literature studying the determinants of money flows to hedge funds (Goetzmann et al. 2003, Fung et al. 2008, Baquero and Verbeek 2009, Li et al. 2011, Aragon et al. 2014, Agarwal et al. 2018, Liang et al. 2019) and the one studying the determinants of hedge fund performance (Aragon 2007, Naik et al. 2007, Liang and Park 2008, Agarwal et al. 2009, Aggarwal and Jorion 2010, Li et al. 2011, Sun et al. 2011).

[5] We expect that most return revisions, typically taking place within three months, do not lead to sign changes in our quarterly performance measures and thus do not affect our streak length indicators. To the extent that they lead to *random* changes in streak lengths, this would result in underestimation of the impact of streaks. Revisions are more frequent with funds-of-funds, which we exclude.

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

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

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

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.

[8] In alternative specifications, we use alphas obtained from the Capital Asset Pricing Model (CAPM) (as suggested by Agarwal et al. 2018) and Sharpe ratios and alphas estimated over a 36-month window preceding each observation. None of these alternatives affect our main findings.

[9] As an alternative, we estimated standard errors based on double clustering at the fund and period level, which produced similar t statistics on most coefficients.

[10] We test the statistical significance of the relative weight of a predictor as in Tonidandel et al. (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.

[11] 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 the eight risk factors of Fung and Hsieh (2004) (including an emerging market index) over the 12-month period between the beginning of quarter t and end of quarter $t+3$.

[12] These results are consistent with Agarwal et al. (2009) and Liang et al. (2019) for share restrictions.

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

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

[15] In their approach, portfolios are sorted on flows in quarter $t-1$ (or the last month of this quarter).

[16] These results ignore 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. Given our earlier results when including contemporaneous flows in the forecasting models, we feel comfortable concluding that the economic impact of these complications is limited.

[17] All investment and divestment rules ignore transaction costs, which are likely to be comparable to the transaction costs faced by investors.

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