Performance-Chasing Behavior and Mutual Funds: New Evidence from Multi-Fund Managers

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Abstract

We study managers who manage multiple mutual funds to provide new evidence on investors' performance-chasing behavior. Consistent with the idea that investors infer managerial ability from past returns, flows into a fund of a multi-fund manager are predicted by the performance in both the corresponding fund and another fund he manages. The relationship is stronger when the other fund does particularly well, and when the styles of the two funds are similar and their performance is more different. Nonetheless, investors do not seem to move their capital sufficiently in response to performance in the manager's other fund; past performance in one fund predicts subsequent performance in the other. This predictability is likely due to the presence of some investors who do not withdraw enough capital from a fund when their manager performs poorly in his other fund.

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1 Introduction

Mutual fund investors allocate capital to funds that have performed well in the past. This performance-chasing behavior can be consistent with investors' rational inferences about managerial ability from past returns (Sirri and Tufano, 1998; Berk and Green, 2004; Huang, Wei, and Yan, 2007, 2012). However, there is no consensus on whether investors in mutual funds have the required level of sophistication. Elton, Gruber, and Busse (2004) and Choi, Laibson, and Madrian (2010) find that some mutual fund investors are unable to make the right choice in the simplest possible context: they choose to stay with more expensive and worse performing index funds when cheaper alternatives are easily available. Bailey, Kumar, and Ng (2010) suggest that trend-chasing appears related to behavioral biases rather than to rational learning.

In this paper, we use managers who simultaneously manage two or more mutual funds ("multi-fund managers") to provide new evidence on the above debate. The advantage of examining multi-fund managers is that there are extra signals on a manager's past performance that investors could use. Specifically, we examine two funds from each multi-fund manager, and test if investors are sophisticated enough to learn about a manager's ability by using the past performance not only in the fund they consider investing in, but also in the other fund he manages.[1]

To further understand investors' response, we then study the cross-fund performance relationship, that is, whether past performance in one fund can predict subsequent performance in the other fund that the same manager manages. Consider a manager with two funds, F1 and F2, and suppose fund F2 has outperformed the benchmark. The question is: if investors of F1 are sophisticated and know that flows drive down fund performance due to decreasing returns to scale, how much more capital should they allocate?[2] If the allocation

[1]While some multi-fund managers have more than two mutual funds, most have two. Throughout our analysis, we pick the two oldest funds in the dataset from each multi-fund manager.

[2]As argued by Berk and Green (2004) and Chen, Hong, Huang, and Kubik (2004), there are decreasing

is not enough, then fund F1 will earn a positive risk-adjusted return since fund F1 will not be "large enough" to erode performance entirely. On the other hand, fund F1 will be "too large" and have negative risk-adjusted returns subsequently if too much capital is allocated. We therefore test whether performance in one fund is followed by subsequent performance in the other fund that (i) has the same sign (insufficient response), (ii) has a different sign (more than sufficient response), or (iii) is not significantly different from zero.

Our first main finding is that, consistent with our conjecture, investors indeed make use of the manager's past performance in his other fund. Using a flow-performance regression framework that is similar to Sirri and Tufano (1998) and Huang, Wei, and Yan (2007), we find that flows into a fund are predicted by the past performance in both of the manager's funds. The effect of the other fund is more prominent when its performance has been exceptionally good; sensitivity to the other fund is one-third to half as strong as the sensitivity to the corresponding fund, if both funds are performing very well. Besides, we show that the flow-performance results are stronger when the styles of the two funds are similar and their performance is more different, i.e., when the signal provided by the other fund is likely to be useful and carry more additional information. The effects are unlikely to be driven by other characteristics. We control for fund family effects, as well as run two sets of "placebo" tests: first, we look at the two funds in a period when they are managed by different managers; second, we replace one of the manager's funds with another fund that is in the same fund family or has similar characteristics, but not managed by the same manager. Neither of the tests gives us the results.

For this performance-chasing behavior to be consistent with investor sophistication, performance in a manager's fund should contain information about his ability in the other fund. In other words, if performance is a signal of skills, skills should not be entirely fund-specific. We study fund holdings and show that there is likely a manager-specific component of skills.

returns to scale because managers of larger funds spread their information-gathering activities too thin and large trades have higher price impact and execution costs. We believe that their argument applies to multi-fund managers as well.

After removing the common holdings of the two funds, we find that abnormal return to the uncommon holdings of one fund is positively correlated with that of the other fund.

From the cross-fund performance relationship, however, we find evidence that investors respond insufficiently to past performance in the manager's other fund. We sort all multi-fund managers into quintiles based on past performance in one of their funds. We examine managers' performance in their other funds across these quintiles, forming portfolios with holding periods varying from 1 to 12 months. Our test shows that the highest quintile portfolio subsequently earns significantly higher alphas than the lowest quintile portfolio, which we also confirm by running a regression of a fund's future return on past performance of both funds. This predictability comes mostly from the lowest-performing group of multi-fund managers. The finding is consistent with our previous result that investors take more into account the manager's performance in his other fund when it is higher.

Our paper contributes to the understanding of performance-chasing behavior in mutual funds that has attracted enormous attention among academics. The results we document help distinguish between rational and behavioral explanations of the behavior. Flow is more sensitive to past performance in the other fund when it is more informative, and we show evidence that the other fund is relevant because skills are transferrable between funds. Moreover, the positive cross-fund performance relationship suggests that investors are rewarded by chasing performance in the other fund, similar in spirit to Gruber's (1996) analysis on own-fund performance persistence and flows. Our findings are unique to the setting of multi-fund managers and are consistent with investor sophistication, under which investors infer managerial ability from past returns; behavioral biases are unlikely the cause of such results. Nevertheless, contrary to the prediction by theory models such as Berk and Green (2004), we believe that capital flows do not respond *enough* to a manager's overall performance. We conclude that investors are generally sophisticated, but may not be up to the level that theory models require.[3]

[3]We acknowledge that the latter result comes with one caveat. We cannot claim that it necessarily

Our paper is related to Huang, Wei, and Yan (2012), who investigate the relationship between investor learning and the sensitivity of fund flows to performance, and to Yadav (2010) and Agarwal and Ma (2012), who also look at multi-fund managers but study their incentives and the determinants and consequences of multitasking.

The remainder of this paper is structured as follows. Section 2 describes the sample of multi-fund managers and the empirical methods. Sections 3 and 4 present, respectively, the results regarding our two hypotheses: performance-chasing in multi-funds and the relationship between past performance in one fund and future performance in the other. Section 5 concludes.

2 Data and Empirical Methodology

2.1 Data Sources and Sample

We primarily use the Center for Research in Security Prices (CRSP) Survivorship Bias Free Mutual Fund Database. The CRSP mutual fund database includes information on fund returns, total net assets (TNA), fees, and other fund characteristics including managers' names. While managers' names are provided by CRSP, a large panel of multi-fund managers is not readily available. This is because the names are not recorded consistently across time and funds: first and middle names are sometimes abbreviated differently and are sometimes excluded. We track all managers carefully and hand-construct our database of multi-fund managers, taking into account spelling differences and format changes. Sometimes the names do not match perfectly: we apply our best judgment by also estimating how common the

extends to the usual setting — investors may respond insufficiently *only* to other funds, but respond to the corresponding fund with the right level of capital flows. For example, Del Guercio and Reuter (2012) argue that funds marketed directly to investors show little evidence of persistence, which supports Berk and Green's (2004) model. Busse, Goyal, and Wahal (2010) also find little to no persistence in institutional investment management. However, our test cannot be used to examine investors' response to the corresponding fund, because fund return predictability is affected by other factors such as flow-induced price pressure on the fund's holdings (Lou, 2012). We will further discuss this issue in Section 4.

names are (e.g., common last names are more likely to refer to different people). We analyze all names that are available in CRSP and drop funds with missing managers' names. From the CRSP data we are able to identify 8,184 distinct managers, with an average experience of about five years.

We focus on funds that are managed by a single person who manages more than one fund. A reason for our exclusion of funds managed by two or more people is that team-managed and solo-managed funds have different organizational structures, as Chen, Hong, Huang, and Kubik (2004) argue. Following Agarwal and Ma (2012), we also exclude cases where a manager runs more than four funds as these managers are likely to be team managers.

To be consistent with other recent papers in the literature, our analysis uses a subset of funds in the CRSP database. We examine funds with investment objectives of growth and income, growth, and aggressive growth. The objectives are identified by the investment objective codes from the Thomson-Reuters Mutual Fund Holdings database (formerly known as CDA/Spectrum), from which we obtain holdings data for our later analysis as well.[4] We only include funds that have more than half of their assets invested in common stocks. Finally, we exclude index funds (funds that are identified by CRSP as index funds or funds that have the word "index" in their reported fund names), as well as funds that are closed to new investors.

During our sample period, many funds have multiple class shares. Since each class share of a fund has the same portfolio holdings, we aggregate all the observations to the fund level, following Kacperczyk, Sialm, and Zheng (2008). For qualitative attributes such as objectives and year of origination, we use the observation of the oldest class. For the TNA under management, we sum the TNAs of all share classes. We take the lagged TNA-weighted average for the rest of the quantitative attributes (e.g., returns, alphas, and expenses).

Data on managers' names from CRSP are available starting in 1992. Our sample covers

[4]We link CRSP and Thomson-Reuters data using the Mutual Fund Links database. We thank Russ Wermers for making this database available. For more detailed information, please see Wermers (2000).

the period 1992 to 2009. The fraction of managers that manage more than one fund in our sample is 27%, and these managers manage 30% of the total assets in domestic equity actively managed mutual funds.[5] Typically, a multi-fund manager manages two or three funds for more than four years. While our paper does not focus on how mutual fund managers become multi-fund managers and managers' incentives, Agarwal and Ma (2012) report that these managers usually performed well in the past and are more experienced. Then they either start new funds or take over other funds within the same fund company. Yadav (2010) shows that star funds can result in investors' flows into other funds managed by the same manager, and managers have an incentive to create more different portfolios to increase the likelihood of generating a star fund. Note that a fraction of well performing mutual fund managers also manage hedge funds simultaneously, as documented by Nohel, Wang, and Zheng (2010) and Deuskar, Pollet, Wang, and Zheng (2011).

In our analysis, we pick the two oldest mutual funds from each multi-fund manager. To be included in the sample, we require that at any given month we have complete data on past monthly returns to estimate a manager's performance (in both funds) in the preceding 12 months. In the end, we have 19,691 fund-month observations in our baseline flow-performance regression.

2.2 Measures and Empirical Methodology

The dependent variable of our first set of regressions, $Flow_{it}$, is the proportional growth in total net assets (TNA_{it}) under management for fund i between the beginning and the end of month t, net of internal growth R_{it}, assuming reinvestment of dividends and distributions.

$$Flow_{it} = \frac{TNA_{it} - TNA_{i,t-1}(1 + R_{it})}{TNA_{i,t-1}}.$$

[5]These aggregate numbers are fairly close to the ones reported in Agarwal and Ma (2012).

We winsorize the top and bottom 2.5% tails of the net flow variable to remove errors associated with mutual fund mergers and splits documented by Elton, Gruber, and Blake (2001).

We use the four-factor alpha ($Alpha_i$) as a measure of fund performance. While there are obviously other measures of performance, risk- or style-adjusted returns are preferred because the two funds managed by the same manager often have different objectives. Our analysis focuses on funds' performance that is not a result of the objectives. $Alpha_i$ is the risk-adjusted returns (α_i) in the preceding 12 months estimated using Carhart (1997) four-factor model. A 12-month window is chosen with the consideration that multi-fund managers typically manage the two funds over a period of four years. The results in all tables are robust to using four-factor alphas estimated from the past 24 months as our performance measure. To preserve space, we do not report these robustness tests.

$Alpha_i$ is the intercept term in the following regression:

$$r_{it} - r_{ft} = \alpha_i + \beta_{i,MKT}MKT_t + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,UMD}UMD_t + \epsilon_{it}.$$

To allow for different flow-performance sensitivities at different levels of performance, we employ the piecewise linear specification from Sirri and Tufano (1998). For each fund i in month t, we assign a fractional performance rank ($Rank_{it}$) ranging from 0 (poorest performance) to 1 (best performance) according to its past 12-month four-factor alpha, relative to all funds in the same month. Then three variables are defined according to $Rank_{it}$: the lowest performance quintile as Low_Alpha_{it} = Min($Rank_{it}$, 0.2), the three medium performance quintiles are grouped as Mid_Alpha_{it} = Min(0.6, $Rank_{it} - Low\_Alpha_{it}$), and the top performance quintile as $High\_Alpha_{it} = Rank_{it} - Mid\_Alpha_{it} - Low\_Alpha_{it}$.

In the first set of tests, we run a flow-performance regression that is similar to Sirri and Tufano (1998) and Huang, Wei, and Yan (2007). The dependent variable is flows into one of the funds of a multi-fund manager, $Flow$ (all the subscripts it are dropped for brevity). Our main coefficient of interest is the lagged performance in the other fund (Low_Alpha2, Mid_Alpha2, and $High\_Alpha2$) of the manager, while we control for the lagged performance in the corresponding fund (Low_Alpha, Mid_Alpha, and $High\_Alpha$). We also include a number of control variables in our analysis. These include a measure of fund age ($ln(FundAge)$) calculated by the natural logarithm of (1 + fund age), lagged fund size ($ln(FundSize)$) measured by the natural logarithm of fund TNA, lagged total expense ($Expense$) which is the sum of expense ratio plus one-seventh of the front-end load, a measure of the total risk of a fund measured by the standard deviation of fund raw returns in the preceding 12 months ($StandardDeviation$), the total flows into the corresponding objective of the fund ($ObjectiveFlows$), and year-month fixed effects. Our baseline regression specification is as follows:

$$\begin{aligned} Flow = \; & \alpha + \beta_1 Low\_Alpha + \beta_2 Mid\_Alpha + \beta_3 High\_Alpha \\ & + \beta_4 Low\_Alpha2 + \beta_5 Mid\_Alpha2 + \beta_6 High\_Alpha2 \\ & + \beta_7 ln(FundAge) + \beta_8 ln(FundSize) + \beta_9 Expense \\ & + \beta_{10} StandardDeviation + \beta_{11} ObjectiveFlows \\ & + \sum_t \beta_t YearMonthFixedEffects_t + \epsilon. \end{aligned} \tag{1}$$

We include both funds of a multi-fund manager. In our sample there are two funds for a given manager in a given month. These are counted as two observations. For example, in one observation, we study the flow into one fund (say, F1) and the performance in the other fund (say, F2) of the manager. Then in another observation, F2 becomes the fund in question and F1 becomes the "other fund." This setting has the advantage of studying flows into the two funds. In particular, Agarwal and Ma (2012) document that multi-fund managers can start multitasking by taking over existing funds. The performance of and the flows into acquired funds and incumbent funds are different after being managed by the same manager. By studying both funds, we make sure that our results are not entirely due to one set of funds. We address concerns regarding correlations between error terms by clustering the standard errors in the regressions at the manager-level. Past flows and manager fixed effects are included in some specifications.[6]

We address concerns that some investors are not sophisticated enough to calculate risk-adjusted fund returns as implied by our regression (1), and use style-adjusted returns instead of alphas in an alternative specification. The style-adjusted return is calculated as the average monthly return on the fund, in excess of the average return on all funds in the same CRSP investment objective code from the prior 12 months. The regression equation for this alternative specification is the same as equation (1), except that the variables Low, Mid, and $High$ of the funds are defined based on the fractional performance rank in style-adjusted returns.

Table 1 reports summary statistics of the main attributes of multi-funds in our sample (Panel A) and of funds that are managed by single-fund managers (Panel B). The single-fund managers are defined as managers who manage only one fund (of investment objectives of growth and income, growth, and aggressive growth; funds that are team-managed are excluded). We report summary statistics on fund flow, performance and risk measures, age, TNA, total expense, and total family TNA. As evident from Table 1, funds managed by multi-fund managers do not seem to be materially different from funds managed by single-fund managers: average flows into these two types of funds are both 0.6% per month, average alphas are at -1 to -5 bps per month, and average total expenses are at 1.5% per year; fund age (median $ln(FundAge)$ is 2.4), size (median $ln(FundSize)$ (in \$ millions) is 5.4 to

[6]Monthly flows are predicted by past fund performance as well as past monthly flows (e.g., Coval and Stafford, 2007). To make sure that $Alpha2$ is not simply capturing the serial correlation between monthly flows, we control for flows in the preceding six months. We also control for manager fixed effects in some of our regressions. A few self-reported surveys and findings in the literature suggest that investors take into account certain family characteristics (e.g., Hortacsu and Syverson, 2004) and manager-specific characteristics (e.g., Kumar, Niessen-Ruenzi, and Spalt, 2011) when choosing their funds. In addition, some papers document that managerial characteristics such as age and education are strongly correlated with managers' performance and the characteristics of their fund families (e.g., Chevalier and Ellison, 1999; Greenwood and Nagel, 2009).

5.8), and family size (median $ln(FamilySize)$ (in \$ millions) is 8.7 to 9.0) are all similar.

Table 2 compares the two funds of multi-fund managers. Again, we pick the two oldest funds: the first fund is the oldest, and the second fund the second oldest. As can be seen, the first fund is older and usually larger in fund size. Other characteristics such as alphas, standard deviation of return, average total expense, and loadings on the Carhart (1997) factors, are similar across the two groups.

3 Results: Cross-Fund Flow-Performance Relationship

In this section we study the first main hypothesis regarding the cross-fund flow-performance relationship. Section 3.1 presents the empirical results of regression (1). After showing that the response is consistent with investor sophistication in Sections 3.2 and 3.3, we conduct some robustness tests in Sections 3.4 and 3.5. These tests aim to confirm that our results are not picking up market- or industry-wide effects that affect mutual fund flows generally, or learning from other managers' funds (as documented by Cohen, Coval, and Pastor, 2005; Jones and Shanken, 2005).

3.1 Flow-Performance Relationship in Multi-funds

Table 3 shows the results of our regression (1). The coefficients of Low_Alpha, Mid_Alpha, and $High\_Alpha$ (i.e., β_1, β_2, and β_3) capture the flow-performance relationship in a piecewise linear regression fashion. For example, if all other independent variables are equal to zero, a fund in the 5^{th} percentile would have flows that equal ($Low\_Alpha \times \beta_1 = 0.05\beta_1$), while a fund in the 95^{th} percentile would have flows that equal ($Low\_Alpha \times \beta_1 + Mid\_Alpha \times \beta_2 + High\_Alpha \times \beta_3 = 0.2\beta_1 + 0.6\beta_2 + 0.15\beta_3$). In the first column, flows into a fund are positively related to past performance of that fund in all quintiles. The strongest effect is observed in the highest-performing group.[7]

Our first main finding comes from the corresponding variables of the performance in the other fund, Low_Alpha2, Mid_Alpha2, and $High\_Alpha2$. Note that in the second column, Low_Alpha2 and $High\_Alpha2$ are positively significant (Mid_Alpha2 is marginally negatively significant), suggesting that investors pay attention and respond to another fund's performance. (Although the coefficient of Mid_Alpha2 is negative, its magnitude is a lot smaller than that of Low_Alpha2 (-0.005 vs 0.035). The estimated performance sensitivity for funds in the three middle quintiles is still positive.) By comparing Columns (1) and (2), we also observe that the coefficients of performance variables in the corresponding fund do not drop substantially after including the other fund's performance. This suggests that the other fund has additional explanatory power, and using only the corresponding fund does not depict the full picture of the flow-performance relationship. On the interpretation of the effects, if skills are entirely manager-specific, then the coefficients of $Alpha$ and $Alpha2$ variables should be the same; if skills are fully fund-specific, the coefficients of $Alpha2$ variables should be zero. Our results therefore suggest that fund managers' skills are neither entirely fund-specific nor manager-specific: information from the other fund can help reveal managers' ability and sophisticated investors should learn from this extra signal. We will revisit this issue in Section 3.2.

The next two columns run the same regressions, adding past flows (in Column (3)) and manager fixed effects (in Column (4)) as extra control variables. The results are similar (albeit weaker): the coefficient of Low_Alpha2 becomes statistically insignificant in Column (4), but $High\_Alpha2$ remains significant. Our results are therefore more prominent when the performance in the other fund is in the top quintile, which is perhaps because mutual fund managers or companies make high-performing funds more visible to investors and investors pay more attention to these funds. When we examine the magnitude of the effect, the

[7] We note that recent working papers by Huang, Wei, and Yan (2012) and Sialm, Starks, and Zhang (2012) also find a lower coefficient of Mid_Alpha than that of Low_Alpha and $High\_Alpha$. Since this is not the main focus of our paper, we leave it to future research.

coefficient of $High\_Alpha2$ is approximately one-third to one-half of that of $High\_Alpha$ (i.e., when the fund in question is in the top quintile) in all three columns.[8] As such, if both funds by the same manager are performing very well, investors' flows into a fund respond to the performance in both funds, with the effect of the other fund one-third to half as strong as the fund in question. Moving $Alpha$ five percentiles in the highest performance group, say, from the 85^{th} to the 90^{th} percentile, corresponds to a greater inflow of 21 to 65 bps per month, while a similar change in $Alpha2$ is associated with a greater inflow of 10 to 21 bps per month.

The significance of the coefficients of $Alpha2$ variables may be attributed to family effects, since the two funds of the multi-fund managers belong to the same fund family. Column (1) of Table 4 addresses this concern by adding dummy variables that represent stellar performance (top 5% based on past alpha) of other funds in its family, following Nanda, Wang, and Zheng (2004). Nanda, Wang, and Zheng (2004) find that the stellar performance can create a spillover effect to increase the inflows into other funds in the family, while Yadav (2010) shows this spillover effect in multi-fund managers' funds. Column (2) includes family fixed effects to control for time-invariant unobservable family characteristics. The results in both columns are generally unaffected by these additional control variables: the coefficients of $Alpha2$ variables are still significant. In Section 3.4 we provide another test to further distinguish between manager and family effects.

As a robustness check, we repeat the regressions using style-adjusted returns instead of past 12-month 4-factor alphas as the performance measure. The style-adjusted return is the past 12-month average return on a fund in excess of the past 12-month average returns on all funds in the same investment objective code. Similar to Table 3, flows respond to past performance in the fund in question, as well as the other fund that the manager manages.

[8] In unreported tests we achieve similar results if we follow Huang, Wei, and Yan (2007, 2012) and include interactive terms between $Alpha$ and $ln(FundAge)$ and between $Alpha$ and $StandardDeviation$ as independent variables. The reason why we exclude these variables in our regression is that the coefficients of $High\_Alpha$ and $High\_Alpha2$ are not directly comparable in the presence of the interactive terms.

The relationship is stronger when the performance in the other fund is in the top quintile. The results using style-adjusted returns are not reported but are available upon request.

3.2 Evidence of Manager-Specific Skills

We argue that the multi-fund performance-chasing behavior is consistent with investor sophistication. We will establish that there is a manager-specific component in skills by examining the fund holdings. Suppose a multi-fund manager holds IBM in both of his two funds: 3% in Fund 1 and 5% in Fund 2. We remove all the common holdings (3% in IBM, and we repeat for all other stocks) and form two portfolios by using only the uncommon parts and rescaling the portfolio weights to 100%. The portfolio returns are calculated from the weighted stock returns, and then the Carhart (1997) four-factor alphas are estimated using the portfolio returns in the past 12 months. Panel A of Table 5 reports summary statistics of the uncommon portfolios. The mean (median) uncommon weight in the funds, before rescaling to 100%, is 54% (58%). The mean (median) alpha of the uncommon portfolios, $UncommonAlpha$, is 30 (24) bps per month.[9]

If skills have a manager-specific component, we expect $UncommonAlpha$ of one fund's portfolio to be positively correlated with $UncommonAlpha$ of the other fund's portfolio. In other words, although the holdings do not overlap in the two funds, managers should show their skills in both portfolios.[10] The results in Panel B of Table 5 confirm this conjecture. We regress $UncommonAlpha$ of the second oldest fund of the manager on $UncommonAlpha$ of the oldest fund of the manager. The relationship is both statistically and economically

[9] The magnitude is smaller than the "Best Ideas" measure in Cohen, Polk, and Silli (2009), who show that the stock that managers display the most conviction towards ex-ante earns an abnormal return of around 67 bps per month. Managers sometimes hold the "Best Ideas" stocks in both funds, and sometimes only hold them in one of the funds; thus we expect that our measure excludes some of the best ideas and is a bit lower than that measure.

[10] It is certainly possible that the alphas of two different stocks are correlated because of return correlation not captured by the Carhart (1997) factors; for example, two stocks are in the same industry or in the same style. We broadly interpret this correlation as skills, because it represents managers' value added relative to strategies based on known factors. We also achieve similar results using a six-factor model, which includes two additional factors constructed based on liquidity and short-term reversal.

significant. In Columns (1) and (2), a 1% increase in *UncommonAlpha* of the oldest fund corresponds to an increase of 10–14 bps in *UncommonAlpha* of the second oldest fund. The two *UncommonAlphas* are still positively related in the presence of control variables such as fund age, size, total expense, flows, as well as time and fund fixed effects.[11]

3.3 Differences in Styles and Performance

If investors are learning about managers' ability in a sophisticated manner, the performance-chasing behavior should be more pronounced when the signal provided by the other fund is more relevant and useful. We believe that the other fund is more informative in situations where styles of the two funds are similar but the performance is different. For example, if a manager has a large-value fund and a small-growth fund, the signal from the other fund is less informative, as abnormal return in one fund is less relevant for investors in the other fund. On the other hand, if a manager has two funds of similar styles but very different alphas, investors should learn from his other fund since it may signal that he is not as skillful as another manager who has two good alphas.

We define style and performance differences as follows:

$$StyleDifference = abs(\frac{\beta_{1,MKT}}{\beta_{2,MKT}} - 1) + abs(\frac{\beta_{1,SMB}}{\beta_{2,SMB}} - 1) + abs(\frac{\beta_{1,HML}}{\beta_{2,HML}} - 1) + abs(\frac{\beta_{1,UMD}}{\beta_{2,UMD}} - 1),$$

where $\beta_{1,X}$ and $\beta_{2,X}$ are the two funds' loadings on the Carhart (1997) factors estimated from the past 12 months. *StyleDifference* is a measure to capture the difference in factor loadings.

$$PerformanceDifference = abs(Alpha1 - Alpha2),$$

where $Alpha1$ and $Alpha2$ are the two funds' Carhart (1997) alphas estimated from the past 12 months.

[11]In unreported analysis, we replace the performance variables with *UncommonAlphas* in the flow-performance regressions. Our conclusions remain unchanged.

We first verify that the signal from the other fund is less relevant when styles are different. In the regression of *UncommonAlpha* of the second oldest fund (Table 5), we add two more independent variables: *StyleDifferenceAboveMedian* (a dummy variable that equals 1 when *StyleDifference* is above the sample median, 0 otherwise), as well as an interaction term of (*UncommonAlpha* of the oldest fund $\times$ *StyleDifferenceAboveMedian*). We find, in Column (3), a significantly weaker relationship between the two *UncommonAlphas* if the styles are more different.

We split the full sample into four subsamples, based on style and performance differences. The subsamples are constructed using independent sorts of *StyleDifference* being above or below the sample median and *PerformanceDifference* being above or below the sample median. For brevity, only one flow-performance regression specification is reported. The reported specification is the most stringent one, with all variables in equation (1) as well as past flows and manager and time fixed effects (i.e., the same as Table 3 column (4)). Table 6 reports the coefficients of the performance variables. The coefficient of $High\_Alpha2$ is statistically significant only when *StyleDifference* is below median and *PerformanceDifference* is above median. In this subsample, the coefficients of $High\_Alpha$ and $High\_Alpha2$ are similar in both statistical significance and magnitude, and are stronger than the main result in Table 3. Note that the results in the remaining three groups are weaker than Table 3, but this is unlikely due entirely to the smaller sample size. In fact, the subsample where we observe significance in $Alpha2$ has the smallest number of observations among the four groups.

We interpret this result as being consistent with sophisticated investors relying more on the signal from the other fund, when the signal is relevant and useful. Taken together, Tables 5 and 6 suggest that the flow-perfomance relationship in multi-funds arises from investor sophistication: mutual investors seem to draw inferences about a manager's skills from the other fund's past performance. Behavioral biases, on the other hand, are unlikely the cause of all the findings.

3.4 Comparison: Placebo Tests Using Funds Not Managed by the Same Manager

We will use two sets of "placebo tests" to further confirm that the documented relationship is due to learning about managers rather than other potential explanations. In particular, while our regressions control for many fund characteristics that are known to predict flows, other market-wide events or factors may impact funds with similar characteristics.

We first examine the two funds in a period when they are managed by different managers. Suppose a multi-fund manager manages the two funds during the time interval $[t_a, t_b]$, and the two funds exist and are managed by different people outside the interval. We use the 12 months ending 12 months prior to t_a and the 12 months beginning 12 months following t_b. We skip 12 months before t_a and 12 months after t_b with the consideration of our alpha estimation. If flows chase past performance because of other common factors impacting the two funds, then we should still see a significant relationship between flows and $Alpha2$ variables. However, Table 7 Column (1) shows that this is not the case. The coefficients of all $Alpha2$ variables are statistically indistinguishable from zero.

Second, we make use of a set of control funds, matching on characteristics that matter for flows. Let F1 be the fund in question and F2 be the other fund. We then find two control funds, M1 and M2, to match F1 and F2, respectively. Our matching algorithm finds the "nearest fund," similar in spirit to the commonly-used stock-matching algorithm employed in Loughran and Ritter (1997).

In particular, in each month we find a match for each multi-fund manager's fund from the universe of single-manager funds using the following:

1. We pick funds (in the same month) that come from the same family and whose assets are 25%–200% of the multi-fund manager's fund.

2. In the event that there is no eligible fund in 1 (family information is missing, or there

are no family funds with 25%–200% assets), we pick funds (in the same month) whose assets are 90%–110% of the multi-fund manager's fund.

3. From all eligible funds we calculate two scores. For M1,

$$
\begin{aligned}
Score1 = \; & abs(\frac{Eligible\ Fund's\ Alpha}{Alpha} - 1) \\
& + abs(\frac{Eligible\ Fund's\ Standard\ Deviation}{Standard\ Deviation} - 1) \\
& + abs(\frac{Eligible\ Fund's\ Fund\ Age}{Fund\ Age} - 1) \\
& + abs(\frac{Eligible\ Fund's\ Expense}{Expense} - 1).
\end{aligned}
$$

For M2,

$$
\begin{aligned}
Score2 = \; & abs(\frac{Eligible\ Fund's\ Standard\ Deviation}{Standard\ Deviation} - 1) \\
& + abs(\frac{Eligible\ Fund's\ Fund\ Age}{Fund\ Age} - 1) \\
& + abs(\frac{Eligible\ Fund's\ Expense}{Expense} - 1).
\end{aligned}
$$

We pick funds with the lowest $Score1$ to be M1 and the lowest $Score2$ to be M2. The idea is to choose funds within the family and/or of similar size, and with the most similar characteristics that are included in the baseline flow-performance regression (Equation (1)). For M1, we match with F1 on $Alpha$, $StandardDeviation$, $FundAge$, and $Expense$. For M2, we try to match with F2 on these characteristics except $Alpha$ (since we need to use the $Alpha$ of M2 in the analysis).

Table 7 Column (2) repeats regression (1), replacing $Alpha2$ (i.e., four-factor alpha of F2) with $Alpha2Matching$ (i.e., four-factor alpha of M2). Given that M2 is similar to F2 but managed by a different manager, would investors in F1 respond to the performance of M2? If our previous results are mostly due to investors' learning about manager-specific skills, the answer should be no. The results are in line with our expectation. Note that none of the variables $Low\_AlphaMatching2$, $Mid\_AlphaMatching2$, and $High\_AlphaMatching2$ is significant. The magnitude of $High\_AlphaMatching2$ is also much smaller than that of $High\_Alpha2$ in Table 3.

We then use M1 to further examine flows into F1. We define the difference in flows as (*Flow* into F1) minus (*Flow* into M1). If there are certain characteristics (besides the manager) that attract investors' flows, flows into F1 and M1 should be similar. Therefore, this difference in flows measure captures the flows into F1 of this particular manager, on top of a similar fund M1. In untabulated analysis, we perform a univariate sort of the $DifferenceInFlows$ (F1 − M1) into quintiles based on *Alpha* of F2. This test also has the advantage that it does not impose a parametric regression model like the previous one, and is therefore free from the concern that our results are driven by the choice of specification. As in Table 3, the results are more prominent among the high-performers. The difference (quintile 5 minus quintile 1) is highly significant.

We have so far established evidence regarding that investors chase performance in a multi-fund manager setting. Section 4 contains the results regarding our second hypothesis: the relationship between past performance in one fund and future performance in the other; this serves as a test of whether investors move "enough" capital across funds in light of the size-performance relationship, in a mechanism similar to moving capital to eliminate performance persistence in the traditional single-fund setting.

4 Results: Cross-Fund Return Predictability

We are interested in whether there is any cross-fund return predictability: can one fund's return predict subsequent performance in the other fund? The sign of such predictability is evidence that investors move too little (positive predictability) or too much (negative predictability) capital across funds. To see this, consider under the null that size erodes performance, if investors move too little capital out of the first fund (so that it is "too large") in response to poor past performance in the second fund, there will be a positive relationship between past performance in the second fund and future performance in the first (they are both negative). A similar argument applies to cases where investors move too little capital into the first fund when the second fund performs well (both performance measures will be positive), and where investors move too much capital (the performance measures will have different signs). If the allocation is "correct," then we would not observe any relationship in the two performance measures.[12]

Our test is derived from the equilibrium in Berk and Green's (2004) model. Berk and Green (2004) argue that investors chase performance because they allocate more money to skillful managers, and diseconomies of scale causes inflows to drive down performance. Investors competitively supply funds so that in equilibrium expected excess returns going forward are zero. Applying this to our multi-fund context, one expects to see zero return predictability across the manager's two funds if investors allocate capital competitively.

Note that mutual fund returns generally show some persistence when the performance is poor, as documented by Carhart (1997). However, Lou (2012) finds that this phenomenon is at least partially driven by the predictable price pressure arising from flows: losing funds liquidate their existing holdings that are concentrated in past losing stocks when facing outflows, so the price pressure drives down the future return of these losing stocks and the funds tend to continue to perform poorly. As such, testing predictability in a single-fund setting may not directly measure investors' response to managers' past performance. We argue that this flow-induced effect is less pronounced in our setting because the holdings of the two funds are not the same. Flows into and out of one fund do not create as much price pressure on the holdings of the other fund. The cross-fund performance predictability test is, therefore, a more direct test of the Berk and Green (2004) equilibrium condition.

[12]Alternatively, it could be because that skills cannot be carried over from one fund to another.

To test our hypothesis, we form portfolios using the second fund (the second oldest fund) of the manager. We sort all the second funds into quintiles, based on the past 12-month alpha of the first fund (the oldest fund) of the manager. In each quintile, we form portfolios that are rebalanced monthly and hold for different time horizons t: 1 month, 3 months, 6 months, and 12 months. Therefore, in each month we rebalance $1/t$ of each portfolio. For every quintile, the portfolio returns are the cumulative after-fee returns of the second funds in the corresponding quintile. The portfolio alphas are calculated by regressing the portfolio returns on Carhart (1997) four factors using the whole sample period.[13]

Table 8 shows the portfolio alphas. Panel A sorts the second funds on after-fee *Alpha* of the first fund, and Panel B sorts on before-fee *Alpha* of the first fund. The two panels show similar patterns: we see increasing portfolio alphas as we move from quintile 1 (lowest *Alpha*) to 5 (highest), with quintile 1 showing negative alphas and quintile 5 showing insignificant alphas. The results hold for different holding periods. The long-short portfolio (5 minus 1) earns an alpha of around 23–33 bps per month.[14]

We interpret the findings as follows: while there is generally insufficient response (i.e., investors do not move capital "enough") such that there is a positive relationship in the quintiles, the insufficient response mostly comes from the negative alphas in lower quintiles. Even after observing these poorly performing other funds, investors do not move enough capital out of their funds, resulting in larger funds and negative performance. One reason is that only existing investors respond to poor performance (because investors cannot short sell mutual funds), but good performance attracts both old and new investors. This finding is broadly consistent with our previous analyses, where we find that investors' response to past performance in the other fund is stronger when the fund is in the top quintile.

[13] The reported t-stats are based on White standard errors. The statistical significance we observe remains unchanged if we use Newey-West standard errors instead. Besides, our results hold if we reverse the ordering of the first and second funds.

[14] Zheng (1999) shows that funds with positive flows outperform those with negative flows for up to 30 months. It is therefore possible that investor flows and future performance in multi-funds take longer than 12 months to reach equilibrium. We end at a 12-month horizon given our data limitations.

Finally, we verify the cross-fund return predictability results using a regression framework. We regress the one-month-ahead risk-adjusted return on past alpha of the other fund, in the presence of past alpha of the fund in question and other characteristics:

$$\begin{aligned} RiskAdjustedReturn_{t+1} = \; & \alpha + \beta_1 Alpha + \beta_2 Alpha2 + \beta_3 Flow + \beta_4 ln(FundAge) \\ & + \beta_5 ln(FundSize) + \beta_6 Expense + \beta_7 ObjectiveFlows \\ & + \sum_t \beta_t YearMonthFixedEffects_t + \epsilon, \end{aligned} \tag{2}$$

where $RiskAdjustedReturn_{t+1}$ is defined as:

$$\begin{aligned} RiskAdjustedReturn_{t+1} = \; & r_{t+1} - (\beta_{MKT} MKT_{t+1} + \beta_{SMB} SMB_{t+1} + \beta_{HML} HML_{t+1} \\ & + \beta_{UMD} UMD_{t+1}). \end{aligned}$$

r_{t+1} is the raw return of fund i in month $t+1$ (the subscript i is dropped). The factor loadings β are estimated using the Carhart (1997) model that also calculates *Alpha*. Other variables in equation (2) are the same as those in equation (1). Similar to equation (1), in one observation, we study the risk-adjusted return of one fund (say, F1) and the alpha of the other fund (say, F2) of the manager. Then in another observation, F2 becomes the fund in question and F1 becomes the "other fund."

Column (1) of Table 9 shows the results. Past alphas of both funds can predict the next-month return. Unsurprisingly, we note that the coefficient of *Alpha*2 is smaller than that of *Alpha*. Increasing *Alpha* (*Alpha*2) by 1% corresponds to an increase of 27 (7) bps in the next-month risk-adjusted return. A three-standard deviation change in *Alpha*2 (approximately going from 10^{th} to 90^{th} percentile) corresponds to a change of 19 bps (0.0682×3×0.0093) per month in the next-month return. This is similar in magnitude to the 5 minus 1 portfolio return in Table 8.[15] Column (2) of Table 9 repeats the regression, replacing *Alpha* and

[15] If we compare poorly performing and well performing *Alpha*2, the estimated coefficient is stronger in the former group (consistent with Table 8) but the difference across the two groups is not significant.

$Alpha2$ with $Rank$ and $Rank2$, which are the fractional performance ranks from 0 (poorest) to 1 (best) based on past alphas, as defined in Section 2.2. The results are similar.

The regression framework also allows us to study the size-performance relationship more closely. Specifically, we observe a negative and statistically significant relationship between the next-month return and size. Although the effect is in line with Berk and Green (2004) and Chen, Hong, Huang, and Kubik (2004), it seems economically small. In Column (1) of Table 9, a one standard deviation increase in $Alpha2$ corresponds to an increase in the next month's risk-adjusted return by 6 bps per month. From the coefficient estimate in the regression, $ln(FundSize)$ needs to increase by 1.07 to eliminate 6 bps; if a fund originally has a size that equals the sample median ($339 million), an increase in log size of 1.07 means that the size has to increase to $965 million. This is of course a rough estimation as we assume a linear size-performance relationship and ignore endogeneity issues.

Tables 8 and 9 reject the hypothesis that the response to $Alpha2$ is sufficient. Our interpretation is that sophisticated investors, who understand the size-performance relationship, do not move their capital with the right amount to erode performance. However, given the joint-hypothesis nature of our test, it is possible to attribute the insufficient response to a weak size-performance relationship. One should therefore be cautious in understanding why Berk and Green's (2004) equlibrium does not hold. A potential direction for future research is to better estimate the size-performance relationship in multi-funds.

5 Conclusion

In this paper we use multi-fund managers, who manage more than one fund, to help distinguish between rational and behavioral explanations of the performance-chasing behavior in mutual funds.

The evidence is broadly consistent with the notion that investors rationally infer managerial ability from past returns. For multi-fund managers, there is one additional piece of information on manager's past performance that investors can use over and above his performance in the fund under consideration — the manager's performance in his other fund. Do investors take this into account? We show that they indeed do: flows into a fund managed by a multi-fund manager are predicted by both the manager's performance in the corresponding fund and in the other fund he manages. Performance in one fund predicts flows into the other fund more strongly when the performance is particularly good, perhaps because fund managers (or companies) strategically create spillover effects by making high-performing funds more visible.

Next, we investigate whether investors allocate their capital across funds in a way similar in spirit to the model by Berk and Green (2004). Under the null hypothesis that fund size erodes fund performance, we suggest a simple test by examining whether past performance in one fund of a multi-fund manager predicts subsequent performance in his other fund. If investors understand the size-performance relationship and take into account the manager's performance in both funds, they would allocate exactly the right amount of capital into every fund in question. As such, there would be no predictability in performance. However, we find evidence of positive cross-fund return predictability; in particular, investors do not seem to withdraw enough capital in response to poor performance in the manager's other fund.

The multi-fund environment provides some unique insights on investor sophistication. The cross-fund flow-performance relationship is stronger when the other fund's performance carries more additional information, that is, when styles of the two funds are similar and performance in the two funds is more different. We also believe that this information is relevant because skills are not entirely fund-specific, which means skills shown in one fund are likely to be applicable to the manager's other fund. Finally, the positive cross-fund performance predictability suggests that investors are rewarded by responding to the other fund's past performance. These results are more consistent with investor sophistication than behavioral biases. However, the sophistication is not up to the level that some theory models assume.

Overall, our paper contributes to the understanding of performance-chasing behavior in mutual funds. The evidence shows mixed results. Future work is needed to understand aspects that we do not find support for. In particular, one could further examine the size-performance relationship in multi-funds. We rely on Berk and Green's (2004) argument that there are diseconomies of scale, because managers have limited time and resources to spend on information-gathering activities and large trades have higher costs. Empirically, in single-fund settings, Chen, Hong, Huang, and Kubik (2004) and Pollet and Wilson (2008) find that fund returns decline with lagged fund size, but Reuter and Zitzewitz (2011) find little evidence that size erodes performance. It will be interesting to examine whether the relationship is different in multi-funds, as well as the reason why the equilibrium conditions fail to hold.

References

Agarwal, V., Ma, L., 2012. Managerial Multitasking in the Mutual Fund Industry. Working Paper.

Bailey, W., Kumar, A., Ng, D., 2010. Behavioral Biases of Mutual Fund Investors. *Journal of Financial Economics* 102, 1–27.

Baks, K.P., 2003. On the Performance of Mutual Fund Managers. Working Paper.

Berk, J.B., Green, R.C., 2004. Mutual Fund Flows and Performance in Rational Markets. *Journal of Political Economy* 112, 1269–1295.

Busse, J.A., Goyal, A., Wahal, S., 2010. Performance and Persistence in Institutional Investment Management. *Journal of Finance* 65, 765–790.

Carhart, M.M., 1997. On Persistence in Mutual Fund Performance. *Journal of Finance* 52, 57–82.

Cohen, R.B., Coval, J.D., Pastor, L., 2005. Judging Fund Managers by the Company They Keep. *Journal of Finance* 60, 1057–1095.

Cohen, R.B., Polk, C., Silli, B., 2009. Best Ideas. Working Paper.

Chen, J., Hong, H., Huang, M., Kubik, J.D., 2004. Does Fund Size Erode Mutual Fund Performance? The Role of Liquidity and Organization. *American Economic Review* 94, 1276–1302.

Chevalier, J.A., Ellison, G., 1997. Risk Taking by Mutual Funds as a Response to Incentives. *Journal of Political Economy* 105, 1167–1200.

Chevalier, J.A., Ellison, G., 1999. Are Some Mutual Fund Managers Better Than Others? Cross-Sectional Patterns in Behavior and Performance. *Journal of Finance* 54, 875–899.

Choi, J., Laibson, D., Madrian, B., 2010. Why Does the Law of One Price Fail? An Experiment on Index Mutual Funds. *Review of Financial Studies* 23, 1405–1432.

Coval, J., Stafford, E., 2007. Asset Fire Sales (and Purchases) in Equity Markets. *Journal of Financial Economics* 86, 479–512.

Del Guercio, D., Reuter, J., 2012. Mutual Fund Performance and the Incentives to Generate Alpha. *Journal of Finance*, forthcoming.

Deuskar, P., Pollet, J.M., Wang, Z.J., Zheng, J., 2011. The Good or the Bad? Which Mutual Fund Managers Join Hedge Funds? *Review of Financial Studies* 24, 3008–3024.

Elton, E.J., Gruber, M.J., Blake, C.R., 2001. A First Look at the Accuracy of CRSP Mutual Fund Database and a Comparison of the CRSP and Morningstar Mutual Fund Database. *Journal of Finance* 56, 2415–2430.

Elton, E.J., Gruber, M.J., Busse, J.A., 2004. Are Investors Rational? Choices among Index Funds. *Journal of Finance* 59, 261–288.

Greenwood, R., Nagel, S. 2009. Inexperienced Investors and Bubbles. *Journal of Financial Economics* 93, 239–258.

Gruber, M.J., 1996. The Growth in Actively Managed Mutual Funds. *Journal of Finance* 51, 783–810.

Hortacsu, A., Syverson, C., 2004. Product Differentiation, Search Costs, and Competition in the Mutual Fund Industry: A Case Study of S&P 500 Index Funds. *Quarterly Journal of Economics* 119, 403–456.

Huang, J., Wei, K.D., Yan, H., 2007. Participation Costs and the Sensitivity of Fund Flows to Past Performance. *Journal of Finance* 62, 1273–1311.

Huang, J., Wei, K.D., Yan, H., 2012. Investor Learning and Mutual Fund Flows. Working Paper.

Jones, C. S., Shanken, J., 2005, Mutual Fund Performance with Learning Across Funds. *Journal of Financial Economics* 78, 507–552.

Kacperczyk, M., Sialm, C., Zheng, L., 2008. Unobserved Actions of Mutual Funds. *Review of Financial Studies* 21, 2379–2416.

Kumar, A., Niessen-Ruenzi, A., Spalt, O.G., 2011. What is in a Name? Mutual Fund Flows When Managers Have Foreign Sounding Names. Working Paper.

Lou, D., 2012. A Flow-Based Explanation for Return Predictability. *Review of Financial Studies*, forthcoming.

Loughran, T., Ritter, J.R., 1997. The Operating Performance of Firms Conducting Seasoned Equity Offerings. *Journal of Finance* 52, 1823–1850.

Nanda, V., Wang, Z.J., Zheng, L. 2004. Family Values and the Star Phenomenon: Strategies of Mutual Fund Families. *Review of Financial Studies* 17, 667–698.

Nohel, T., Wang, Z.J., Zheng, L. 2010. Side-by-Side Management of Hedge Funds and Mutual Funds. *Review of Financial Studies* 23, 2342–2373.

Pastor, L., Stambaugh, R.F., 2003. Liquidity Risk and Expected Stock Returns. *Journal of Political Economy* 111, 642–685.

Pollet, J., Wilson, M., 2008. How Does Size Affect Mutual Fund Behavior? *Journal of Finance* 63, 2941–2969.

Reuter, J., Zitzewitz, E. 2011. How Much Does Size Erode Mutual Fund Performance? A Regression Discontinuity Approach. Working Paper.

Sialm, C., Starks, L., Zhang, H. 2012. Defined Contribution Pension Plans: Sticky or Discerning Money? Working Paper.

Sirri, E. R., Tufano, P. 1998. Costly Search and Mutual Fund Flows. *Journal of Finance* 53, 1589–1622.

Wermers, R., 2000. Mutual Fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transaction Costs, and Expenses. *Journal of Finance* 55, 1655–1695.

Yadav, V., 2010. Portfolio Matching by Multi-Fund Managers: Effects on Fund Performance and Flows. Working Paper.

Zheng, L., 1999. Is Money Smart? A Study of Mutual Fund Investors' Fund Selection Ability. *Journal of Finance* 54, 901–933.

Table 1
Summary Statistics of Multi-Funds and Single-Funds

This table presents summary statistics of multi-funds (funds that are managed by people who manage more than one fund) in Panel A, and of single-funds (funds that are managed by people who manage only one fund) in Panel B. *Flow* is the proportional monthly growth in total assets under management, net of internal growth (assuming reinvestment of dividends and distributions). *Alpha* is the risk-adjusted returns in the preceding 12 months estimated using Carhart (1997) four-factor model. *Standard Deviation* is the standard deviation of fund raw returns in the preceding 12 months. *Fund Age* is the number of years since fund inception. *Fund Size* is the fund total net asset. *Expense* is the sum of expense ratio plus one-seventh of the front-end load. *Family Size* is the total net asset of the fund's family.

N = 27,313

Panel A: Multi-Fund Managers' Funds

	Mean	Median	Standard Deviation	25th Percentile	75th Percentile
Flow (%)	0.569	-0.236	4.398	-1.442	1.528
Alpha (%)	-0.052	-0.072	0.925	-0.495	0.342
Standard Deviation (%)	4.928	4.447	2.556	3.051	6.156
log Fund Age (years)	2.415	2.398	0.800	1.792	2.890
log Fund Size ($ millions)	5.823	5.803	1.507	4.694	6.880
Expense (%)	1.510	1.491	0.562	1.060	1.940
log Family Size ($ millions) [1]	8.808	8.722	2.702	7.298	10.464

N = 57,112

Panel B: Single-Fund Managers' Funds

	Mean	Median	Standard Deviation	25th Percentile	75th Percentile
Flow (%)	0.563	-0.123	4.240	-1.289	1.526
Alpha (%)	-0.014	-0.041	0.902	-0.422	0.351
Standard Deviation (%)	4.627	4.074	2.541	2.811	5.774
log Fund Age (years)	2.434	2.398	0.795	1.946	2.944
log Fund Size ($ millions)	5.599	5.440	1.638	4.374	6.652
Expense (%)	1.511	1.469	0.565	1.040	1.936
log Family Size ($ millions) [1]	8.996	8.975	2.850	7.098	11.044

[1] For *log Family Size*, N = 14,792 in Panel A and N = 25,112 in Panel B due to missing family information.

Table 2
Summary Statistics of the Two Funds of Multi-Fund Managers

This table presents summary statistics of the two funds of multi-fund managers. We pick the two oldest funds from each multi-fund manager. The oldest fund is the first fund (Panels A and C), and the second oldest fund is the second fund (Panels B and D). *Alpha* is the risk-adjusted returns in the preceding 12 months estimated using Carhart (1997) four-factor model. *Standard Deviation* is the standard deviation of fund raw returns in the preceding 12 months. *Fund Age* is the number of years since fund inception. *Fund Size* is the fund total net asset. *Expense* is the sum of expense ratio plus one-seventh of the front-end load. *MKT*, *SMB*, *HML*, and *UMD* are the funds' loadings on the Carhart (1997) factors.

N = 9,932

Panel A: First Fund's Characteristics

	Mean	Median	Standard Deviation	25th Percentile	75th Percentile
Alpha (%)	-0.047	-0.064	0.862	-0.465	0.304
Standard Deviation (%)	4.856	4.396	2.449	3.012	6.111
log Fund Age (years)	2.615	2.565	0.753	2.079	3.091
log Fund Size ($ millions)	6.266	6.265	1.480	5.148	7.389
Expense (%)	1.442	1.448	0.540	1.016	1.889

N = 9,759

Panel B: Second Fund's Characteristics

	Mean	Median	Standard Deviation	25th Percentile	75th Percentile
Alpha (%)	-0.032	-0.060	0.924	-0.485	0.386
Standard Deviation (%)	5.043	4.536	2.663	3.151	6.189
log Fund Age (years)	2.279	2.303	0.803	1.609	2.773
log Fund Size ($ millions)	5.675	5.580	1.443	4.651	6.642
Expense (%)	1.514	1.499	0.551	1.010	1.950

N = 9,932

Panel C: First Fund's Loadings

	Mean	Median	Standard Deviation	25th Percentile	75th Percentile
MKT	0.979	0.969	0.294	0.820	1.118
SMB	0.155	0.062	0.432	-0.132	0.405
HML	-0.020	0.003	0.518	-0.293	0.286
UMD	0.035	0.017	0.319	-0.125	0.187

N = 9,759

Panel D: Second Fund's Loadings

	Mean	Median	Standard Deviation	25th Percentile	75th Percentile
MKT	0.982	0.974	0.342	0.812	1.139
SMB	0.192	0.102	0.467	-0.119	0.460
HML	-0.007	0.014	0.573	-0.305	0.304
UMD	0.049	0.020	0.369	-0.131	0.204

Table 3
Flow-Performance Regression in Multi-Funds

This table presents the results of the flow-performance regressions. The dependent variable is *Flow*, which is the proportional monthly growth in total assets under management, net of internal growth (assuming reinvestment of dividends and distributions). *Alpha* and *Alpha2* are the risk-adjusted returns, respectively, of the fund in question and of the other fund managed by the same manager in the preceding 12 months estimated using Carhart (1997) four-factor model. For each month, we assign a fractional performance rank ranging from 0 (poorest performance) to 1 (best performance) to funds according to their *Alpha* and *Alpha2*. Then we define three variables according to the rank: the lowest performance quintile as *Low_Alpha* = Min(*Rank*, 0.2), the three medium performance quintiles as *Mid_Alpha* = Min(0.6, *Rank* - *Low_Alpha*), and the top performance quintile as *High_Alpha* = *Rank* - *Mid_Alpha* - *Low_Alpha*.

Other control variables include: *ln(Fund Age)*, calculated by the natural logarithm of (1+fund age); *ln(Fund Size)*, measured by the natural logarithm of lagged fund TNA; *Expense*, the lagged sum of expense ratio plus one-seventh of the front-end load; *Standard Deviation*, the standard deviation of fund raw returns in the preceding 12 months; *Objective Flows*, the total flows into the corresponding objective of the fund, and year-month and manager fixed effects. The coefficients of fixed effects are not reported. Standard errors are clustered at the manager level. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

	(1)		(2)		(3)		(4)	
		t-stat		t-stat		t-stat		t-stat
Intercept	-0.0140*	(-1.95)	-0.0178**	(-2.38)	-0.0100*	(-1.92)	-0.0012	(-0.14)
Low_Alpha	0.0768***	(7.38)	0.0640***	(5.89)	0.0196***	(3.15)	0.0207***	(3.13)
Mid_Alpha	0.0204***	(7.22)	0.0207***	(6.92)	0.0078***	(5.14)	0.0095***	(5.74)
High_Alpha	0.137***	(6.71)	0.1295***	(6.65)	0.0426***	(4.64)	0.0491***	(4.55)
Low_Alpha2			0.0346***	(2.82)	0.0145**	(2.07)	0.0121	(1.58)
Mid_Alpha2			-0.0052*	(-1.75)	-0.0023	(-1.37)	-0.0033*	(-1.70)
High_Alpha2			0.0415**	(2.30)	0.0198**	(2.31)	0.0237**	(2.56)
ln(Fund Age)	-0.0072***	(-7.05)	-0.0076***	(-7.12)	-0.0010***	(-2.75)	-0.0008	(-1.20)
ln(Fund Size)	0.0021***	(4.42)	0.0022***	(4.68)	-0.0002	(-1.26)	-0.0020***	(-4.20)
Expense	0.3739***	(2.64)	0.3247**	(2.14)	0.0323	(0.58)	-0.0783	(-0.64)
Standard Deviation	-0.0874**	(-2.30)	-0.0727*	(-1.86)	-0.0429***	(-2.75)	-0.0313	(-0.76)
Objective Flows	0.0006*	(1.70)	0.0006	(1.64)	0.0002*	(1.70)	0.0003	(1.59)
Past Flows	No		No		Yes		Yes	
Manager Fixed Effects	No		No		No		Yes	
Year-Month Fixed Effects	Yes		Yes		Yes		Yes	
N	22,536		19,691		19,644		19,644	
R-squared	0.131		0.139		0.379		0.402	

Table 4
Flow-Performance Regression in Multi-Funds (Controlling for Family Effects)

This table presents the results of the flow-performance regressions, controlling for family effects. The first column controls for a dummy that represents the stellar performance of other funds in its family, *Star Manager Dummy* (Nanda, Wang, and Zheng, 2004). The second column controls for *Family Fixed Effects*. The dependent variable is *Flow*, which is the proportional monthly growth in total assets under management, net of internal growth (assuming reinvestment of dividends and distributions). *Alpha* and *Alpha2* are the risk-adjusted returns, respectively, of the fund in question and of the other fund managed by the same manager in the preceding 12 months estimated using Carhart (1997) four-factor model. For each month, we assign a fractional performance rank ranging from 0 (poorest performance) to 1 (best performance) to funds according to their *Alpha* and *Alpha2*. Then we define three variables according to the rank: the lowest performance quintile as *Low_Alpha* = Min(*Rank*, 0.2), the three medium performance quintiles as *Mid_Alpha* = Min(0.6, *Rank* - *Low_Alpha*), and the top performance quintile as *High_Alpha* = *Rank* - *Mid_Alpha* - *Low_Alpha*.

Other control variables include: *ln(Fund Age)*, calculated by the natural logarithm of (1+fund age); *ln(Fund Size)*, measured by the natural logarithm of lagged fund TNA; *Expense*, the lagged sum of expense ratio plus one-seventh of the front-end load; *Standard Deviation*, the standard deviation of fund raw returns in the preceding 12 months; *Objective Flows*, the total flows into the corresponding objective of the fund, and year-month and manager fixed effects. The coefficients of fixed effects are not reported. Standard errors are clustered at the manager level. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

	(1)	t-stat	(2)	t-stat
Intercept	-0.0235***	(-2.92)	-0.0078	(-1.30)
Low_Alpha	0.0435***	(3.83)	0.0388***	(3.43)
Mid_Alpha	0.0192***	(5.74)	0.0184***	(7.47)
High_Alpha	0.1047***	(4.37)	0.0837***	(6.19)
Low_Alpha2	0.0322**	(2.14)	0.0324***	(2.94)
Mid_Alpha2	-0.0078**	(-2.09)	-0.0084***	(-3.34)
High_Alpha2	0.0490**	(2.17)	0.0343**	(2.53)
ln(Fund Age)	-0.0057***	(-4.37)	-0.0053***	(-6.48)
ln(Fund Size)	0.0025***	(4.44)	0.0012***	(2.78)
Expense	0.4434***	(2.94)	0.0768	(0.65)
Standard Deviation	-0.0461	(-1.07)	0.0402*	(1.88)
Objective Flows	0.0021***	(2.65)	0.0036***	(13.72)
Star Manager Dummy	Yes		No	
Family Fixed Effects	No		Yes	
Year-Month Fixed Effects	Yes		Yes	
N	11,029		11,029	
R-squared	0.120		0.204	

Table 5
Uncommon Alphas: Portfolios of Two Funds With Common Holdings Removed

This table shows summary statistics of uncommon alphas (Panel A) and regressions of uncommon alphas (Panel B). For each multi-fund manager, all the common holdings in a quarter across the two funds are removed. Then two portfolios are formed using only the uncommon parts and rescaling the weights to 100%. The portfolio returns are calculated from weighted stock returns. *Uncommon Alpha* is the Cahart (1997) four-factor alpha calculated using the portfolio returns.

In Panel B, *Uncommon Alpha* of the second oldest fund (*Uncommon Alpha 2*) is regressed on *Uncommon Alpha* of the oldest fund (*Uncommon Alpha 1*). *Style Difference Above Median* is a dummy variable that equals 1 when the factor loadings distance between the two funds is above the sample median, 0 otherwise. Other control variables include: *ln(Fund Age)*, calculated by the natural logarithm of (1+fund age); *ln(Fund Size)*, measured by the natural logarithm of lagged fund TNA; *Expense*, the lagged sum of expense ratio plus one-seventh of the front-end load; *Objective Flows*, the total flows into the corresponding objective of the fund; *Flow*, the proportional monthly growth in total assets under management, net of internal growth (assuming reinvestment of dividends and distributions), and year-month and fund fixed effects. The coefficients of fixed effects are not reported. Standard errors are clustered at the manager level. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

Panel A: Uncommon Weight and Uncommon Alpha

	Mean	Median	Standard Deviation	25th Percentile	75th Percentile
Uncommon Weight (%)	54.240	58.798	32.425	23.813	83.634
Uncommon Alpha (%)	0.302	0.237	1.432	-0.376	0.890

Panel B: Regression of Uncommon Alpha 2

	(1)	t-stat	(2)	t-stat	(3)	t-stat
Intercept	0.0027***	(5.58)	-0.0056	(-0.73)	-0.006	(-0.81)
Uncommon Alpha 1	0.1372***	(2.74)	0.1302**	(2.26)	0.297***	(3.86)
Uncommon Alpha 1 x Style Difference Above Median					-0.257***	(-3.81)
Style Difference Above Median					0.001	(1.54)
ln(Fund Age)			0.0019	(0.75)	0.002	(0.64)
ln(Fund Size)			0.0004	(0.39)	0.000	(0.50)
Expense			0.1314	(0.63)	0.120	(0.57)
Objective Flows			0.0000	(0.11)	0.000	(0.19)
Flow			0.0382***	(4.03)	0.037***	(3.92)
Fund Fixed Effects			Yes		Yes	
Year-Month Fixed Effects			Yes		Yes	
N	8,629		8,191		8,191	
R-squared	0.017		0.354		0.365	

Table 6

Flow-Performance Regression in Multi-Funds
(Subsample Analysis Based on Style and Performances)

This table presents the results of the flow-performance regressions, splitting the whole sample into four based on *Style Difference* and *Performance Difference*. *Style Difference* is the distance in factor loadings in the preceding 12 months estimated using Carhart (1997) four-factor model. *Performance Difference* is the absolute difference between *Alpha* and *Alpha2*. The four subsamples are constructed based on whether *Style Difference* and *Performance Difference* are above or below the sample medians. The dependent variable is *Flow*, which is the proportional monthly growth in total assets under management, net of internal growth (assuming reinvestment of dividends and distributions). *Alpha* and *Alpha2* are the risk-adjusted returns, respectively, of the fund in question and of the other fund managed by the same manager in the preceding 12 months estimated using Carhart (1997) four-factor model. For each month, we assign a fractional performance rank ranging from 0 (poorest performance) to 1 (best performance) to funds according to their *Alpha* and *Alpha2*. Then we define three variables according to the rank: the lowest performance quintile as *Low_Alpha* = Min(*Rank*, 0.2), the three medium performance quintiles as *Mid_Alpha* = Min(0.6, *Rank* - *Low_Alpha*), and the top performance quintile as *High_Alpha* = *Rank* - *Mid_Alpha* - *Low_Alpha*.

Other control variables include: *ln(Fund Age)*, calculated by the natural logarithm of (1+fund age); *ln(Fund Size)*, measured by the natural logarithm of lagged fund TNA; *Expense*, the lagged sum of expense ratio plus one-seventh of the front-end load; *Standard Deviation*, the standard deviation of fund raw returns in the preceding 12 months; *Objective Flows*, the total flows into the corresponding objective of the fund, and year-month and manager fixed effects. The coefficients of control variables and fixed effects are not reported. Standard errors are clustered at the manager level. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

		Performance Difference			
		Above Median		Below Median	
			t-stat		t-stat
Style Difference Above Median	Low_Alpha	0.0053	(0.34)	0.0462	(1.47)
	Mid_Alpha	0.0095**	(2.50)	0.0096*	(1.82)
	High_Alpha	0.0504**	(2.55)	0.0717	(1.30)
	Low_Alpha2	-0.0002	(-0.01)	0.0059	(0.20)
	Mid_Alpha2	-0.0024	(-0.65)	-0.0045	(-0.96)
	High_Alpha2	0.0158	(1.09)	0.0186	(0.35)
	N	6,107		3,605	
	R-squared	0.417		0.483	
			t-stat		t-stat
Style Difference Below Median	Low_Alpha	0.0170	(0.81)	0.0256	(1.41)
	Mid_Alpha	0.0103**	(2.23)	0.0105**	(2.21)
	High_Alpha	0.0862***	(3.03)	0.0756**	(2.46)
	Low_Alpha2	0.0169	(0.88)	-0.0134	(-0.72)
	Mid_Alpha2	-0.0050	(-0.99)	-0.0012	(-0.24)
	High_Alpha2	0.0831***	(3.35)	-0.0402	(-1.45)
	N	3,543		6,389	
	R-squared	0.485		0.477	

Table 7
Comparison: Flow-Performance Using Funds By Different Managers

This table presents the results of the flow-performance regressions using funds that are managed by different managers. The dependent variable is *Flow*, which is the proportional monthly growth in total assets under management, net of internal growth (assuming reinvestment of dividends and distributions). *Alpha*, *Alpha2 Before/After*, and *Alpha2 Matching* are the risk-adjusted returns, respectively, of the fund in question, of a fund that has been or will be managed by the multi-fund manager, and of a control fund (M2) in the preceding 12 months estimated using Carhart (1997) four-factor model. In Column (1), the fund that has been or will be managed by the multi-fund manager is identified as follows. Suppose a multi-fund manager manages two funds during $[t_a, t_b]$. We use this manager's other fund, but using a 12-month period ending 12 months before t_a and a 12-month period beginning 12 months after t_b. In Column (2), the control fund (M2) is a fund that has similar characteristics as the other fund managed by the same manager. For each month, we assign a fractional performance rank ranging from 0 (poorest performance) to 1 (best performance) to funds according to their *Alpha*, *Alpha2 Before/After*, and *Alpha2 Matching* . Then we define three variables according to the rank: the lowest performance quintile as *Low_Alpha* = Min(*Rank*, 0.2), the three medium performance quintiles as *Mid_Alpha* = Min(0.6, *Rank* - *Low_Alpha*), and the top performance quintile as *High_Alpha* = *Rank* - *Mid_Alpha* - *Low_Alpha*.

Other control variables include: *ln(Fund Age)*, calculated by the natural logarithm of (1+fund age); *ln(Fund Size)*, measured by the natural logarithm of lagged fund TNA; *Expense*, the lagged sum of expense ratio plus one-seventh of the front-end load; *Standard Deviation*, the standard deviation of fund raw returns in the preceding 12 months; *Objective Flows*, the total flows into the corresponding objective of the fund, and year-month and manager fixed effects. The coefficients of control variables and fixed effects are not reported. Standard errors are clustered at the manager level. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

	(1)		(2)	
		t-stat		t-stat
Low_Alpha	0.0137	(1.46)	0.0195***	(2.74)
Mid_Alpha	0.0123***	(5.69)	0.0117***	(6.20)
High_Alpha	0.0255**	(2.51)	0.0491***	(4.08)
Low_Alpha2 Before/After	-0.0052	(-0.66)		
Mid_Alpha2 Before/After	-0.0018	(-0.89)		
High_Alpha2 Before/After	-0.0107	(-1.22)		
Low_Alpha2 Matching			0.0000	(0.00)
Mid_Alpha2 Matching			-0.0019	(-1.29)
High_Alpha2 Matching			-0.0092	(-1.46)
Other Control Variables	Yes		Yes	
Past Flows	Yes		Yes	
Manager Fixed Effects	Yes		Yes	
Year-Month Fixed Effects	Yes		Yes	
N	16,829		17,832	
R-squared	0.311		0.378	

Table 8
Portfolios Formed Based on Past Performance in the Other Fund the Manager Manages

Portfolios are formed using the second fund of the manager. We sort all the second funds into quintiles, based on the past 12-month Carhart (1997) alpha of the first fund of the manager. Panel A sorts second funds on after-fee alpha of the first fund, and Panel B sorts on before-fee alpha of the first fund. In each quintile, portfolios are rebalanced monthly and held for different time horizons t: 1 month, 3 months, 6 months, and 12 months. The portfolio returns are the cumulative after-fee returns of the second funds in the corresponding quintile. The portfolio alphas, reported in the table, are calculated by regressing the portfolio returns on Carhart (1997) four factors using the whole sample period. For each manager in a given month, the oldest fund is the first fund, and the second oldest fund is the second fund. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

Panel A: Sorted on Past Alpha of the Second Fund (After Fees)

Holding Period	1-month		3-month		6-month		12-month	
Quintiles	Alpha (%)	t-stat	Alpha (%)	t-stat	Alpha (%)	t-stat	Alpha (%)	t-stat
1 (Lowest)	-0.21**	(-2.15)	-0.19*	(-1.99)	-0.18**	(-2.01)	-0.15*	(-1.78)
2	-0.11	(-1.53)	-0.10	(-1.57)	-0.12*	(-1.94)	-0.12**	(-2.13)
3	-0.10	(-1.43)	-0.08	(-1.30)	-0.11*	(-1.86)	-0.08	(-1.33)
4	-0.08	(-1.11)	-0.11*	(-1.79)	-0.06	(-0.98)	-0.10	(-1.57)
5 (Highest)	0.12	(1.28)	0.11	(1.23)	0.10	(1.26)	0.10	(1.19)
5-1	0.33**	(2.44)	0.30**	(2.30)	0.29**	(2.34)	0.24**	(2.11)

Panel B: Sorted on Past Alpha of the Second Fund (Before Fees)

Holding Period	1-month		3-month		6-month		12-month	
Quintiles	Alpha (%)	t-stat	Alpha (%)	t-stat	Alpha (%)	t-stat	Alpha (%)	t-stat
1 (Lowest)	-0.19*	(-1.91)	-0.21**	(-2.17)	-0.18**	(-2.01)	-0.14	(-1.62)
2	-0.10	(-1.40)	-0.11*	(-1.77)	-0.13**	(-2.33)	-0.12**	(-2.12)
3	-0.12*	(-1.74)	-0.12**	(-2.00)	-0.15***	(-2.61)	-0.09*	(-1.67)
4	-0.06	(-0.95)	-0.09	(-1.53)	-0.05	(-0.88)	-0.09	(-1.42)
5 (Highest)	0.10	(1.06)	0.12	(1.34)	0.12	(1.41)	0.09	(1.16)
5-1	0.29**	(2.11)	0.32**	(2.50)	0.30**	(2.43)	0.23**	(1.97)

Table 9
Regression of Future Performance on Past Performance

This table presents the results of the regressions of future performance on past performance. The dependent variable is *Next Month Risk Adjusted Return*, which is the raw return minus the factor loadings times realized factor premiums in the next month. The factor loadings are estimated from the preceding 12 months using Carhart (1997) four-factor model. *Alpha* and *Alpha2* are the risk-adjusted returns, respectively, of the fund in question and of the other fund managed by the same manager in the preceding 12 months estimated using Carhart (1997) four-factor model. *Rank(Alpha)* and *Rank(Alpha2)* are fractional performance ranks ranging from 0 (poorest performance) to 1 (best performance) to funds according to their *Alpha* and *Alpha2*.

Other control variables include: *ln(Fund Age)*, calculated by the natural logarithm of (1+fund age); *ln(Fund Size)*, measured by the natural logarithm of lagged fund TNA; *Expense*, the lagged sum of expense ratio plus one-seventh of the front-end load; *Objective Flows*, the total flows into the corresponding objective of the fund; *Flow*, the proportional monthly growth in total assets under management, net of internal growth (assuming reinvestment of dividends and distributions), and past flows and year-month fixed effects. The coefficients of past flows and fixed effects are not reported. Standard errors are clustered at the manager level. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

	(1)		(2)	
		t-stat		t-stat
Alpha	0.2687***	(5.64)		
Alpha2	0.0682**	(2.14)		
Rank(Alpha)			0.0072***	(7.44)
Rank(Alpha2)			0.0019**	(2.09)
ln(Fund Age)	0.0002	(0.87)	0.0002	(0.81)
ln(Fund Size)	-0.0006***	(-3.54)	-0.0006***	(-3.44)
Expense	-0.0628	(-1.57)	-0.0525	(-1.33)
Objective Flows	0.0002*	(1.77)	0.0002*	(1.75)
Flow	0.0099	(1.47)	0.0126**	(2.07)
Past Flows	Yes		Yes	
Year-Month Fixed Effects	Yes		Yes	
N	23,729		23,729	
R-squared	0.063		0.072	