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

Darwin Choi, HKUST

C. Bige Kahraman, SIFR and Stockholm School of Economics

Abhiroop Mukherjee, HKUST*

August 2012

Abstract

We study managers who simultaneously manage multiple mutual funds to provide new evidence on Berk and Green's (2004) explanation for investors' performance-chasing behavior. Consistent with their model in which investors infer managerial ability from past performance, we find that flows into a fund of a multi-fund manager are predicted by the performance in both the corresponding fund and the other fund he manages. Performance in one fund predicts flows into the other fund more prominently when the fund does particularly well. Nonetheless, investors do not seem to move their capital sufficiently in response to performance in the manager's other fund. As a result, past performance in one fund predicts subsequent performance in the other, in contrast to the equilibrium in Berk and Green (2004). This performance 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.

---

*Author Contact Information: Darwin Choi, Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong, dchoi@ust.hk. C. Bige Kahraman, Stockholm School of Economics and SIFR – The Institute for Financial Research, Drottninggatan 89, 113 60 Stockholm, Sweden, bige.kahraman@sifr.org. Abhiroop Mukherjee, Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong, amukherjee@ust.hk. We thank Nick Barberis, Magnus Dahlquist, William Goetzmann, Jennifer Huang, Jonathan Reuter, Mark Seasholes, Paolo Sodini, Per Stromberg, and seminar participants at SIFR for helpful comments. All errors are our own.

Mutual fund investors chase performance even though it does not seem to persist. Berk and Green (2004) construct a theoretical model to argue that this seemingly puzzling finding can indeed be rational: investors allocate more money to skillful managers; but inflows drive down fund performance, because of diseconomies of scale, to the extent that there is no persistence. However, it is not clear whether individual investors in mutual funds have the required level of sophistication. For example, Bailey, Kumar, and Ng (2010) suggest that trend-chasing appears related to behavioral biases, rather than to rational inferences about managerial skill from past performance. A debate also exists on whether the resulting increase in fund size from flows could erode performance at all, and if it could, whether size increases to the point at which performance does not persist.

In this paper, we utilize a recent development in the mutual fund industry — the emergence of managers who simultaneously manage multiple funds (aka "multi-fund" managers) — to shed new light on the above debates. Berk and Green's (2004) model is difficult to test using the observed performance-chasing behavior as there are different potential explanations for the phenomenon. The advantage of examining multi-fund managers is that we can derive new empirical predictions in the spirit of their model outside the traditional one-fund-one-manager setting; we investigate how investors allocate their capital across different funds of the same manager, as well as whether the allocation into these funds eliminates the manager's performance persistence. By conducting these tests, our paper can provide new evidence on the assumptions made by Berk and Green (2004).

Specifically, we hypothesize that rational investors should learn about a manager's ability by using the past performance not only in the fund they consider to invest in, but also in the other fund he manages.[1] Then we study the cross-fund performance relationship to see if investors allocate their capital "correctly" across funds such that predictability is eliminated, in a manner similar to eliminating persistence in a single-fund setting. The idea behind this test can be understood through a simple example. Consider a manager with two funds, F1 and F2. Suppose investor A is the representative investor in fund F1, and fund F2 outperformed the benchmark. The question is: how much more capital should she allocate to fund F1, knowing the size-performance relationship? Suppose the "right number" is $100,000. If investor A allocates less than $100,000, fund F1 will earn a positive risk-adjusted return since fund F1 will not be "large enough" to erode performance entirely. Similarly, if she allocates more than $100,000, then fund F1 will be "too large" and will have negative risk-adjusted returns subsequently. We therefore test whether performance in one fund is followed by subsequent performance in the other fund that (i) has the same sign (not enough capital allocated), (ii) has a different sign (too much capital allocated), or (iii) is not significantly different from zero (just the right level of capital flows).

Our first main finding is that, consistent with our conjecture, investors indeed make use of the data on manager's past performance in his other fund, i.e., flows into a fund managed by a multi-fund manager is predicted by his performance in both the corresponding fund and the other fund he manages. We take the flow-performance regression specification employed by Sirri and Tufano (1998) and Huang, Wei, and Yan (2007), and to this specification we add the past performance of the manager in his other fund. We find that performance in the other fund predicts flows into a fund, especially when the performance of the multi-fund manager in his other fund has been exceptionally good. If both of the funds by the same manager are performing very well, the effect of the other fund is about half as strong as the fund in question. As a

[1] While most multi-fund managers manage two funds, some manage more than two. Throughout our analysis, we pick two funds with smaller identification number in the dataset (which usually corresponds to older funds) from each multi-fund manager.

robustness check, we also run further tests using two sets of "control funds," i.e., funds that have similar characteristics but not managed by the same manager. First, flows into a multi-fund manager's fund do not respond to the past performance in a control fund that is chosen to be similar to the multi-fund manager's other fund. Next, we match a given fund of a multi-fund manager to a fund of a single-fund manager. A multi-fund manager fund receives more flows than its matching fund when the multi-fund manager's past performance in his other fund is higher, as expected.

However, we find evidence of "under-allocation" from the cross-fund performance relationship: investors do not seem to move enough capital across funds in response to past performance in the manager's other fund. We sort all multi-fund managers into quintiles based on the past performance in one of their funds. We examine managers' performances in their other funds across these quintiles, forming portfolios with holding periods varying from 1 to 12 months. Our results show that the lowest quintile portfolio subsequently earns significantly lower alphas than the highest quintile portfolio. This predictability comes mostly from the lowest-quintile portfolio 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. Existing theoretical models can explain many empirically documented patterns, but as Berk and Tonks (2007) argue, "a test of a theoretical model is not simply its ability to explain facts that are already known. Rather, it should also be able to explain new features in the data — empirical facts that were not known at the time the model was developed." We believe that our setting achieves this. We interpret our findings as broadly consistent with the conjecture in Berk and Green (2004) that performance-chasing behavior is related to learning about managers. Contrary to their prediction, however, we find that capital flows do not respond enough to a manager's overall performance. We acknowledge that the latter result comes with one caveat: we cannot claim that it extends to the usual one-fund-one-manager setting — it is plausible that investors respond to performance in the corresponding fund with the right level of capital flows, but under-allocate when it comes to the other funds managed by their fund manager.

As a test of theoretical models on flow-performance relationship in mutual funds, our work is related to a number of papers. Chen, Hong, Huang, and Kubik (2004), and Pollet and Wilson (2008) provide supporting evidence for Berk and Green in the sense that they find evidence consistent with diseconomies of scale in mutual fund industry. Reuter and Zitzewitz (2011), on the other hand, use a regression discontinuity analysis and find little evidence that size erodes performance. Another paper that finds mixed support for the model is Glode, Hollifield, Kacperczyk, and Kogan (2011). They document that mutual fund returns are persistent after periods of high market returns but not after periods of low market returns. Our paper is also related to Huang, Wei, and Yan (2012), who investigate the relationship between investor learning and the sensitivity of fund flows to performance, and Agarwal and Ma (2011), who also look at multi-fund managers, but ask a different question regarding the effects of managerial multi-tasking in the mutual fund industry.

The remainder of this paper is structured as follows. Section 2 describes the sample of multi-fund managers and the empirical methods. Section 3 presents and discusses 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 4 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. However, while managers' names are provided by CRSP, a large panel of multi-fund managers is not readily available. This is because managers' names in CRSP are not recorded consistently across time and funds: first and middle names are sometimes abbreviated differently and are sometimes excluded. We hand-construct our database of multi-fund managers by tracking all the managers carefully as well as taking into account spelling differences and format changes. We focus on funds that are managed by a single person who manages more than one fund (i.e., we exclude funds that are managed by two or more people). Following Agarwal and Ma (2011), we also exclude cases where a manager runs more than four funds as these managers are likely to be team managed.

We run our analysis using funds with investment objectives of growth and income, growth, and aggressive growth. We identify the fund investment objectives using the investment objective codes from the Thomson-Reuters Mutual Fund Holdings database (formerly known as CDA/Spectrum). To be consistent with recent papers in the literature, among these, we only include funds that have more than half of their assets invested in common stocks. We exclude index (that is, funds that are identified by CRSP as index funds or funds that have the word "index" in their reported fund names) and 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. For qualitative attributes of the funds (e.g. objectives, year of origination), we use the observation of the oldest class. For the TNA under management, we sum the TNAs of all share classes. For the rest of the quantitative attributes (e.g. returns, alphas, expenses), we take the lagged TNA-weighted average of the attributes of all classes, following Kacperczyk, Sialm and Zheng (2007).

Multi-fund managing is a rather contemporary development in the mutual fund industry. Thus, our sample covers from 1992 to 2009. Although new, it is a fairly common practice: The fraction of managers that manage more than one fund in our sample is about 27%, and also these managers seem to manage about 30% of the total assets managed in the domestic equity actively managed mutual funds.[2] Typically, a multi-fund manager manages two or three funds for more than four years.

In our analysis, we pick two funds from each multi-fund manager with smaller identification number (which usually corresponds to older funds) provided by the Mutual Fund Links database.[3] 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. At the end, we have 20,383 fund-month observations in our baseline regression.

2.2 Measures and Empirical Methodology

The dependent variable of our 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).

---

[2] These aggregate numbers are fairly close to the ones reported in Agarwal and Ma (2011) who identify multi-fund managers using a different data source.

[3] We thank Russ Wermers for making this dataset available. For more detailed information on dataset, please see Wermers (2000).

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

Following Huang et al. (2007), we winsorize the top and bottom 2.5 percent tails of the net flow variable to remove errors associated with mutual fund mergers and splits documented by Elton et al. (2001).

We use the four-factor alpha $Alpha_i$ as a measure of fund performance. $Alpha_i$ is the risk-adjusted returns (α_i) in the preceding 12 months estimated using Cahart (1997) four-factor model:

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

To allow for different flow-performance sensitivities at different levels of performance, we follow the specification in Sirri and Tufano (1998).[4] For each month, we assign a fractional performance rank (*Rank*) ranging from 0 (poorest performance) to 1 (best performance) to funds according to their past 12-month four-factor alpha. Then we define three variables according to *Rank*: the lowest performance quintile as *Lowperf_Alpha* = Min(*Rank*, 0.2), the three medium performance quintiles as *Midperf_Alpha* = Min(0.6, *Rank* – *Low*), and the top performance quintile as *Highperf_Alpha* = *Rank* – *Mid* – *Low*.

In our 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

[4] The "convexity" of the flow-performance relationship is a well-documented empirical fact (e.g., Chevailier and Elison (1997)) that motivates this choice of specification in our regression.

funds of a multi-fund manager, *Flow* (the subscript *it* is dropped for brevity). Our main coefficient of interest is the lagged performance in the other fund (*Lowperf_Alpha2*, *Midperf_Alpha2*, and *Highperf_Alpha2*) of the same manager, while we control for the lagged performance in the same fund (*Lowperf_Alpha*, *Midperf_Alpha*, and *Highperf_Alpha*). We also include a number of control variables in our analysis. To this end, we include a measure of fund age (*ln(Fund Age)*) calculated by the natural logarithm of (1 + fund age) and its interaction with *Alpha*, lagged fund size (*ln(Fund Size)*) measured by the natural logarithm of fund TNA, lagged total expense (*Average Total 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 (*Standard Deviation*) and its interaction with *Alpha*, the total flows into the corresponding objective of the fund (*Objective Flows*), and finally month fixed effects. Our baseline regression specification is as follows:

$$\begin{aligned}
Flow = {} & \alpha + \beta_1 Lowperf_Alpha + \beta_2 Midperf_Alpha + \beta_3 Highperf_Alpha \\
& + \beta_4 Lowperf_Alpha2 + \beta_5 Midperf_Alpha2 + \beta_6 Highperf_Alpha2 \\
& + \beta_5 \ln(Fund\ Age) + \beta_6 Alpha * \ln(Fund\ Age) + \beta_7 \ln(Fund\ Size) \\
& + \beta_8 Average\ Total\ Expense + \beta_9 Standard\ Deviation \\
& + \beta_{10} Alpha * Standard\ Deviation + \beta_{11} Objective\ Flows \\
& + \textstyle\sum_{Dec2009}^{Feb1992} \beta_t Month\ Fixed\ Effects_t + \varepsilon \qquad (1)
\end{aligned}$$

We include both funds of a multi-fund manager in most of our analyses. 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." We address concerns regarding correlations between error terms by clustering the standard errors in the regressions at the manager-level. We also include past flows, as well as manager fixed effects in some specifications.[5]

We also address concerns that investors are not sophisticated enough to calculate excess fund returns as implied by our use of alphas in (1), and use style-adjusted returns instead of alphas in an alternative specification. The style-adjusted return is calculated as the average monthly return for the fund, in excess of the average return on all funds in the same CRSP investment objective code. The regression equation for this alternative specification is:

$$
\begin{aligned}
Flow = {} & \alpha + \beta_1 Lowperf\_adj\_ret + \beta_2 Midperf\_adj\_ret + \beta_3 Highperf\_adj\_ret \\
& + \beta_4 Lowperf\_adj\_ret2 + \beta_5 Midperf\_adj\_ret2 + \beta_6 Highperf\_adj\_ret2 \\
& + \beta_5 \ln(Fund\ Age) + \beta_6 adj\_ret * \ln(Fund\ Age) + \beta_7 \ln(Fund\ Size) \\
& + \beta_8 Average\ Total\ Expense + \beta_9 Standard\ Deviation \\
& + \beta_{10} Alpha * Standard\ Deviation + \beta_{11} Objective\ Flows \\
& + \sum_{Dec2009}^{Feb1992} \beta_t Month\ Fixed\ Effects_t + \varepsilon
\end{aligned}
\tag{2}
$$

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). We report summary

[5] Monthly flows are predicted by fund performance in the preceding 12 months 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 the monthly flows, we control for flows in the preceding 6 months. We also control for manager fixed effects in 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).

statistics on fund flow, TNA, performance and risk measures, age, total expenses 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: the average flows into these two types of funds are slightly higher for multi-funds (0.85% per month vs. 0.21% for single-fund managers' funds), average alphas are similar (at around -3 bps per month), average fund age and size are similar (about 15 years and $1 billion, respectively), and the average total expense for both types is about 1.6% per year. The most prominent difference is observed in the size of the fund families: multi-fund managers seem to be more employed by fund families that are bigger in size ($24 billion vs. $13 billion).

3. Results

In this section, we first present the empirical results of the regressions in equations (1) and (2) in Section 3.1. After showing that flows into a fund can be predicted by the lagged performance in the other fund from the same manager, Section 3.2 conducts some robustness tests that make use of a set of control funds, matching on characteristics that matter for flows. These tests aim to confirm that our results are not picking up market- or industry-wide effects that affect mutual fund flows generally. Section 3.3 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.

3.1 Flow-Performance Relationship in Multi-funds

Table 2 shows the results of our regression (1). The coefficients of *Lowperf_Alpha*, *Midperf_Alpha*, and *Highperf_Alpha* capture the flow-performance relationship in a piecewise linear regression fashion. As defined in Section 2.2, *Lowperf_Alpha* represents the lowest quintile in performance, *Midperf_Alpha* represents the middle three quintiles, while *Highperf_Alpha* is the highest. We obtain similar results as previous studies: flows into a fund are positively related to past 12-month alphas of that fund in all of *Lowperf_Alpha*, *Midperf_Alpha*, and *Highperf_Alpha*, with the strongest effect observed among the highest performing quintile.

Our first main finding comes from the corresponding variables of the performance in the other fund, *Lowperf_Alpha2*, *Midperf_Alpha2*, and *Highperf_Alpha2*. Note that in the first column, *Lowperf_Alpha2* and *Highperf_Alpha2* are significant (*Midperf_Alpha2* is not), suggesting that investors pay attention and respond to another fund's performance, particularly when it is in the lowest or the top quintile. This is broadly consistent with Berk and Green's (2004) framework, where investors rationally learn about the skills of mutual fund managers from past performance. To the extent that mutual fund managers' skills are entirely not fund-specific (as documented by Baks (2003)), information from the other fund can help reveal managers' ability and investors should learn from this extra signal.[6]

The next two columns run the same regressions, but adding past flows as an extra control variable (in column (2)), as well as manager fixed effects (in column (3)). The results are similar but weaker: in particular, the coefficient of *Lowperf_Alpha2* becomes statistically insignificant,

[6] In unreported tests, we also find evidence that multi-fund managers' ability is not entirely fund-specific. Results are available upon request. Another concern is that the performance of the two funds is very similar. However, since we include in the regression the performance of the fund in question (*Alpha*), we interpret the significance in the coefficients of *Alpha2* as additional explanatory power.

but *Highperf_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. If we examine the magnitude of the effect, the coefficient of *Highperf_Alpha2* is approximately one-half of that of *Highperf_Alpha* (i.e., when the fund in question is in the top quintile) in all three columns. As such, if both of the 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 about half as strong as the fund in question.

As a robustness check, we repeat the regressions using style-adjusted returns instead of past 12-month 4-factor alphas as the performance measure.[7] The style-adjusted return is the past 12-month return on a fund in excess of the past 12-month returns on all funds in the same investment objective code. The results are reported in Table 3. Similar to Table 2, flows respond to past performance in the fund in question, as well as the other fund that the manager manages. The relationship is stronger when the performance in the other fund is in the top quintile.

3.2 Comparison: A Placebo Test Using Matching Funds Not Managed by the Same Manager

While our regressions control for many fund characteristics that are known to predict flows, there could be other market-wide events or factors impacting funds with similar characteristics. We now provide additional evidence with two sets of control funds. Let F1 be the fund in question and F2 be the other fund.[8] We then find two control funds, M1 and M2, to

[7] The results in all tables are robust to using style-adjusted returns or past 24-month four-factor alphas as our performance measure. To preserve space, we only report some of these robustness tests.

[8] As stated in Section 2.2, we use both funds of the manager in the analysis. So a particular fund is F1 in one observation and F2 in another.

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).[9]

We use the same algorithm across all the analyses. In particular, we simply find a match for each multi-fund manager's fund from the universe of single-manager funds (within the same investment objective and month) that has the most similar characteristics included in the baseline flow-performance regression (Table 2, column 1). For M1, we match with F1 on *Alpha*, *ln(Fund Age), ln(Fund Size)*, *Standard Deviation*, and *Average Total 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 4 repeats the regressions in Table 2, replacing *Alpha2* (i.e., four-factor alpha of F2) with *Alpha Matching 2* (i.e., four-factor alpha of M2). We consider this as a "placebo" test: 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 *Lowperf_Alpha Matching 2*, *Midperf_Alpha Matching 2*, and *Highperf_Alpha Matching 2* is statistically significant. The magnitude of *Highperf_Alpha Matching 2* is also much smaller than that of *Highperf_Alpha2* in Table 2.

3.3 Non-parametric Tests Based on Flows into Characteristic-matched Funds

We now use M1 to further examine the 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 measure

[9] We follow a dependent sort, similar to other papers. Yet, one difference in our approach is that, we seek for a sequence of dependent sort procedure that is the "nearest" in the sense that the given sequence minimizes the differences between the pairs. Such flexibility comes with an improvement in the matching performance.

captures the flows into F1 of this particular manager, on top of a similar fund M1. Panel A of Table 5 presents a univariate sort of the *Difference in Flows* (F1-M1) on *Alpha* of F2.[10] This test 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. We observe a nearly monotonic relationship across the quintiles, consistent with our previous results. That is, investors respond to *Alpha* of F2 in deciding how much to invest in F1, controlling for other characteristics. As in Table 2, the results are more prominent among the high-performers. When we compare the magnitude, the difference in flows is 1.02% per month in quintile 5 (the highest group), while the difference in flows is -0.55% per month in quintile 1. Panels B and C show the same sorts when *Alpha* of F2 is in the bottom three quintiles (bottom 60%) and in the top three quintiles (top 60%), respectively. In both cases we observe nearly monotonic relationships.[11]

Table 6 conducts another "placebo" test, similar to Table 4. We repeat the univariate sorts in Table 5, but instead of sorting on *Alpha* of F2, we sort on *Alpha* of the control fund M2. Again, the results further confirm that investors respond to past performance in F2 but not M2. In Panels A to C, we do not observe any monotonic relationship in the difference in flows, and the fifth quintile minus first quintile difference is not significant.

We have so far established evidence regarding one component in Berk and Green's (2004) framework, where investors chase performance in a multi-fund manager setting. In the next subsection, we turn to another component, whether investors move "enough" capital across funds in a manner that is consistent with Berk and Green (2004).

---

[10] The t-stats in the analyses with portfolio sorts (Tables 5-8) are based on White standard errors. The statistical significance we observe remains unchanged if we use Newey-West standard errors instead.

[11] The results hold for different cut-offs as well.

3.4 Relationship between Past Performance in One Fund and Future Performance in the Other

We are interested in whether there is any cross-fund 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 into the first fund (so that it is "too small") in response to good 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 positive). A similar argument applies to cases where investors move too little capital out of the first fund when the second fund performs poorly (both performance measures will be negative), or 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.

The cross-fund performance predictability 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 predictability across the manager's two funds if investors allocate capital competitively.

To test our hypothesis, we form portfolios using the first fund of the manager. We sort all the first funds into quintiles, based on the past 12-month alpha of the second fund of the manager. Unlike the previous analyses, each manager-month is regarded as one observation to avoid double counting. We consider the fund with the larger identification number (WFICN) as the first fund, and the fund with the smaller identification number as the second fund. Specifically, 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 first 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.[12]

Table 7 shows the portfolio alphas. Panel A sorts first funds on after-fee *Alpha* of the second fund, and Panel B sorts on before-fee *Alpha* of the second 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 20-31 bps per month.

Table 8 repeats the analysis using style-adjusted return of the second fund in the sorting, instead of past 12-month alpha. The results are similar (and somewhat stronger): the monotonic relationship is still observed and the long-short portfolio (5 minus 1) earns an alpha of between 30 and 67 bps per month.

We interpret the findings as follows: while there is generally under-allocation (i.e., investors do not move capital "enough") such that there is a positive relationship in the quintiles, the under-allocation 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. This is broadly consistent with our

[12] Our results hold if we reverse the ordering of the first and second funds, or if we calculate portfolio alphas using a five-factor model (which includes Pastor and Stambaugh (2003) Liquidity factor).

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.

4. Conclusion

In this paper we use a recent development — that of mutual fund managers who manage more than one fund — to provide new evidence on the predictions of a theoretical model that seeks to explain performance-chasing behavior in mutual funds.

We first test the key conjecture in Berk and Green (2004) that investors rationally use the information on their manager's past performance while deciding upon the amount of money they want to invest in a fund. The advantage of our setting in testing this conjecture is that 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 as the theory models would predict? 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 in the other fund is particularly good, consistent with a strategy in which 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 "correctly," as described in Berk and Green (2004). Under the null hypothesis that increase in fund size erodes fund performance, we suggest a simple test by examining whether past performance in one fund of a multi-fund manager predicts his subsequent performance in his other fund. If investors understand the size-performance relationship and take into account the manager's performance in both his funds, they would allocate exactly the right amount of capital into each and every fund in question. And, thus, there would be no predictability in performance. However, we find evidence of under-allocation; in particular, investors do not seem to withdraw enough capital in response to poor performance in the manager's other fund.

Overall, this paper contributes to our understanding of performance-chasing behavior in mutual funds by subjecting the existing theoretical explanations to a stringent test — asking whether Berk and Green's (2004) model is able to explain the empirical facts that were not known at the time it was developed. Our evidence shows mixed results. Certain predictions from the models are borne out in the data, while further work is needed to understand other aspects that we do not find support for.

References

Agarwal, V., Ma, L., 2011. Managerial Multitasking in the Mutual Fund Industry. Working Paper, Georgia State University.

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, Emory University.

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

Berk, J. B., I. Tonks, 2007. Return Persistence and Fund Flows in the Worst Performing Mutual Funds. Working Paper, University of California, Berkeley.

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

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

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

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.

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

Elton, E. J., M. J. Gruber, C. R. Blake, 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.

Glode, V., Hollifield, B., Kacperczyk, M., Kogan, S., 2011, Time-Varying Predictability in Mutual Fund Returns, Working Paper, NBER.

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

Hortacsu, A., C. Syverson, 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., K. D. Wei, H. Yan, 2007. Participation Costs and the Sensitivity of Fund Flows to Past Performance. Journal of Finance 62, 1273–1311.

Huang, J., K. D. Wei, H. Yan, 2012. Investor Learning and Mutual Fund Flows. Working Paper, University of Texas at Austin.

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

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

Pastor, L., R. F. Stambaugh, 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., E. Zitzewitz, 2010. How Much Does Size Erode Mutual Fund Performance? A Regression Discontinuity Approach, Working Paper, NBER.

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

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

This table presents the 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. *Average Total 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.

Panel A. Multi-Fund Managers' Funds

	Mean	Median	Standard Deviation	25th Percentile	75th Percentile
Flow (%)	0.854	-0.164	4.889	-1.420	1.790
Alpha (%)	-0.036	-0.058	0.892	-0.457	0.335
Standard Deviation (%)	4.946	4.411	2.695	3.018	6.189
Fund Age (years)	14.365	10	15.470	5	17
Fund Size ($ millions)	919.151	227.384	2430.890	61.596	793.512
Average Total Expense (%)	1.648	1.521	1.674	1.080	1.971
Family Size ($ millions)	23899.490	2645.000	84569.780	353.400	11299.600

Panel B. Single-Fund Managers' Funds

	Mean	Median	Standard Deviation	25th Percentile	75th Percentile
Flow (%)	0.210	-0.343	3.933	-1.502	1.126
Alpha (%)	-0.024	-0.052	0.821	-0.527	0.218
Standard Deviation (%)	5.010	4.295	3.078	3.158	5.755
Fund Age (years)	16.605	12	14.765	7	20
Fund Size ($ millions)	1536.770	261.800	5778.120	70.200	944.900
Average Total Expense (%)	1.572	1.492	1.193	1.070	1.957
Family Size ($ millions)	13354.810	520.200	65941.180	19.400	4780.800

Table 2
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 *Lowperf* = Min(*Rank*, 0.2), the three medium performance quintiles as *Midperf* = Min(0.6, *Rank* - *Low*), and the top performance quintile as *Highperf* = *Rank* - *Mid* - *Low*.

Other control variables include: *ln(Fund Age)*, calculated by the natural logarithm of (1+Fund Age) and its interaction with *Alpha*; *ln(Fund Size)*, measured by the natural logarithm of lagged fund TNA; *Average Total 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 and its interaction with *Alpha*; *Objective Flows*, the total flows into the corresponding objective of the fund, and 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)	
		t-stat		**t-stat**		**t-stat**
Intercept	-0.0129*	(-1.70)	-0.0074	(-1.50)	0.0054	(1.19)
Lowperf_Alpha	0.0581***	(4.80)	0.0127*	(1.94)	0.0070	(0.90)
Midperf_Alpha	0.0259***	(7.33)	0.0100***	(5.72)	0.0113***	(5.51)
Highperf_Alpha	0.124***	(5.80)	0.0348***	(3.66)	0.0387***	(3.26)
Lowperf_Alpha2	0.0257**	(2.09)	0.0076	(1.12)	0.0017	(0.21)
Midperf_Alpha2	-0.0047	(-1.61)	-0.0021	(-1.24)	-0.0024	(-1.27)
Highperf_Alpha2	0.0400**	(2.21)	0.0162*	(1.89)	0.0199**	(2.18)
ln(Fund Age)	-0.0075***	(-7.17)	-0.0009**	(-2.49)	-0.0006	(-0.84)
Alpha*ln(Fund Age)	-0.0178***	(-3.57)	-0.0047**	(-2.38)	-0.0047*	(-1.95)
ln(Fund Size)	0.0017***	(3.55)	-0.0004**	(-2.08)	-0.0020***	(-4.24)
Average Total Expense	0.3286**	(2.21)	0.0384	(0.69)	-0.1081	(-0.93)
Standard Deviation	-0.0888**	(-2.32)	-0.0465***	(-3.09)	0.0211	(0.88)
Alpha*Standard Deviation	2.5200*	(1.73)	1.4211**	(2.03)	2.3131**	(2.32)
Objective Flows	0.0006*	(1.67)	0.0002*	(1.81)	0.0014***	(10.19)
Past Flows	No		Yes		Yes	
Manager Fixed Effects	No		No		Yes	
Month Fixed Effects	Yes		Yes		Yes	
R-squared	0.139		0.365		0.374	

Table 3
Flow-Performance Regression in Multi-Funds (Using Style-Adjusted Returns)

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). *Style Adj Return* and *Style Adj Return2* are the style-adjusted returns, respectively, of the fund in question and of 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 *Style Adj Return* and *Style Adj Return2*. Then we define three variables according to the rank: the lowest performance quintile as *Lowperf* = Min(*Rank*, 0.2), the three medium performance quintiles as *Midperf* = Min(0.6, *Rank - Low*), and the top performance quintile as *Highperf* = *Rank - Mid - Low*.

Other control variables include: *ln(Fund Age)*, calculated by the natural logarithm of (1+Fund Age) and its interaction with *Style Adj Return*; *ln(Fund Size)*, measured by the natural logarithm of lagged fund TNA; *Average Total 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 and its interaction with *Style Adj Return*; *Objective Flows*, the total flows into the corresponding objective of the fund, and 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)	
		t-stat		**t-stat**		**t-stat**
Intercept	-0.0112*	(-1.68)	-0.0090**	(-2.21)	-0.0014	(-0.53)
Lowperf_Style Adj Return	0.0514***	(4.45)	0.0188***	(2.62)	0.0188**	(2.37)
Midperf_Style Adj Return	0.0386***	(10.55)	0.0170***	(9.14)	0.0200***	(9.72)
Highperf_Style Adj Return	0.1381***	(6.69)	0.0504***	(4.80)	0.0653***	(5.29)
Lowperf_Style Adj Return2	0.0214**	(2.14)	0.0081	(1.46)	-0.0029	(-0.41)
Midperf_Style Adj Return2	0.0001	(0.03)	0.0006	(0.43)	-0.0005	(-0.30)
Highperf_Style Adj Return2	0.0438***	(2.59)	0.0165*	(1.91)	0.0307***	(2.93)
ln(Fund Age)	-0.0066***	(-6.86)	-0.0014***	(-3.81)	-0.0005	(-0.69)
Style Adj Return*ln(Fund Age)	-0.0120***	(-2.62)	-0.0039	(-1.61)	-0.0070***	(-2.96)
ln(Fund Size)	0.0005	(1.34)	-0.0005***	(-2.82)	-0.0022***	(-4.53)
Average Total Expense	0.2123***	(7.16)	0.0799***	(7.35)	0.0997***	(8.36)
Standard Deviation	-0.0634*	(-1.70)	-0.0321*	(-1.76)	0.0287	(1.22)
Style Adj Return*Standard Deviation	-0.0814	(-0.07)	-0.1798	(-0.29)	0.4796	(0.71)
Objective Flows	0.0007**	(2.25)	0.0004***	(2.66)	0.0015***	(8.88)
Past Flows	No		Yes		Yes	
Manager Fixed Effects	No		No		Yes	
Month Fixed Effects	Yes		Yes		Yes	
R-squared	0.169		0.340		0.354	

Table 4
Comparison: Flow-Performance Regression Using Matching Funds

This table presents the results of the flow-performance regressions using matching funds. 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 *Alpha Matching 2* are the risk-adjusted returns, respectively, of the fund in question and of a control fund (M2) in the preceding 12 months estimated using Carhart (1997) four-factor model. 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* and *Alpha Matching 2*. Then we define three variables according to the rank: the lowest performance quintile as *Lowperf* = Min(*Rank*, 0.2), the three medium performance quintiles as *Midperf* = Min(0.6, *Rank* - *Low*), and the top performance quintile as *Highperf* = *Rank* - *Mid* - *Low*.

Other control variables include: *ln(Fund Age)*, calculated by the natural logarithm of (1+Fund Age) and its interaction with *Alpha*; *ln(Fund Size)*, measured by the natural logarithm of lagged fund TNA; *Average Total 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 and its interaction with *Alpha*; *Objective Flows*, the total flows into the corresponding objective of the fund, and 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)	
		t-stat		**t-stat**		**t-stat**
Intercept	0.0043	(0.57)	0.0133***	(2.75)	-0.0081**	(-2.51)
Lowperf_Alpha	0.0431***	(3.59)	0.0021	(0.23)	-0.0002	(-0.02)
Midperf_Alpha	0.0229***	(10.33)	0.0103***	(5.71)	0.0091***	(5.17)
Highperf_Alpha	0.0982***	(6.48)	0.0374***	(3.58)	0.0352***	(3.09)
Lowperf_Alpha Matching 2	0.0070	(0.91)	0.0017	(0.25)	0.0030	(0.39)
Midperf_Alpha Matching 2	-0.0028	(-1.36)	-0.0019	(-1.19)	-0.0027	(-1.58)
Highperf_Alpha Matching 2	-0.0053	(-0.54)	0.0011	(0.16)	0.0022	(0.26)
ln(Fund Age)	-0.0061***	(-9.93)	-0.0011**	(-2.53)	-0.0007	(-1.10)
Alpha*ln(Fund Age)	-0.0108***	(-2.76)	-0.0042*	(-1.75)	-0.0007	(-0.30)
ln(Fund Size)	0.0009***	(3.56)	-0.0004*	(-1.72)	-0.0002	(-0.98)
Average Total Expense	0.0459	(0.69)	-0.0732	(-1.53)	-0.0888*	(-1.88)
Standard Deviation	-0.0467**	(-1.97)	-0.0247	(-1.47)	0.0021	(0.13)
Alpha*Standard Deviation	0.6311	(0.64)	-0.3739	(-0.54)	-0.0326	(-0.05)
Objective Flows	0.0004***	(3.34)	0.0002**	(2.17)	0.0007***	(9.68)
Past Flows	No		Yes		Yes	
Manager Fixed Effects	No		No		Yes	
Month Fixed Effects	Yes		Yes		Yes	
R-squared	0.113		0.319		0.322	

Table 5

Flows Into A Fund (Over the Matching Fund), Sorted By Performance in the Other Fund the Manager Manages

This table presents a univariate sort of *Difference in Flows* into quintiles, based on *Alpha* of Fund 2. *Difference in Flows* is the *Flow* into Fund 1 (the fund in question) minus the *Flow* into a control fund (M1). The control fund (M1) is a fund that has similar characteristics as the fund in question. Fund 2 is the other fund managed by the same manager. *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. Panel A shows the results using the whole sample. Panels B and C show the results when *Alpha* of Fund 2 is in the lower 60% and upper 60%, respectively. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

Difference in Flows (%) (Fund 1 minus Matching)

Panel A: Main Result

Quintiles Sorted by Alpha of Fund 2	Mean	t-stat	p-value
1 (Lowest)	-0.554**	(-2.44)	0.021
2	-0.046	(-0.25)	0.803
3	0.393*	(1.78)	0.085
4	0.385	(1.67)	0.104
5 (Highest)	1.021***	(3.72)	0.001
5-1	1.574***	(4.11)	0.000

Difference in Flows (%) (Fund 1 minus Matching)

Panel B: Alpha of Fund 2 is Low

Quintiles Sorted by Alpha of Fund 2	Mean	t-stat	p-value
1 (Lowest)	-0.432	(-1.38)	0.177
2	-0.564**	(-2.13)	0.041
3	-0.142	(-0.49)	0.629
4	0.231	(0.97)	0.340
5 (Highest)	0.502*	(2.02)	0.052
5-1	0.933**	(2.29)	0.029

Difference in Flows (%) (Fund 1 minus Matching)

Panel B: Alpha of Fund 2 is High

Quintiles Sorted by Alpha of Fund 2	Mean	t-stat	p-value
1 (Lowest)	0.399	(1.05)	0.301
2	0.291	(0.81)	0.423
3	1.083***	(2.96)	0.006
4	1.554***	(4.53)	<.0001
5 (Highest)	1.989***	(4.18)	0.000
5-1	1.590**	(2.56)	0.015

Table 6

Comparison: Flows Into A Fund (Over the Matching Fund), Sorted By Performance in Another Matching Fund

This table presents a univariate sort of *Difference in Flows* into quintiles, based on *Alpha* of Matching Fund 2 (M2). *Difference in Flows* is the *Flow* into Fund 1 (the fund in question) minus the *Flow* into a control fund (M1). The control fund (M1) is a fund that has similar characteristics as the fund in question. Matching Fund 2 (M2) is a fund that has similar characteristics as the other fund managed by the same manager. *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. Panel A shows the results using the whole sample. Panels B and C show the results when *Alpha* of Fund 2 is in the lower 60% and upper 60%, respectively. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

Difference in Flows (%) (Fund 1 minus Matching)

Panel A: Main Result

Quintiles Sorted by Alpha of Matching Fund 2	Mean	t-stat	p-value
1 (Lowest)	-0.489	(-1.42)	0.164
2	0.312	(0.88)	0.384
3	-0.319	(-1.27)	0.214
4	0.232	(0.63)	0.535
5 (Highest)	-0.068	(-0.21)	0.833
5-1	0.421	(0.80)	0.429

Difference in Flows (%) (Fund 1 minus Matching)

Panel B: Alpha of Matching Fund 2 is Low

Quintiles Sorted by Alpha of Matching Fund 2	Mean	t-stat	p-value
1 (Lowest)	-0.443	(-1.22)	0.230
2	-0.415	(-1.33)	0.192
3	0.061	(0.20)	0.845
4	0.309	(0.98)	0.337
5 (Highest)	-0.543	(-1.45)	0.158
5-1	-0.100	(-0.17)	0.865

Difference in Flows (%) (Fund 1 minus Matching)

Panel B: Alpha of Matching Fund 2 is High

Quintiles Sorted by Alpha of Matching Fund 2	Mean	t-stat	p-value
1 (Lowest)	2.043	(1.44)	0.161
2	0.829	(1.30)	0.203
3	0.509	(0.74)	0.467
4	0.172	(0.30)	0.769
5 (Highest)	1.340	(1.58)	0.126
5-1	-0.703	(-0.28)	0.779

Table 7

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

Portfolios are formed using the first fund of the manager. We sort all the first funds into quintiles, based on the past 12-month Carhart (1997) alpha of the second fund of the manager. Panel A sorts first funds on after-fee alpha of the second fund, and Panel B sorts on before-fee alpha of the second 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 first 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 fund with the larger identification number (WFICN) is defined the first fund, and the fund with the smaller identification number is defined as 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)	-0.23**	(-2.32)	-0.24**	(-2.55)	-0.20**	(-2.24)	-0.15*	(-1.78)
2	-0.10	(-1.35)	-0.10	(-1.57)	-0.16***	(-2.71)	-0.15***	(-2.57)
3	-0.10	(-1.54)	-0.10	(-1.64)	-0.09	(-1.59)	-0.07	(-1.20)
4	-0.06	(-0.83)	-0.08	(-1.21)	-0.05	(-0.70)	-0.09	(-1.48)
5 (Highest)	0.04	(0.47)	0.07	(0.80)	0.07	(0.85)	0.06	(0.79)
5-1	0.27**	(2.24)	0.31***	(2.74)	0.27***	(2.59)	0.21**	(2.21)

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)	-0.23**	(-2.35)	-0.24**	(-2.52)	-0.21**	(-2.35)	-0.14*	(-1.66)
2	-0.11	(-1.51)	-0.11*	(-1.72)	-0.16***	(-2.61)	-0.15***	(-2.67)
3	-0.08	(-1.23)	-0.11*	(-1.76)	-0.09	(-1.58)	-0.07	(-1.24)
4	-0.06	(-0.82)	-0.07	(-0.94)	-0.05	(-0.80)	-0.09	(-1.32)
5 (Highest)	0.03	(0.37)	0.06	(0.74)	0.08	(1.01)	0.06	(0.70)
5-1	0.26**	(2.19)	0.30***	(2.70)	0.29***	(2.81)	0.20**	(2.06)

Table 8

Portfolios Formed Based on Past Performance in the Other Fund the Manager Manages (Using Style-Adjusted Returns)

Portfolios are formed using the first fund of the manager. We sort all the first funds into quintiles, based on the style-adjusted return of the second fund of the manager. 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 first 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 fund with the larger identification number (WFICN) is defined the first fund, and the fund with the smaller identification number is defined as the second fund. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

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)	-0.46***	(-3.68)	-0.40***	(-3.07)	-0.41***	(-3.11)	-0.38***	(-2.94)
2	-0.20***	(-2.80)	-0.19**	(-2.56)	-0.15**	(-2.10)	-0.10	(-1.51)
3	-0.09	(-1.32)	-0.11	(-1.45)	-0.08	(-1.16)	-0.07	(-1.02)
4	-0.03	(-0.45)	-0.08	(-1.14)	-0.07	(-1.14)	-0.10	(-1.63)
5 (Highest)	0.21**	(1.96)	0.08	(0.75)	-0.01	(-0.08)	-0.08	(-0.86)
5-1	0.67***	(3.81)	0.48***	(2.78)	0.41**	(2.56)	0.30**	(2.07)